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Deepika Koundal · Deepak Kumar Jain · Yanhui Guo · Amira S. Ashour · Atef Zaguia *Editors*

Data Analysis for Neurodegenerative Disorders

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Data Analysis for Neurodegenerative Disorders

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Preface

The aim of **this book** is to explore the challenges of handling the medical big data in diagnosis of neurological disorders. **The book** discusses how to optimize or even reduce the number of neuropsychological tests which are used to classify neurological disorders by using feature selection algorithms and to develop and validate an accurate classification model based on the diagnostic information of enrolled subjects. **This book** includes the definitions/different models and their applications in different signal/image processing of neurological disorders' data. An extensive discussion for the possibility of prolonging the abilities of the AI systems using the different data analyses is included. **The volume** recollects several applicable basic preliminaries of the different AI networks and models along with highlighting the basic processes in image processing of different neurological disorders' cases. **This book** also reports several applications to image processing and involves numerous topics related to the role of the big data analysis to address signal and image processing in different real-life scenarios of the neurological disorders. **This cutting-edge book** highlights the analysis of the medical data and its novel procedures and challenges to handle neurological signals and image. It supports engineers, researchers, and software developers to understand the concepts and different models of the AI and data analysis. **This book** will play a pivotal role in laying the foundation of related domain and will help readers to construct a holistic understanding about the subject. **Three key features will be provided by the book:**

- **This book includes** outstanding concepts and models of the AI in clinical applications of neurological disorders with clear description of the image representation, feature extraction, and selection.
- **This book highlights** the different techniques of the AI and big data with the measurement of different metrics to evaluate the performance of the proposed CAD systems for the diagnosis of the neurological disorders.

- **This book contains** different signal and image processing methods for efficient decision support systems. The soft computing, machine learning, and the optimization algorithms are also involved to improve the different CAD systems.

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Overview of Neurodegenerative Disorders

Overview of Neurodegenerative Disorders

Shanoo Sharma, Tannu Priya, Neelam Goel, Dharambir Kashyap, and Vivek Kumar Garg

Abstract Neurodegenerative disorders (NDDs) place a significant medical and public health burden on people all over the world. Three important NDDs are Alzheimer's disease (AD), Parkinson's disease (PD), amyotrophic lateral sclerosis (ALS), spinocerebellar ataxia (SCA), epilepsy, Lewy body disease, Huntington's Disorder (HD), and cerebral aneurysm. The number of cases is anticipated to keep increasing in the near future as life expectancies in many nations rise, as the prevalence and incidence of many diseases dramatically increase with age. With a few notable exceptions, it is difficult to determine how genetic and environmental factors interact causally. While identifying high-risk genes for familial NDDs, classifying disease prognostic factors, determining common genetic variants that may predict susceptibility to non-familial forms of these diseases, and quantifying environmental exposures have all been accomplished using molecular epidemiology approaches. Brief overviews of the epidemiologic features of PD, AD, ALS, SCA, epilepsy, Lewy body disease, HD, and cerebral aneurysm, are provided in this chapter, can help in diagnosis of underlying disease and their associated risk factors, potentially improving medical care and, in the end, illness prevention.

Keywords Amyotrophic lateral sclerosis (ALS) · Neurodegenerative disorders · Parkinson's disease · Alzheimer's disease

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1 Introduction

Neurological disorders affect millions of people globally [1]. Progressive disorder of synapses, neuron, glial cells and their networks are the characteristics of neurodegenerative diseases (NDDs). The accumulation of physiochemically altered alternatives of physiological proteins in the nervous system is a critical element of NDDs. Significantly, neurons as well as glial cells collect these pathological proteins [2]. NDDs represent a serious health risk to humans. Certain age-related illnesses are becoming more widespread, in part due to the large increase in the population of the elderly [3].

Alzheimer's disease (AD), spinocerebellar ataxias (SCA), Huntington's disease (HD), amyotrophic lateral sclerosis (ALS), and Parkinson's disease (PD), epilepsy, cerebral aneurysm, and Lewy body disease are the examples of neurodegenerative diseases. The pathophysiology among these disorders differs, a few affecting memory and cerebral impairments and others factors that affect a person's ability to move, speak, and respire [4–7].

Despite the fact that age is the single most important risk factor for the development of all NDs, current studies have shown that a person's genetic make-up in addition to environmental factors might increase their risk for NDDs [8]. AD, PD, and ALS, among others, are incessantly progressive and evenly potentially lethal neurological diseases distinguished by irretrievable neuron loss and gliosis. Although dementia occurrence as a proportion of the aged has reduced in developed countries, the overall incidence of dementia is rising as the population ages [9]. External factors, nutrient deficiencies, genetic factors, infectious diseases, lifestyle-related causes, and physical injuries can all contribute to the above-mentioned disorders [10].

A physiological protein's structural conformation variations, results in impaired function or neurotoxic extra or intracellular formation. Mutations in the encoding genes have been related to inherited diseases. Molecular pathological, biochemical, and hereditary studies resulted in the reclassification of several dysfunction, along with the opening of totally different avenues for biomarker development or targeted therapies [11].

2 Neurodegenerative Disorders (NDDs)

2.1 Alzheimer's Disease

The most severe group of neurological disorders, AD accounts for over two-thirds of dementia cases in individuals with 65 years of age and older [10, 12, 13]. According to WHO, research estimates that 50 million individuals worldwide have some form of dementia, with AD responsible for 60–70% of those occurrences [14]. Around 5.8 million Americans already suffer with Alzheimer's disease, and by the middle of the next century, that figure is predicted to reach 13.8 million [15]. The development

of amyloid plaques formed of aggregated amyloid beta (Ab), neurofibrillary tangles, which are intracellular collections of hyperphosphorylated tau protein, and brain atrophy brought on by the loss of synapses and neurons are all made possible by a pathological explanation of AD [16]. Basically two neuropathological features of AD are (i) extracellular plaques made of the 40–42 residue Aβ peptide and (ii) neurofibrillary tangles, which are constituted of abnormally phosphorylated Tau protein [17, 18]. More and more data suggests that Aβ peptides build up inside neurons in addition to the parenchyma's well-known amyloid plaques accumulation [19]. To explain this complex condition, a number of ideas have been proposed, including the cholinergic theory, the inflammatory hypothesis, the tau hypothesis, and the Ab hypothesis [20]. According to the tau hypothesis, abnormally high levels of tau phosphorylation cause adult tau to transform into PHF-tau (paired helical filament) and neurofibrillary tangles [21]. In the pathological condition, tau is more frequently hyperphosphorylated, which causes protein denaturation and ultimately disrupts with cytoplasmic function and axonal transport, perhaps leading to apoptosis [10]. Therapeutic strategies for AD concentrate on lowering levels of Aβ oligomers and phosphorylated tau, minimizing OS, and maintaining epigenetic alterations [22, 23]. The majority of anti-AD medications use components with neuroprotective, anti-inflammatory, and antioxidant characteristics [24, 25].

2.2 Parkinson's Disease

PD is one of the diseases, which is related to brain. This disease is related to aging, which causes impairment in the various regions of the brain. This disease can cause seizures, balancing problems while standing, slow movements of limbs, tremors etc. This can be inherited or can be caused in humans due to unknown reasons [26]. This type of disease has no cure but there are different treatments available to control its effect on to the body. This disease affects basal ganglia of brain. As this specific area starts deteriorating, the person starts losing abilities to perform normal functions [27]. In normal conditions, our brain uses some chemical messengers known as neurotransmitters to send messages to brain cells and communicate with each other but person with Parkinson's lacks dopamine, which is one of the important neurotransmitters. So, when your brain sends signals to activate muscles to move or perform certain action via chemical messengers, it fails to do so because of dopamine insufficiency. Due to this body feels tremors and slow body movements known as Parkinson's disease [28].

2.2.1 Symptoms

- Bradykinesia means person shows typically slow movements.
- Tremors-continuous shaking of muscles even the body is at resting.
- Unstable posture.

- Less blinking than usual.
- Micrographia
- Dysphagia [26].

2.2.2 Stages of Parkinson's Disease

This disease occurs in different types of stages. At the initial stage, mild symptoms show up like slow movements and then the symptoms come in stages [27].

Stage I

This is the very first initial stage of Parkinson's disease. In this stage only mild symptoms appear which includes slow body part movements, difficulty while walking, changes in posture, changes in facial expressions etc. Also, one side of the body is affected in initial period [27].

Stage II

In this stage patient faces some serious disabilities related to walking, tremors, difficult speech, rigidity, or muscle spasms on both sides of the body unlike Stage I in which it affects one side of the body [27].

Stage III

It is considered mid-stage of Parkinson's disease. In this specific stage, person starts facing serious illness and most of the body shows tremors and body balancing issues. Drooling and dysphagia are other symptoms related to this stage. Falls commonly happens [27].

Stage IV

At this stage, symptoms move from mild to severity with serious consequences. Person is unable to walk without support or walker and is unable to perform daily activities [27].

Stage V

This is the most serious and end stage of this disease. Person is unable to stand and is bed ridden. To perform daily activities is impossible and assistance is required 24 h. Person can experience episodes of hallucinogens and delusions [27].

2.3 Huntington Disorder

Another type of inherited NDDs condition known as HD causes irrational behaviour, emotional problems, and cognitive decline [28, 29]. Less often occurring juvenile HD begins in infancy or adolescence. It also leads to changes in the thoughts and emotions as well as problems with movement. Some signs of the juvenile form include rigidity,

slurred speech, drooling, slow movements, and frequent falls. We may also state that these are the first symptoms to manifest [30]. Academic achievement declines as one's capacity for cognition and reasoning weakens. This disorder is also known as Huntington chorea because it is likely to be associated with basal ganglia and causes hyperkinetic movement disorder known as chorea. As this disorder reaches to the later stage, more prominent and specific symptoms come up of involuntary body movements. After the person is suffers from it than the physical activity of the patient gradually worsens making it difficult for person to speak [31].

2.4 Lewy Body Disease

The protein alpha-synuclein abnormally accumulates in the brain in this condition. The chemical structure of the brain is altered by these Lewy body deposits, and this alteration can result in issues with cognition, behaviour, movement, and mood. One of the most common forms of dementia is Lewy body dementia [32]. It is a kind of progressive disorder which get worsens over the time with symptoms gradually increased and confused with other brain disorders. In early stage of LWD, person can work normally but with the worsening of the disease person has decline thinking and movement abilities [33].

2.5 Cerebral Aneurysm

It is an abnormal localised dilatation of a cerebral artery caused by thinning of the inner muscular layer (the intima) of the blood vessel wall [34]. The vessel dilates in a way that feels like a "blister," which can thin out and suddenly explode. The resulting bleeding into the region around the brain is known medically as a subarachnoid haemorrhage (SAH) [35]. Such haemorrhage could cause a stroke, unconsciousness, or even death. However, several factors, are believed to contribute in the development of cerebral aneurysms like Hypertension (high blood pressure), smoking cigarettes, birth defect or genetic predisposition, blood vessel damage or trauma, a side effect of certain blood illnesses [36]. An extension of the blood artery wall that affects all of the wall's layers is considered a genuine aneurysm. Saccular and fusiform aneurysms are the two most well-known varieties, whereas mycotic, pseudo, and blister aneurysms are more uncommon. The majority of aneurysms are sporadic; however they can also be brought on by other illnesses such Ehlers-Danlos syndrome, fibromuscular dysplasia (FMD), polycystic kidney disease, and Marfan's syndrome [3, 37].

2.6 Epilepsy

It is a disorder when a person gets continuous or repeated seizures. According to standard definitions, a seizure is a transient interruption in the electrical activity of the brain that results in an abrupt change in behaviour [38]. Ordinarily, the brain generates tiny electrical impulses with a known sequence [39, 40]. Neurotransmitters are chemical messengers that transfer these messages along neurons, the network of nerve cells in the brain, and all over the whole body [41]. When these brain electrical signals become disrupted due to any reasons results in recurrent seizures and affects persons consciousness, movements, and muscle spasms [42, 43].

2.7 Spinocerebellar Ataxia (SCA)

This is another type of neurogenerative disorder in which ataxia is a symptom not a disease. Ataxia means poor coordination of the movements of different parts of the body. Person has an unsteady and uncoordinated walking. Also, ataxia affects movement of fingers, hands, spasm, and sometimes eye movements [44]. Most frequently, the cerebellum, that regulates motor coordination in the brain, is harmed, or shrinks (atrophy) as a result of ataxia [45]. The two important types of ataxia include congenital and acquired ataxia. Congenital ataxia is an ataxia, which passed from family. This is also known as inherited ataxia. The majority of hereditary ataxia types are inherited in an autosomal dominant form, while a small number (such as Friedreich ataxia) are inherited in an autosomal recessive style [44]. Acquired ataxia is a type which is caused due to some environmental factors like tumor, injury to the brain, stroke, swelling etc. Acquired ataxia is not passed on to offspring or children so there is no increased risk of ataxia in children [46, 47].

2.8 Amyotrophic Lateral Sclerosis (ALS)

Upper and lower motor neurons both degenerate in ALS, also known as motor neuron disease (MND), which results in muscle weakening and eventually paralysis [48]. Until recently, ALS was primarily categorized as belonging to the neuromuscular domain, however newer imaging and neuropathological studies have shown that the non-motor neuraxis is involved in disease pathology [49]. Although a small percentage of ALS patients have a family disease and carry gene abnormalities that affect many aspects of neuronal function, the processes underlying the disease's development in the majority of individuals are still poorly understood [50]. For ALS, there are two potential disease-modifying treatments that may decrease the disease's development, although most symptomatic treatments, such as speech therapy for dysarthria and the use of muscle relaxants for spasticity are used to manage patients [51].

3 Conclusion

Significant adverse effects can result from conventional pharmaceutical therapies for NDDs. Currently, improvements in the research of gene replacement and addition, as well as stem cell therapies, offer effective, promising therapies for a wide range of diseases. The recent translation of several of these medications into clinical trials and the growing importance of preclinical research have set the stage for continued improvement, even if there is still more work to be done. Future clinical approaches for treating NDD may heavily rely on the use of stem cells and gene therapy to replace damaged neurons and provide neuroprotective and neurorestorative effects. Additionally, recent technological developments utilising nanoparticles and hydrogels have increased the efficacy of drug delivery and regeneration therapy. Hence, it's expected that brain replacement and regenerative therapies will soon be successfully used in the therapeutic setting.

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Conflict of Interest None.

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AI and Machine Learning Models for Neurodegenerative Disorders

Artificial Intelligence and Machine Learning Models for Diagnosing Neurodegenerative Disorders

Kamini and Shalli Rani

Abstract Gradual loss of neuron tissues lying within brain causes abnormality in cognitive and motor which are further responsible for developing neurodegenerative disorders. With the increasing prevalence of these disorders, there is a growing need for accurate and reliable diagnosis, as well as effective treatment strategies. Artificial Intelligence and Machine learning demonstrated great improvement in diagnosing such disorders. Keeping such scenario in mind, AI and ML models can be trained to analyze large datasets of medical imaging and clinical data to identify patterns and biomarkers associated with neurodegenerative disorders. These models can also be used to predict disease progression and response to treatment, enabling personalized care for patients. Some of the Artificial Intelligence (AI) and Machine Learning (ML) models that have been developed for neurodegenerative disorders include deep learning algorithms, graphical convolutional networks etc. for analyzing a variety of data, including structural and functional neuroimaging, genomic data, and electronic health records. While these models have shown promise in improving the diagnosis and management of neurodegenerative disorders, there are also challenges that need to be addressed. These include issues related to data quality, model interpretability, and ethical considerations. Overall, AI and ML models have the potential to revolutionize the field of neurodegenerative disorders, providing clinicians with new tools to improve patient outcomes and enhance our understanding of these devastating diseases.

Keywords Artificial intelligence · Machine learning · Health · Increased life expectancy · Neurodegenerative disorders

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1 Introduction

Neurodegenerative disorders are a group of conditions that affect neuron tissues lying within brain as well as spinal cord. These disorders are characterized by the progressive loss of neurons, which can lead to cognitive, motor, and behavioral impairments. Alzheimer's disease is characterized by the accumulation of abnormal proteins in the brain, which leads to the formation of plaques and tangles. This can lead to memory loss, language problems, and changes in behavior and mood.

Parkinson's disease is caused by the degeneration of dopamine-producing neurons in the brain, which leads to tremors, rigidity, and problems with movement. Huntington's disease is a rare genetic disorder that causes the degeneration of neurons in the brain. It is characterized by involuntary movements, cognitive impairments, and behavioral changes. Amyotrophic Lateral Sclerosis can lead to muscle weakness, difficulty speaking and swallowing, and respiratory problems.

The exact causes of neurodegenerative disorders are not fully understood, and there is currently no cure for these conditions. However, advances in research, including the use of AI and ML models, are providing new insights into the underlying mechanisms of these disorders and improving diagnosis, prognosis, and treatment options. AI and ML models can be trained to analyze large and complex datasets, including medical imaging, genetic, and clinical data, to identify patterns and biomarkers associated with these disorders.

In recent years, several AI and ML models have been developed and tested for neurodegenerative disorders for analyzing a variety of data types, including structural and functional neuroimaging, genomics data, and electronic health records. The potential of AI and ML models in the field of neurodegenerative disorders is vast. These models have the potential to improve diagnostic accuracy, predict disease progression, and enhance treatment strategies for patients. However, there are also challenges that need to be addressed, including issues related to data quality, model interpretability, and ethical considerations.

Early diagnosis and accurate prognosis of these diseases are crucial for effective treatment and management. Various studies have proposed AI and ML models for the diagnosis and prediction of neurodegenerative disorders. Kazemifar et al. [1] developed convolutional neural network model in collaboration with LSTM for diagnosing Alzheimer and achieved 95% accuracy and 99% sensitivity. Another study by Zhu et al. [2] proposed a framework called GCA-CNN, which integrates Graph Convolutional Network (GCN) and CNN to diagnose Parkinson's disease with an accuracy of 91.4%.

Thus, AI and ML models have shown significant promise in the diagnosis, prognosis, and early detection of neurodegenerative disorders. These models have the potential to revolutionize the field of neurodegenerative disease management, providing more accurate and timely diagnoses, personalized treatment plans, and improved patient outcomes.

2 Description of Medical Examination

AI and ML-based medical examinations have been proposed by various authors for diagnosing neurodegenerative disorders. Electro-Encephalo-Graphy (EEG) is a non-invasive technique that measures electrical activity in the brain and has been found to be useful in detecting abnormal brain activity associated with AD. Machine learning algorithms have been applied to EEG data to develop models that can accurately classify individuals as either AD patients or healthy controls.

For instance, a study by Xu et al. [3] used EEG recordings from both AD patients and healthy controls to develop a deep learning model for AD diagnosis. Another study by Besga et al. [4] proposed a machine learning-based approach for diagnosing Parkinson using gait analysis. The results showed that the model had high accuracy in differentiating between PD patients and healthy controls, demonstrating the potential for using wearable sensors and machine learning for PD diagnosis. Overall, AI and ML-based medical examinations as shown in Fig. 1 lead to earlier detection and better treatment outcomes.

2.1 Brain Imaging

Brain imaging techniques have been widely used to study the structure and function of the brain and help diagnose neurodegenerative disorders. For example, a study by Liu et al. [5] used a convolutional neural network (CNN) to analyze input MRI images for diagnosing Alzheimer. The CNN was trained to classify MRI scans as Alzheimer's disease or normal controls and achieved an accuracy of 91.4%. Li et al. [6] used an approach based on deep neural networks for analyzing positron emission tomography (PET) data for the diagnosis of Parkinson's disease. The authors developed a deep learning framework that combined a 3DCNN with LSTM network for classifying PET scans as Parkinson's disease or healthy controls, achieving an accuracy of 94.3%.

Overall, AI and ML-based medical examinations using brain imaging data have shown promising results for the diagnosis of neurodegenerative disorders.

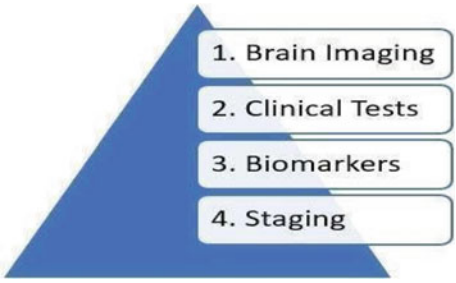

Fig. 1 Techniques to diagnose neurodegenerative disorder

2.2 Clinical Tests

Several clinical tests have been used in AI and ML-based medical examinations for diagnosing neurodegenerative disorders. These tests involve assessing cognitive and motor functions to detect any impairments, which can indicate the presence of a neurodegenerative disorder.

For example, the Montreal Cognitive Assessment accesses cognitive abilities. Based on it, in a study done by Tsanas et al. [7], the MoCA was used along with other clinical tests to predict continuation of Parkinson using machine learning models. Another clinical test, the Unified Parkinson's Disease Rating Scale accesses the motor function of individuals with Parkinson's disease. In a study by Arora et al. [8], the UPDRS was used along with other clinical features to predict the progression of Parkinson's disease using machine learning models.

Overall, these clinical tests, along with brain imaging and other medical examinations, provide valuable data for developing AI and ML models to diagnose and predict the progression of neurodegenerative disorders.

2.3 Biomarkers

Biomarkers are measurable indicators in biological samples, such as blood or cerebrospinal fluid (CSF), that reflect underlying physiological or pathological processes. Several studies have explored the use of biomarkers in combination with AI and ML algorithms for the diagnosis of neurodegenerative disorders.

Javed et al. [9] used a combination of machine learning algorithms and biomarker data to accurately diagnose Alzheimer's disease with a sensitivity of 92% and a specificity of 91%. The authors used CSF biomarker data for beta-amyloid, tau, and phosphorylated tau as input features for their machine learning models. Zou et al. [10] demonstrated utilization of clinical and imaging biomarkers with algorithms of machine learning for prediction of Alzheimer and achieved a prediction accuracy of 80% using a random forest algorithm with imaging and clinical biomarkers as input features.

Furthermore, Li et al. [11] collaborated machine learning algorithms with multimodal biomarker data, including imaging, CSF, and blood biomarkers, to diagnose and stage Parkinson's disease. The authors achieved an accuracy of 90% for the diagnosis and 83% for the staging of Parkinson's disease using their approach. These studies demonstrate the potential of combining AI and ML with biomarkers for the accurate diagnosis and prediction of neurodegenerative disorders. However, further research is needed to validate these approaches and to develop standardized biomarker panels for clinical use.

2.4 Staging

In neurodegenerative disorders, the staging of the disease can provide important insights for diagnosis, prognosis, and treatment. AI and ML-based medical examinations have been used to develop staging systems that utilize biomarkers and imaging data to identify disease stages.

For example, a study by Lehmann et al. [12] used a machine learning approach to develop a staging system for Alzheimer's disease based on ADNI. The model used baseline data from structural MRI, FDG-PET, and CSF biomarkers to predict cognitive decline over time and stratify patients into three distinct stages. Another study by Zeighami et al. [13] developed a machine learning-based model to stage Parkinson's disease using imaging and clinical data. The model used a combination of features from diffusion tensor imaging, resting-state fMRI, and clinical scales to classify patients into early, intermediate, and advanced stages of the disease.

These studies demonstrate the potential for AI and ML-based medical examinations to develop accurate and objective staging systems for neurodegenerative disorders, which could have significant implications for diagnosis, prognosis, and treatment planning.

3 Datasets for Diagnosing Neurodegenerative Disorders

Following datasets are used by various researchers for analysis of a particular disorder:

3.1 Alzheimer Dataset

There are several publicly available datasets that have been used in research related to Alzheimer's disease. Following is the description of a few datasets:

i. ADNI (Alzheimer's Disease Neuroimaging Initiative): ADNI is a large, longitudinal dataset [14] that includes clinical, imaging, genetic, and other biomarker data from individuals with Alzheimer. Dataset has been used in a wide variety of studies related to Alzheimer's disease, including for the development and validation of predictive models using machine learning techniques.
ii. OASIS (Open Access Series of Imaging Studies): It includes structural MRI, PET, and clinical data from individuals with Alzheimer [15]. Dataset has been used in studies for diagnosing Alzheimer disorder via developing models on the basis of machine learning.
iii. AIBL (Australian Imaging, Biomarkers and Lifestyle Study of Ageing): AIBL is a longitudinal study [16] that includes imaging, clinical, genetic, and other biomarker data from individuals with Alzheimer to detect Alzheimer disorder.

iv. Dementia Bank: Dementia Bank is a dataset of audio and video recordings of individuals [17] with Alzheimer. Dataset has been used to for automatic detection of Alzheimer's disease from speech and language features.
v. TADPOLE (Prediction of Longitudinal Evolution in Alzheimer's Disease): TADPOLE is a challenge dataset [18] that includes imaging, clinical, genetic, and other biomarker data from individuals with Alzheimer's disease. Dataset has been used to diagnose Alzheimer's disease progression via developing machine learning model.

3.2 Parkinson Dataset

Following is the description of Parkinson dataset:

i. Parkinson's Disease Classification Dataset: This dataset contains 5875 voice samples from 42 people with Parkinson and 20 healthy ones. The samples were recorded during sustained phonation, reading, and speech tasks, and include features such as fundamental frequency, jitter, and noise-to-harmonics ratio. The dataset is available on the UCI Machine Learning Repository [19].
ii. Parkinson's Telemonitoring Dataset: This dataset includes time-series data from 42 people suffering from Parkinson via remotely monitoring using sensors and smartphones. The data includes accelerometer and gyroscope measurements, as well as demographic and clinical information [20].
iii. Parkinson's Disease Spiral Drawings Dataset: This dataset includes spiral drawings from 42 individuals suffering from Parkinson and 43 normal ones. Participants were asked to draw spirals using a digital pen, and the data includes features such as pen velocity, pen pressure, and pen angle [21].
iv. Parkinson's Disease Progression Markers Initiative (PPMI) Dataset: This dataset includes a range of clinical, imaging, and biological data from individuals with Parkinson's disease and healthy controls. The dataset is available on the PPMI website [22].
v. Parkinson's Disease Data Set (PDDBI): This dataset includes data on individuals with Parkinson's disease and healthy controls, collected from multiple sources. The dataset includes information on demographics, clinical data, imaging data, and genetic data. The dataset is available on the Parkinson's Disease Biomarker Program (PDBP) Data Management Resource (DMR) web-site [23].

3.3 Huntington Dataset

Huntington's disease (HD) is generally caused by genetic disorder which is responsible for damaging brain cells that further develops abnormality in cognitive and motor parts. Research in HD often involves the analysis of large datasets to better understand the underlying mechanisms of the disease and develop effective therapies. Here are some of the commonly used datasets in HD research:

i. Enroll-HD: Enroll-HD is a global observational study of individuals with HD and their family members [24]. The study collects a variety of data, including clinical information, genetic information, and imaging data, from participants at different stages of the disease. Enroll-HD is a valuable resource for researchers studying HD, and has led to many important discoveries. The details available to qualified researchers upon request, and details can be found at https://www.enroll-hd.org/.
ii. TRACK-HD: TRACK-HD is a longitudinal study that follows individuals with HD and healthy controls over time [25]. The study collects clinical, cognitive, and imaging data, and has contributed to a better understanding of the progression of the disease. Following is the link for TRACK-HD dataset: https://www.huntingtonstudygroup.org/tracks/hd/.
iii. PREDICT-HD: PREDICT-HD is another longitudinal study that follows individuals with the HD gene mutation before they develop symptoms of the disease [26]. The study collects a range of data, including clinical, cognitive, and imaging data for identification of biomarkers to predict on-set and progression of HD. The data is publicly available at the following link: https://www.predict-hd.net/.
iv. HD-in-HD: It is a dataset that contains high-resolution magnetic resonance imaging (MRI) data from individuals with HD and healthy controls [27]. The data is publicly available at the following link: https://www.hdinhd.org/.
v. Gene expression datasets: Several gene expression datasets are available that have been generated from brain tissue samples from individuals with HD and healthy controls [28]. These datasets have been used to study the molecular mechanisms underlying HD. Geo dataset (https://www.ncbi.nlm.nih.gov/geo/), the Allen Brain Atlas (https://portal.brain-map.org/), and the HD-in-HD gene expression dataset (https://www.hdinhd.org/) are used for such purposes.

3.4 Amyotrophic Lateral Sclerosis Dataset

This disorder occurs due to damaged nerve tissues lying within brain as well as spinal cord. Researchers have collected and analyzed a variety of datasets to better understand the underlying mechanisms of the disease and develop effective treatments. Here are some of the commonly used datasets in ALS research:

i. Pooled Resource Open-Access ALS Clinical Trials (PRO-ACT) Database: The PRO-ACT database is a collection of de-identified data from 17 completed clinical trials for ALS [29]. The database contains clinical, genetic, and demographic data from over 10,000 individuals with ALS, including disease progression and treatment outcomes. The data is available to qualified researchers upon request, and details can be found at https://nctu.partners.org/ProACT/.
ii. Answer ALS: Answer ALS is a comprehensive research project aimed at developing a better understanding of the disease and identifying new treatment options for individuals with ALS [30]. The project collects data from multiple sources,

including clinical assessments, patient surveys, and genetic and molecular data. Data is publicly available at the following link: https://www.answerals.org/.

iii. Genomic Data Commons (GDC): The GDC is a publicly available data repository that contains genomic data from multiple types of cancer, as well as ALS and other neurological diseases [31]. The ALS datasets include genomic data from both tumor and non-tumor tissue samples, as well as clinical and demographic information. The data is available at https://portal.gdc.cancer.gov/.

iv. Human Spinal Cord Injury Transcriptome (HSCT) Database: The HSCT database is a publicly available resource that contains gene expression data from spinal cord tissue samples from individuals with ALS and healthy controls [32]. The database has been used to identify potential therapeutic targets for the disease. The data is available at http://bioinfo.hrbmu.edu.cn/HSCT/.

v. National ALS Registry: The registry [33] includes information on demographics, clinical features, environmental and occupational exposures, and family history. The data is available at https://www.cdc.gov/als/registry.html.

4 Methodology of AI and ML Models for Diagnosing Neurodegenerative Disorder

Following is the basic methodology of AI and ML models as shown in Fig. 2 implemented by various authors while diagnosing neurodegenerative disorders:

i. Data Collection: Collection of data is performed at first for performing the required procedure or to correct distortions and noise from the input images.

ii. Pre-Processing: The input images are pre-processed to extract the specific region. It further includes normalization, scaling, data-augmentation etc.

iii. Features Extraction: It is basically performed for analysis of data on the basis of shape and texture features via measuring atrophy, asymmetry and local intensity variation, contrast respectively. Selection of features is also performed.

Fig. 2 Methodology for diagnosing neurodegenerative disorder

iv. Classification: A linear SVM is trained on the selected features to classify input data into healthy and infected images.

Overall, these steps are essential for ensuring the accuracy and reliability of the models.

5 AI and ML Models in Diagnosing Neurodegenerative Disorders

5.1 Convolutional Neural Network Model

CNNs are effective for image analysis as well as recognition of objects. These are also capable of automatically learning and detecting intricate features in images and have shown promise in the field of medical imaging analysis, including the diagnosis of neurodegenerative disorders. Sarraf et al. [34] proposes a model based on CNN pipeline for diagnosing Alzheimer's disease using fMRI data as shown in Fig. 3 [35].

The architecture consists of the following layers:

i. Input layer: The input to the model is a 3D fMRI volume of the brain.
ii. Convolutional layers: These layers are responsible for extraction of features which are further passed to filters for removal of noise and forwarded to ReLU activation layer.

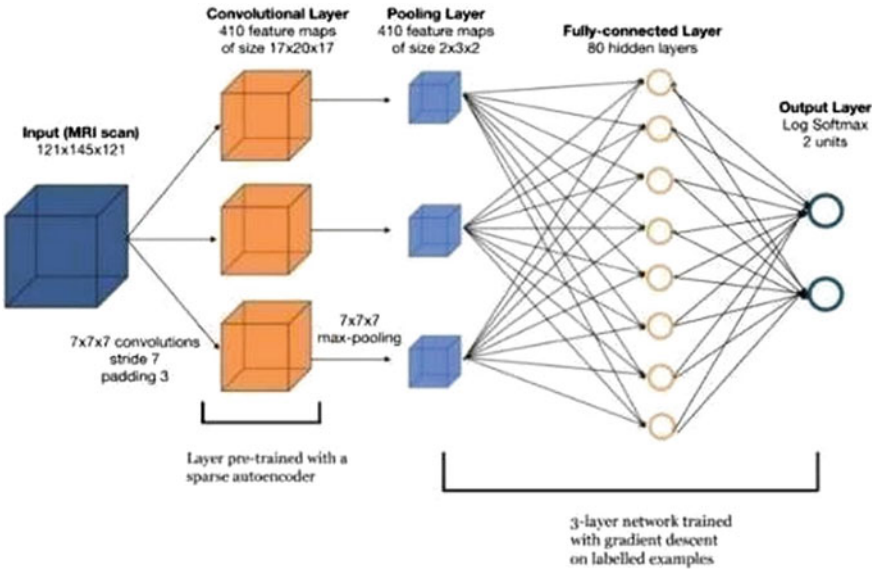

Fig. 3 Architecture of CNN model [35]

iii. Max pooling layers: The max pooling layers downsample the feature maps produced by the convolutional layers.
iv. Flatten layer: It receives features from Max pooling layer as an input and transforms into its respective vectors in one-dimensional category.
v. Dropout layer: The dropout layer helps prevent overfitting via dropping a few neurons while training model.
vi. Fully connected layer: It receives one-dimensional feature vector as input and produces a binary classification output (normal vs. Alzheimer's disease).

This example illustrates how CNN models can be used to extract features from medical imaging data and make accurate diagnoses of neurodegenerative disorders. The specific architecture and layer parameters can be customized based on the specific imaging modality and dataset used.

Thus, CNNs work by processing an input image through multiple convolutional layers, which apply a set of learned filters to the image to extract relevant features. Each filter extracts a specific type of feature, such as edges, lines, or shapes, by performing a mathematical operation called a convolution. Then pooling layer is responsible for reduction of received features' size for smooth flattening via last convolutional layer and classification is performed for differentiating affected images from healthy ones via utilization of any of the classifiers. In other words, these layers take the extracted features and use them to make a prediction, such as whether an image belongs to a particular class or not.

In the context of diagnosing neurodegenerative disorders, CNNs have been used to analyze medical images and identify patterns that are indicative of specific diseases. Liu et al. [36] analyzed structural MRI scans to identify features that were characteristic of Alzheimer's disease. Similarly, Rajamani et al. [37] used CNNs for analyzing combination of MRI and fMRI data to detect Parkinson's disease. The use of CNNs for diagnosing neurodegenerative disorders has shown promising results, with some studies achieving high accuracy in distinguishing between diseased and healthy subjects. However, there are still challenges in developing models that are robust and generalizable to new datasets and populations.

CNN Model Methodology The methodology of using a convolutional neural network (CNN) for diagnosing neurodegenerative disorders [38] involves several steps. The following is a general outline of the methodology:

i. Data Collection: Large amounts of neuroimaging data, such as Magnetic Resonance Imaging (MRI) scans, are collected from patients diagnosed with a particular neurodegenerative disorder, as well as from healthy control subjects.
ii. Preprocessing: The collected images are then pre-processed to ensure they are normalized and standardized in size and format. This step is essential to ensure that the data are consistent and model can be given training.
iii. Training CNN Model: The pre-processed data is then used to train the CNN model. During training, the model learns to recognize patterns in the images that are associated with the specific neurodegenerative disorder. The model is trained using a supervised learning approach, where the model is given labeled

images as input, and it learns to predict the correct label based on the input image.

iv. Testing and Validation: CNN Model is tested on separate set of neuroimaging data to validate its accuracy. The validation data should be collected from different subjects than the ones used in the training dataset. This helps to ensure that the model can generalize to new data and is not overfitting to the training data.

v. Evaluating Performance: Various factors are considered for ensuring the performance of developed model by various researchers such as Accuracy, Sensitivity, Specificity, Region of Interest, Receiver Operating Characteristics etc. while diagnosing any of the neurodegenerative disorders.

For instance, Sarraf et al. [34] also used a 3D CNN to diagnose Alzheimer's disease using MRI scans. The model achieved an accuracy of 91.4% in differentiating between Alzheimer's disease patients and healthy controls. Another study by Suk et al. [38] used a multi-modal CNN to diagnose Parkinson's disease using MRI and functional MRI data. The model achieved an accuracy of 96.6% in distinguishing Parkinson images from normal ones.

Liu et al. [36] suggested an approach on the basis of CNN for the diagnosis of Alzheimer's disease (AD) using structural magnetic resonance imaging (MRI) Data. The results showed that their model achieved high accuracy in classifying AD patients from healthy controls. Another study by Rajamani et al. [37] proposed a CNN model using a combination of MRI and functional MRI (fMRI) data for diagnosing Parkinson. Their model included several convolutional and pooling layers, followed by fully connected layers, and was trained on a large dataset of MRI and fMRI scans from PD patients and healthy controls. The results showed that their model achieved high accuracy in detecting PD, with the potential to aid in early diagnosis and intervention. Overall, CNN models have shown great promise in the diagnosis of neurodegenerative disorders and have the potential to improve early detection and intervention, leading to improved patient outcomes.

5.2 Deep Learning Model

In the context of neurodegenerative disorders, deep learning model which generally comprises of CNNs and RNNs are typically trained on large datasets of brain imaging data for learning patterns and features that are indicative of specific diseases. These models can then be used to classify new imaging data as belonging to a particular disease or to a healthy control group.

A study by Sarraf et al. [34] utilized a model comprises of deep neural networks for classification of input MRI images into one of three classes: Alzheimer's disease, mild cognitive impairment, or healthy scans. Better accuracy has been achieved by these models in distinguishing between different classes, demonstrating the potential of deep learning models for diagnosing neurodegenerative disorders.

Similarly, the study by Wang et al. [39] used an LSTM network to analyze PET scans and predict continuation status of Alzheimer. Their model was able to accurately predict progression of such disorders up to 24 months in advance, providing insights into the natural history of the disease and potential targets for intervention. Overall, deep learning models have shown promise in diagnosing neurodegenerative disorders, particularly in analyzing large and complex datasets such as brain imaging data. However, there are still challenges in developing models that are robust and generalizable to new datasets and populations.

Here's an example of a reference to a paper describing architecture based on deep neural network model as shown in Fig. 4 [40] for diagnosing neurodegenerative disorders: Girshick et al. [41] proposes a deep learning architecture called "Regions with CNN features" (R-CNN) for object detection and semantic segmentation in images. The R-CNN architecture consists of three main components:

i. Region Proposal: A Selective Search algorithm is used to propose a set of regions in the input image comprises of objects.
ii. Feature Extraction: A Convolutional Neural Network (CNN) is used to extract features from each proposed region. The CNN is pre-trained on a large dataset of natural images to learn a rich set of features.
iii. Classification: For classification of proposed region into categorical way, training has been provided to linear Support Vector Machines.

This architecture was later adapted to detect neurodegenerative diseases in the following paper: Korolev et al. [42] suggested a model on the basis of deep neural

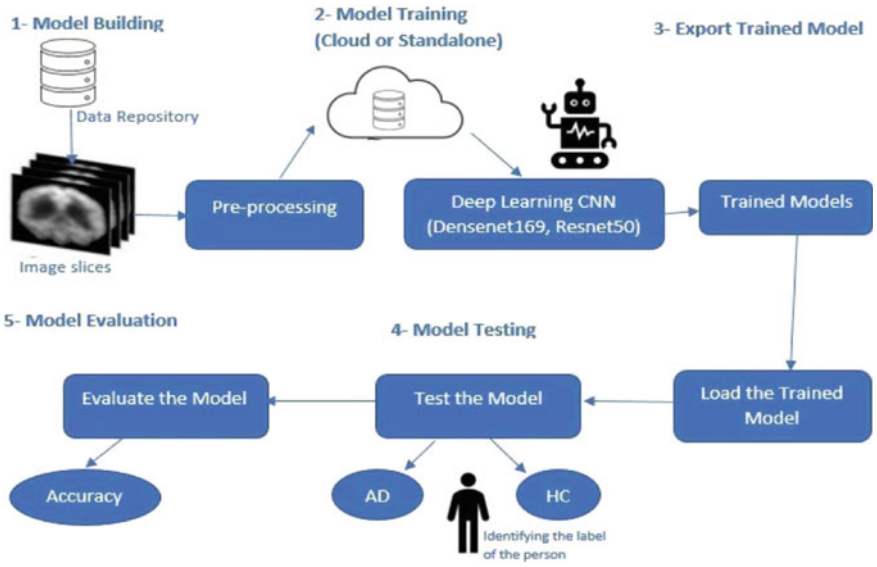

Fig. 4 Architecture of DL model [40]

networks to classify 3D brain MRI scans into normal and abnormal categories. The model consisted of multiple convolutional layers, followed by batch normalization and ReLU activation layers. The output of the last convolutional layer was given to rest fully connected layers for classification purpose. Such model was trained on a large dataset of 3D brain MRI scans labeled as normal or abnormal. Overall, this example shows how Deep Learning models can be adapted and customized for the specific task of diagnosing neurodegenerative disorders, using architecture inspired by previous research in computer vision and image analysis.

DL Model Methodology For analyzing medical images, various models comprising of deep neural networks have been utilized while diagnosing neurodegenerative disorders. The following is a generalized methodology for the application of deep learning models in diagnosing neurodegenerative disorders:

i. Data Acquisition: The first step is the acquisition of medical imaging data while developing models based on deep neural networks. This data is typically collected from patients who have been diagnosed with a neurodegenerative disorder and healthy individuals.
ii. Data Pre-processing: The acquired data is pre-processed by removing noise, normalizing intensities, and resizing images to a standard resolution. Pre-processing ensures that the images are consistent and of high quality, which is essential for accurate diagnosis.
iii. Model Training: A deep learning model is trained on the pre-processed data using a large dataset. The model is trained to learn features from the images that can differentiate between healthy and diseased brains.
iv. Model Validation: The trained model is then validated using a separate dataset that was not used for training. On the basis of various parameters, evaluation of models' performance has been done to ensure better approach than the existing ones to diagnose neurodegenerative disorders.
v. Model Optimization: Adjustment of hyperparameters has been done while optimizing model for improvement in models' performance.
vi. Model Deployment: Once the model is optimized, it can be deployed to diagnose new patients. The model takes medical images as an input and produces a diagnosis as output.

Several studies have used this generalized methodology while developing models on the basis of deep neural networks for detection of neurodegenerative diseases. For instance, Sarraf et al. [34] developed a model to diagnose Alzheimer at an early stage via utilization of MRI scans. In another study of Havaei et al. [43], they used such models for prediction of Parkinson's disorder continuation at current moment via utilizing MRI scans.

5.3 *Long Short Term Memory Models*

LSTM is designed to handle sequential data, such as time series or text. It consists of a series of memory cells that are connected through gates which further allow the model to selectively forget or remember information from previous time steps, which enables it to capture long-term dependencies in the data. In the context of diagnosing neurodegenerative disorders, LSTM models have been used to analyze time series data, such as electroencephalogram (EEG) signals or gait patterns, to identify features that are indicative of specific diseases as shown in Fig. 5 [44].

A study by Zhang et al. [45], their LSTM model analyzed gait patterns to detect Parkinson's disease, achieving high accuracy in distinguishing between PD patients and healthy controls. Similarly, the study by Lee et al. [46] used an LSTM model to analyze EEG signals to detect Alzheimer's disease, achieving high accuracy in distinguishing between AD patients and healthy controls. Their model identified specific spectral power and connectivity patterns that were associated with AD, providing insights into the underlying mechanisms of the disease. The use of LSTM models for diagnosing neurodegenerative disorders has shown promise, particularly in analyzing sequential data that contains temporal information. However, there are still challenges in developing models that are robust and generalizable to new datasets and populations.

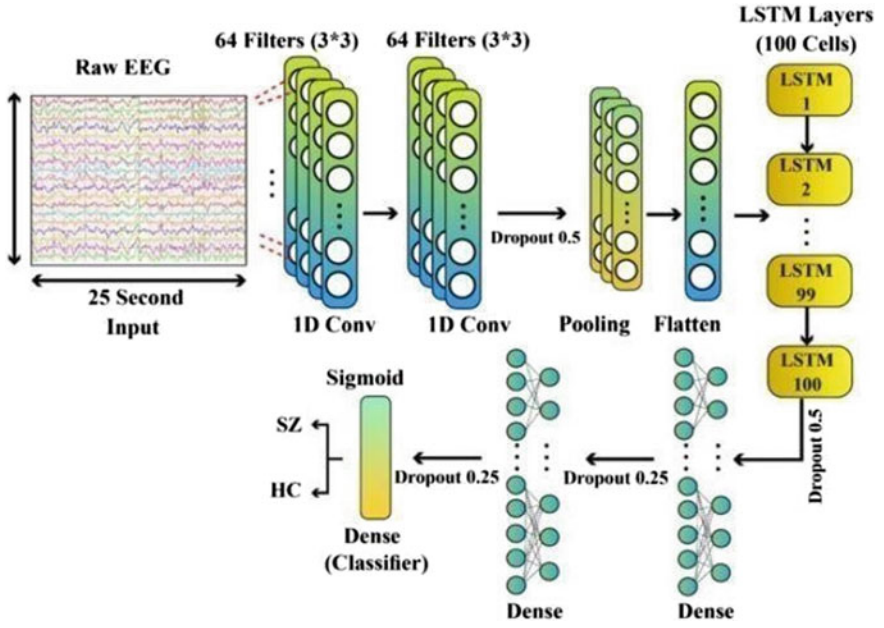

Fig. 5 Architecture of LSTM model [44]

Here's an example of an architecture of an LSTM model for diagnosing neurodegenerative disorders (Fig. 5).

Wang et al. [47] proposes a 3D convolutional neural network (CNN) with along short-term memory (LSTM) layer for the diagnosis of Alzheimer's disease. The architecture consists of the following layers:

i. 3D CNN layers: The 3D CNN layers extract features from the input MRI volumes of the brain. The authors used 3 layers of convolutional with respect to filters followed by ReLu activation layer and a max-pooling layer.
ii. Flatten layer: It is responsible for conversion of output of max pooling into one-dimensional feature vector.
iii. LSTM layer: The LSTM layer takes the one-dimensional feature vector as input and learns the temporal dependencies of the data over time.
iv. Fully connected layer: It receives LSTM layer output as input and generates binary classification output (normal vs. Alzheimer's disease). The LSTM layer permits model to consider temporary data which can be useful in diagnosing neurodegenerative disorders where the progression of the disease over time is important.

Training has been given to the proposed model which is further evaluated on the basis of input MRI images comprising of normal or Alzheimer and gained high accuracy while diagnosing disease. This example shows how LSTM layers can be incorporated into CNN models to improve the accuracy of neurodegenerative disorder diagnosis. The specific architecture and layer parameters can be customized based on the specific dataset and task at hand.

LSTM Model Methodology Here is an example of the methodology used by various authors in developing LSTM models. A study by Tabar et al. [48], an LSTM model was developed to predict the progression of Parkinson's disease. The model was trained on data from 1065 patients suffering from Parkinson and tested on 223 patients' dataset. It considered clinical and demographic variables, as well as data from a gait analysis as an input. The model was able to predict the progression of Parkinson's disease with an accuracy of 79.6%. Similarly, in a study by Chen et al. [49], an LSTM model was developed to predict the progression of Alzheimer's disease. The model was trained on data from 1797 patients with Alzheimer's disease and validated on an independent dataset of 614 patients. The model took as input clinical and demographic variables, as well as data from brain magnetic resonance imaging (MRI) scans. The model predicted Alzheimer disorder accurately with 74.3%.

In both studies, the LSTM models were trained via following approaches. The supervised learning involved training the model on labeled data, while the unsupervised learning involved training the model on unlabeled data to learn patterns and relationships in the data. The models were also optimized using various techniques such as dropout regularization, early stopping, and learning rate decay. Overall, these studies demonstrate the potential of LSTM models for predicting the progression of neurodegenerative disorders. However, further validation and refinement of these models is necessary before they can be used in clinical practice.

5.4 *Graph Convolutional Network Model*

It is designed to work with graph-structured data. It applies convolutional operations to graph data, allowing it to capture local and global features of the graph. In the context of diagnosing neurodegenerative disorders, GCN models have been used to analyze brain networks constructed from imaging data, such as MRI or PET scans. These brain networks represent patterns to identify features that are indicative of specific diseases.

In the study by Zhao et al. [50], their GCN model analyzed brain networks constructed from MRI scans to detect Alzheimer's disease, achieving high accuracy in distinguishing between AD patients and healthy controls. Their model identified specific brain regions and connections that were associated with AD, providing insights into the underlying mechanisms of the disease. Similarly, Shi et al. [51] used GCN for analyzing brain networks constructed from PET scans to detect Parkinson's disease, achieving high accuracy in distinguishing between PD patients and healthy controls. Their model identified specific metabolic patterns in the brain that were associated with PD. Utilizing models based on GCN for diagnosing neurodegenerative disorders has shown promise, particularly in analyzing graph-structured data such as brain networks. However, there are still challenges in developing models that are robust and generalizable to new datasets and populations.

Here's an example of an architecture of a GCN (Graph Convolutional Network) model for diagnosing neurodegenerative disorders as shown in Fig. 6 [52].

Wang et al. [53] proposes a multimodal GCN model to diagnose Alzheimer at an early stage. The description of architecture has been given below:

i. Graph construction: The authors constructed a brain connectivity graph using functional MRI data, where each node represents region of brain, and functional connectivity between the regions has been represented by edges.
ii. Multimodal feature extraction: The authors extracted features from three modalities:
    (a) structural MRI data,
    (b) functional MRI data, and
    (c) cerebrospinal fluid (CSF) biomarker data.

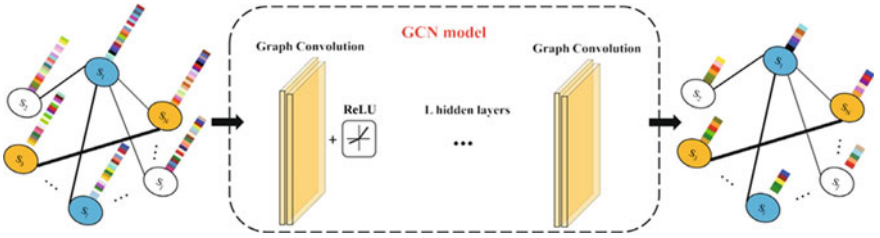

Fig. 6 Architecture of GCN model [52]

For each modality, the authors used a separate feature extraction subnetwork that consists of multiple layers of fully connected (FC) layers.

iii. Graph convolutional layers: The GCN layers take the brain connectivity graph as input, and learn to propagate the features across the graph while accounting for the graph structure. The authors used two GCN layers with 64 and 32 filters, respectively.
iv. Fully connected layer: It receives output from last GCN layer then generates binary classification output comprising of healthy and Alzheimer images. Training has been provided to the model for achieving better accuracy and validation has been performed on MRI scans dataset and CSF biomarker data labeled as normal or Alzheimer's disease. Such model achieved high accuracy while diagnosing Alzheimer.

GCN Model Methodology This example shows how GCN layers can be incorporated into a multimodal model to integrate multiple sources of data and account for the brain connectivity structure, leading to improved accuracy in neurodegenerative disorder diagnosis. The specific architecture and layer parameters can be customized based on the specific dataset and task at hand.

Li et al. [54] proposed a methodology which involved preprocessing the functional magnetic resonance imaging (fMRI) data to obtain correlation matrices, which were then used to construct graph representations of the brain networks. Training has been provided to models for classification input MRI scans into healthy or Parkinson images and such model gained 85% accuracy. Whereas Wang et al. [55] used a GCN model to analyze the structural connectivity of brain networks in patients with Parkinson disorder.

Methodology of GCN involved constructing a graph representation of the brain network using diffusion tensor imaging (DTI) data. The GCN model was trained for classification of normal and Parkinson images and such model gained 84.5% accuracy. It is noticed that GCN models effectively captured complex relationships between regions of brain and identified patterns in data for differentiating patients with neurodegenerative disorders and healthy controls.

5.5 Support Vector Machine Model

Support Vector Machines (SVM) is a popular machine learning algorithm for binary classification tasks, including diagnosing neurodegenerative disorders. SVM can be used to train a model that can classify patients into normal and disease groups based on the features extracted from different imaging modalities, such as MRI, CT, PET, and SPECT.

Here's an example of an architecture of an SVM model to diagnose Alzheimer's disorder as shown in Fig. 7 [56].

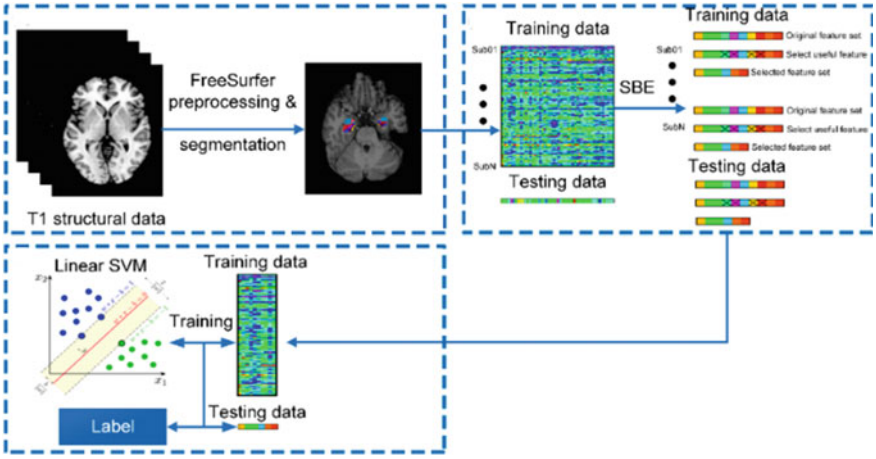

Fig. 7 Architecture of SVM model [56]

i. Feature extraction: Extract of features from imaging modalities may include intensity-based features such as voxel intensity or texture-based features such as gray-level co-occurrence matrix or gray-level run length matrix (GLRLM). The specific features and imaging modalities used can vary based on the study.
ii. Feature selection: The extracted features may contain redundant or irrelevant information, which can negatively impact the performance of the model. For identification of the most relevant features for the classification task, feature selection is performed.
iii. SVM training: Selected features are used to train an SVM classifier, which learns to classify patients into normal and disease groups. The SVM algorithm tries to find an optimal hyperplane that separates the two classes while maximizing the margin between them.
iv. Model evaluation: For assessment of models' performance, training is provided to the model which is further being tested on the basis of specific dataset to achieve better results as compared to the existing approaches.

SVM Model Methodology Chen et al. [57] proposed an SVM-based framework for classification of Alzheimer disorder on the basis of resting-state functional MRI (fMRI) data. This example describes how SVM can be used to diagnose neurodegenerative disorders based on imaging features. The specific feature extraction and selection methods, as well as the SVM hyperparameters, can be customized based on the specific dataset and task at hand.

5.6 *Random Forest Model*

It is a machine learning algorithm to build collaborative decision trees and combines their outputs to make a prediction. In the context of diagnosing neurodegenerative disorders, it has been used for classification and feature selection tasks. The random forest algorithm works by creating a large number of decision trees, each of which uses a random subset of the available features to make a decision. The algorithm then combines the outputs of all the trees to arrive at a final prediction. This combination helps to reduce the variance and overfitting that can be a problem with individual decision trees as shown in Fig. 8 [58]. In the context of diagnosing neurodegenerative disorders, prediction of disease progression and classification of patients as healthy or having a specific disorder based on clinical data or neuroimaging data has been done via deploying RF algorithm.

Here's an example of a high-level architecture of an RF model as shown in Fig. 8 [58] for diagnosing neurodegenerative disorders demonstrated by Wang et al. [59] and Mestre et al. [60] and their working procedure has been described below:

i. Feature extraction: Extraction of features has been performed on the basis of imaging modalities. The specific features and imaging modalities used can vary based on the study.
ii. Feature selection: The extracted features may contain redundant or irrelevant information, which can negatively impact the performance of the model. Thus, Selection of features has been done for identification of the specific features to perform classification.
iii. RF training: Utilization of selected features is done for providing training to RF classifier, which consists of multiple decision trees. Each decision tree is trained

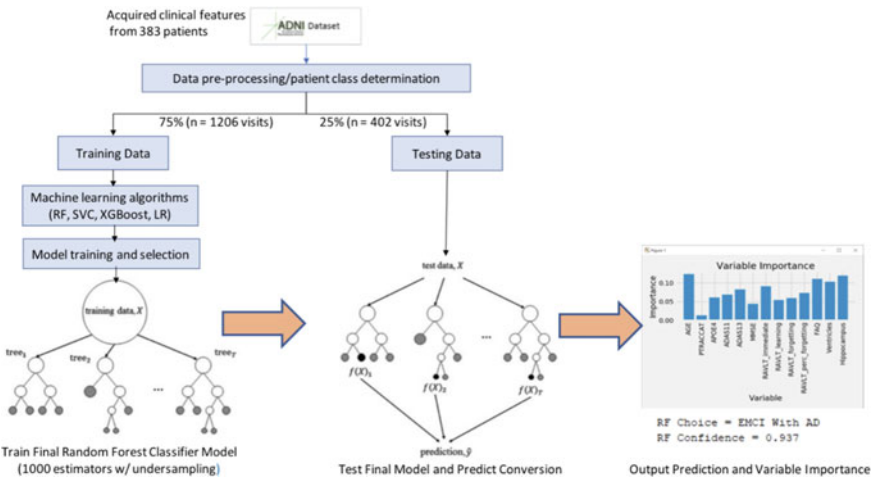

Fig. 8 Architecture of RF model [58]

on a subset of the training data, and the RF algorithm combines the predictions of the individual trees to make the final classification decision.

iv. Model evaluation: Evaluation of trained model has been performed on testing set for assessing its performance. This example describes how RF can be used to diagnose neurodegenerative disorders based on imaging features. The specific feature extraction, selection and RF hyper-parameters, can be customized based on the specific dataset and task at hand.

RF Model Methodology Korolev et al. [61] proposed an RF-based framework for predicting the Alzheimer progress. A study by Mwangi et al. [62] used random forest to classify individuals as healthy controls, individuals with Alzheimer's disease, or individuals with mild cognitive impairment based on structural MRI data. Another study by Hwang et al. [63] used random forest to predict Alzheimer's disease progression based on baseline cognitive measures and clinical data. Its ability to handle large amounts of data and nonlinear relationships between features makes it a useful tool in the context of diagnosing neurodegenerative disorders.

Hybrid Model A hybrid model in diagnosing neurodegenerative disorders can combine different types of models, such as deep learning, support vector machine, or random forest, to leverage the strengths of each type of model and improve overall performance.

Here's an example of a study that used a hybrid model for diagnosing Alzheimer's disease as shown in Fig. 9 [64].

Wang et al. [65] proposed model consisting of a deep learning network and SVM for early diagnosis of Alzheimer's disease. The architecture of the proposed model is as follows:

i. Preprocessing: The authors preprocessed the magnetic resonance imaging (MRI) data by segmenting the brain and extracting the gray matter via using a software namely Statistical Parametric Mapping.

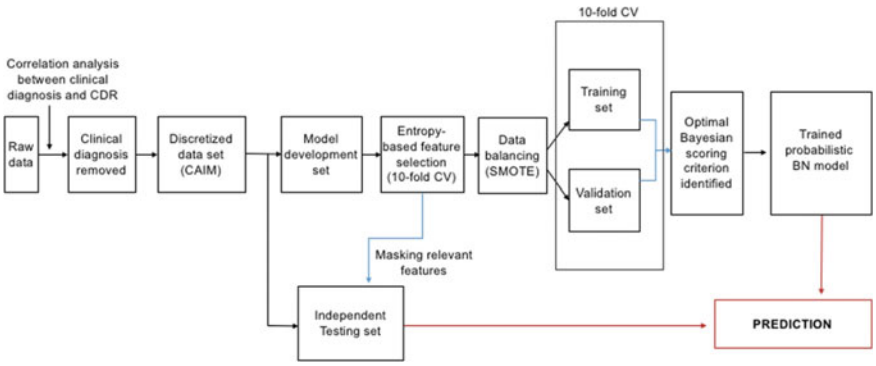

Fig. 9 Architecture of hybrid model [64]

ii. Deep learning network: Training has been provided to model via pre-processed MRI data to extract features that were relevant to Alzheimer's disease diagnosis.
iii. SVM classification: SVM classifier was utilized to classify the MRI data into Alzheimer's disease and normal control groups. The hyperparameters of the SVM model, such as the regularization parameter and kernel function, were tuned using a grid search method.
iv. Model evaluation: The trained hybrid model was evaluated on a separate test set, and the performance was assessed using various metrics such as accuracy, sensitivity, specificity, and area under the ROC curve. The proposed hybrid model achieved higher accuracy than existing ones.

This example describes how a hybrid model can combine the strengths of deep learning and SVM to improve the accuracy of neurodegenerative disorder diagnosis.

Hybrid Model Methodology Wang et al. [65] proposed a hybrid model consisting of a deep learning network and a support vector machine (SVM) to detect Alzheimer at an early stage. DNN was used to extract relevant features from MRI data, and the SVM was used for classification. The proposed hybrid model achieved high accuracy while diagnosing Alzheimer, outperforming another CNN model and SVM model alone.

5.7 Survival Analysis Model

It is commonly used for analyzing time-to-event data, such as the time until particular outcome, such as death or disease progression. In the context of neurodegenerative disorders, survival analysis models can be used to predict the time until a patient reaches a specific clinical milestone, such as the onset of symptoms or the need for institutionalization. The SAM model uses an attention mechanism to highlight important features in medical images, such as MRI scans, and improve the accuracy of disease diagnosis as shown in Fig. 10 [66].

A study that used the SAM model for diagnosing Parkinson's disease: Zhang et al. [67] proposed a spatial attention deep learning model based on the SAM architecture for diagnosing Parkinson's disease. The SAM model was used to highlight the most relevant regions of the brain in MRI scans for disease diagnosis.

The SAM model architecture typically consists of the following components:

i. Pre-processing: The input medical image data is pre-processed to standardize image size, resolution, and orientation.
ii. Convolutional Neural Network: The pre-processed image data is passed through CNN for extraction of relevant features to diagnose disease.
iii. Spatial Attention Module: The output features from the CNN are then passed through a spatial attention module for highlighting the important image regions for better diagnosis.

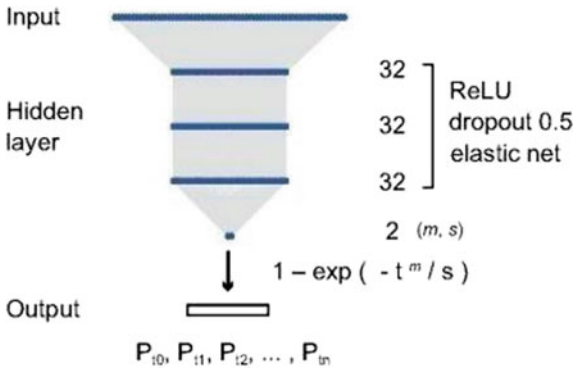

Fig. 10 Architecture of survival analysis model [66]

iv. Classifier: The highlighted features are then passed through a classifier, such as a fully connected neural network or support vector machine, to make a diagnosis.

The SAM model is applied for diagnosing various neurodegenerative disorders. By selectively highlighting the most relevant features in medical images, the SAM model can improve the accuracy of diagnosis and reduce the number of false positives or false negatives.

SAM Methodology Wang et al. [68] proposed a model based on SAM to diagnose Alzheimer on the basis of MRI input scans. The model achieved high accuracy and outperformed other models based on deep neural networks such as VGG-16 and ResNet-50. This study demonstrated the effectiveness of the SAM model for neurodegenerative disorder diagnosis. Nie et al. [69], deployed SAM for analysis of neurodegenerative disease via collaborating clinical and neuroimaging data.

They also used Cox proportional hazards model, a commonly used SAM model for prediction of time until transformation into Alzheimer. The model achieved high accuracy in predicting the risk of conversion and was able to identify key clinical and imaging predictors of disease progression.

On another hand, Zhang et al. [70] used collaboration of clinical, cognitive, and neuroimaging data to predict Parkinson in patients. The authors used a machine learning approach, which combined Cox proportional hazards models with gradient boosting, to predict the time until conversion to Parkinson's disease. The model achieved high accuracy in predicting the risk of conversion and was able to identify key predictors of disease progression. Overall, survival analysis models have shown promise in diagnosing neurodegenerative disorders by predicting the time until notices progression of disorder.

6 Contributions of AI and ML Models in Diagnosing Neurodegenerative Disorders

6.1 Contributions of DL Models

Deep learning models have contributed significantly to the field of neurodegenerative disorders diagnosis in analyzing medical data. Here are some examples of the contributions of deep learning models:

i. Development of model on the basis of deep neural network in diagnosing Alzheimer via diffusion-weighted MRI (DW-MRI) inputs at an early stage. This model gained 93.5% accuracy [71] in identifying Alzheimer controls from healthy ones.
ii. Implementation of deep neural network based model for automated classification of Parkinson on speech signals. The model achieved classification accuracy of 93.33% [72] while diagnosing Parkinson's disease.
iii. Developing deep neural network based models to detect and classify Alzheimer disorder automatically on the basis of input MRI scans which further gained 88.3% accuracy while identifying patients with Alzheimer's disease [73].
iv. Use of a deep learning model for identifying patients with Huntington's disease from MRI scans and such model gained 89.0% accuracy while identifying patients with Huntington's disease [74].
v. Implementing deep neural network model to diagnose ALS automatically on the basis of input MRI scans and such model further achieved 85.7% accuracy while identifying patients with ALS [75].

6.2 Contributions of CNN Models

Wang et al. [76] suggested a model based on 3D-CNN model for classification of MRI input images on the basis of Alzheimer and healthy ones and achieved an accuracy of 86.3% whereas Liu et al. [77] developed CNN model for prediction of transforming cognitive abnormalities into Alzheimer via MRI input scans and gained 87.5% accuracy and demonstrated better performance than existing approaches. Aksman et al. [78] also developed CNN model for differentiating Parkinson with and without dementia using DaTscan SPECT images and achieved 98% accuracy. Li et al. [79] also proposed a CNN model for predicting continuation of PD via longitudinal data from wearable sensors. The model achieved an accuracy of 78.7% and demonstrated better accuracy than traditional approaches.

6.3 Contributions of LSTM Models

Several studies have proposed utilization of LSTM models to diagnose neurodegenerative diseases. Some of the contributions of LSTM models in this field are:

i. Accurate classification: Sarraf et al. [34] used an LSTM model to classify Alzheimer's disease patients and healthy controls and achieved an accuracy of 84%.
ii. Early diagnosis: LSTM models have also been explored for early diagnosis of neurodegenerative disorders. A study by Atrey et al. [80] proposed an LSTM model for early diagnosis of Parkinson's disease based on handwriting analysis, achieving an accuracy of 94.44%.
iii. Personalized treatment: LSTM models can also help in personalized treatment by predicting disease progression and identifying patients who are likely to respond to a particular treatment. A study by Zhang et al. [81] used an LSTM model to predict the disease progression of Parkinson's disease patients based on their clinical features and achieved a mean absolute error of 1.76 during prediction of UPDRS score.

6.4 Contributions of GCN Models

Graph convolutional networks (GCNs) are a type of deep learning model that can process data in graph structures. They have shown promise in the diagnosis of neurodegenerative disorders, particularly in the analysis of brain networks. Here are some contributions of GCN models in diagnosing neurodegenerative disorders:

i. Feng et al. [82] suggested a model on the basis of graphical convolutional network to diagnose Alzheimer at an early stage via utilizing MRI data to construct brain networks, which were then analyzed using a GCN to identify the AD-related biomarkers. It performed better than existing traditional machine learning methods in terms of its performance metrics.
ii. Another study by Li et al. [83] developed a GCN-based model for the diagnosis of PD. The model used functional MRI (fMRI) images to construct brain networks, which were then analyzed using a GCN to identify the PD-related biomarkers.
iii. Sarica et al. [84] developed GCN model to diagnosis multiple sclerosis (MS). The model used diffusion tensor imaging (DTI) data to construct brain networks, which were then analyzed using a GCN to identify the MS-related biomarkers.

Such models have shown great improvement in diagnosing neurodegenerative disorders than existing approaches.

6.5 Contributions of SVM Models

Support Vector Machine (SVM) is a type of machine learning algorithm that is widely used in the field of neurodegenerative disorders. Here are some contributions of SVM models in diagnosing neurodegenerative disorders:

i. In a study by Casanova et al. [85], SVM was used to classify patients with Alzheimer on the basis of their brain scans and achieved 87.22% accuracy. Another study by Jafari Jouzani et al. [86] used SVM to classify infected people with Parkinson on the basis of received speech signals and achieved 97.333% accuracy. SVM has also been used in combination with other machine learning algorithms in the diagnosis of Huntington's disease. In study by Tabrizi et al. [87], a combination of SVM and decision tree was used to classify patients with Huntington's disease and healthy controls based on their clinical scores. The SVM model achieved an accuracy of 78.2%.

6.6 Contributions of RF Models

Random Forest (RF) models have also been used in diagnosing neurodegenerative disorders, with some notable contributions from various authors. In a study done by Gaser et al. [88], they used an RF model to classify patients with Alzheimer's disease (AD) based on structural MRI data, and achieved an accuracy of 85.6% in identifying patients with AD versus healthy controls (HC).In another study done by Hacker et al. [89], they used an RF model for predicting progression of PD via multimodal imaging data, achieving 0.76 AUC. In recent studies of Lopez-Sanz et al. [90], an RF model was used to predict cognitive decline in patients with mild cognitive impairment (MCI), achieving an AUC of 0.85.

6.7 Contributions of Hybrid Models

Hybrid models, which combine different machine learning algorithms, have shown promise in diagnosing neurodegenerative disorders. Here are some contributions of hybrid models in this area:

A hybrid model combining convolutional neural net-works (CNNs) and a support vector machine (SVM) was used by Zhou et al. [91] to diagnose Parkinson's disease (PD) based on speech signals. The model achieved an accuracy of 94.242%. Another hybrid model combining CNNs and long short-term memory (LSTM) networks was used by Yang et al. [92] to classify MRI images into Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy controls. The model achieved high accuracy and outperformed other models based on CNN or LSTM alone.

A hybrid model combining a deep belief network (DBN) and a random forest (RF) classifier was used by Lu et al. [93] to diagnose AD based on multiple biomarkers.

The model achieved high accuracy and outperformed other models based on DBN or RF alone. A hybrid model combining features extracted from electroencephalography (EEG) signals and a deep neural network was used by Wang et al. [94] to diagnose AD based on resting-state EEG data. The model achieved high accuracy and outperformed other models based on EEG features or deep neural networks alone. These studies demonstrate that hybrid models can improve the accuracy of diagnosing neurodegenerative disorders by combining the strengths of different machine learning algorithms. A hybrid model combining deep neural network (DNN) and survival analysis was used by Xu et al. [95] for prediction of continuation of Alzheimer and such model gained concordance index of 0.81 in predicting the progression rate of AD.

6.8 Contributions of Survival Analysis Models

Survival analysis models have been used in various studies for diagnosing neurodegenerative disorders. These models are used to analyze and model the time-to-event data, such as the time between the onset of symptoms and the occurrence of a particular event (such as disease progression or death). The following are some of the contributions of survival analysis models in diagnosing neurodegenerative disorders, along with references:

In a study, Lee et al. [96] used a Cox proportional hazards model to analyze the progression of PD and predict the time to the next clinical milestone. The authors used several clinical variables as predictors and found that the model accurately predicted the time to the next clinical mile-stone in PD patients. In another study, Zheng et al. [97] used a random survival forest model to predict the progression of Alzheimer's disease (AD) based on neuroimaging data. The authors used several imaging features as predictors and found that the model accurately predicted the time to AD progression in a test dataset.

Moreover, Villemagne et al. [98] used a Cox proportional hazards model to predict the time to conversion from mild cognitive impairment (MCI) to AD based on several biomarkers, including amyloid-beta PET imaging, cerebrospinal fluid biomarkers, and neuropsychological tests. The authors found that the model accurately predicted the time to conversion in a test dataset.

These studies demonstrate the potential of survival analysis models in predicting the progression of neurodegenerative disorders based on clinical, imaging, and biomarker data.

7 Challenges and Opportunities for Diagnosing Neurodegenerative Disorders

Artificial intelligence (AI) and machine learning (ML) models have shown promise in the diagnosis, classification [99, 100] and managing neurodegenerative disorders. However, there are also several challenges which requires addressing at priority for realizing potential of these models. Some of the challenges in developing AI and ML models for neurodegenerative disorders include:

i. Lack of data: Neurodegenerative disorders are relatively rare and longitudinal data is often required to develop accurate models. Obtaining sufficient data for training and testing can be a challenge.
ii. Data quality: There is a great significance of input data provided to the model as it must be qualitative in nature for achieving better accuracy. Medical imaging data such as MRI scans can be noisy or have artifacts, which can reduce the performance of the models.
iii. Interpretability: Due to the achievement of high accuracy based on AI and ML models, there is a high probability of considering such models in the category of black box with limited interpretability. This can make it difficult for clinicians to understand the rationale behind the model's predictions.
iv. Generalizability: AI and ML models developed using data from one population may not generalize well to other populations due to differences in demographics, genetics, and disease progression.

Despite these challenges, AI and ML models offer several opportunities for improving the diagnosis and management of neurodegenerative disorders. Some of the opportunities include:

i. Early diagnosis: AI and ML models can detect neurodegenerative disorders at an early stage, allowing for earlier intervention and potentially better outcomes.
ii. Precision medicine: By analyzing individual patient data, AI and ML models can help personalize treatment plans based on the patient's specific disease characteristics.
iii. Biomarker identification: AI and ML models can be used to identify new biomarkers for neurodegenerative disorders, which can help with early diagnosis and monitoring disease progression [101].
iv. Drug discovery: AI and ML models can help identify new drug targets and optimize existing drug candidates, potentially leading to the development of new treatments for neurodegenerative disorders [102].

8 Results and Discussion

There have been many studies that have explored the use of AI and ML models while detection as well as prediction of neurodegenerative diseases [104]. Here are a few examples:

i. In a study by Zhu et al. [2], a model on the basis of deep neural network was developed for diagnosing Parkinson's disease (PD) and gained 91.4% accuracy in distinguishing PD patients from healthy controls. Thus, deep neural networks performs efficiently while diagnosing Parkinson disorder.
ii. Jie et al. [103] used combination of deep learning and survival analysis for prediction of progression of Huntington's disease (HD) using MRI scans. The model achieved an accuracy of 72.7% in predicting the progression of HD, which outperformed traditional machine learning models. The results suggest that model can be effective in predicting the progression of HD using MRI scans.
iii. In a study done by Guo et al. [56], they developed a hybrid model combining deep learning and support vector machine (SVM) techniques to diagnose AD via collaboration of MRI and PET scans. They also gained 91.23% accuracy in classification of an individuals' images suffering from AD and normal ones. The study demonstrates that combining multiple imaging modalities and machine learning techniques can improve the accuracy of AD diagnosis.
iv. In a study by Velazquez et al. [58], a random forest model was used to predict the onset of dementia using electronic health records (EHR) data. The model achieved an accuracy. Results suggest that EHR data in combination of machine learning models can be used for prediction of dementia on-set.
v. Zhang et al. [71] developed a deep Neural Network based model to detect Alzheimer from MRI inputs and such model achieved accuracy of 93.5% in differentiating AD sufferers from healthy ones. The study shows that deep learning models can provide an accurate diagnosis of AD using MRI scans.

However, there are still challenges to be addressed, such as the need for larger datasets and more diverse patient populations, as well as the interpretability and explainability of the models.

9 Conclusion

AI and ML models have shown promising results in diagnosing as well as predicting neurodegenerative disorders, such as Alzheimer, Parkinson, Huntington, and others. These models have provided great significant in improving accuracy while diagnosing such disorders and becoming efficient enough leading to earlier interventions and better outcomes of patients. However, there are challenges that need to be addressed, such as the need for larger and more diverse datasets, interpretability and explainability of the models, and ethical concerns related to patient privacy and data sharing. As AI and ML continue to evolve, it is likely that they will play important role in the field of neurodegenerative disorders, providing new insights and opportunities for diagnosis and treatment.

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Neurodegenerative Alzheimer's Disease Disorders and Deep Learning Approaches

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Abstract Convolutional neural networks (CNN) can no longer make a significant contribution to Alzheimer's disease diagnosis because there is insufficient data to work with. We have built a cutting-edge deep learning system and are currently putting it to use to increase the effectiveness of the work we are doing to achieve this goal. To achieve the highest level of performance, we combine the advantages of fully stacked bidirectional long short-term memory (FSBi-LSTM) with those of three-dimensional convolutional neural networks. These two methods of data storage are stacked one on top of the other. Before interpreting the MRI and PET images, it is critical to train a three-dimensional convolutional neural network. This must be completed to proceed to the next stage. The essential qualities of the deep features can be agreed upon. Before any further inquiry into the matter can proceed, this must be done. Here is only one example of how this method may be applied. Even if only one individual is made aware of this, the ramifications might be terrible. Lastly, we compared our findings to those of an Alzheimer's disease neuroimaging research study to show definitively that our technique is beneficial in Alzheimer's disease management. According to our observations, our approach surpasses other theoretically comparable algorithms published in academic literature. These algorithms were evaluated based on their ability to tackle the same issue. This is true regardless of whether our technique is technically equivalent to other published methods: cases of pMCI can be distinguished from NC with a success rate of 94.82%; cases of sMCI can be distinguished from NC with an 86.30% success rate; and cases of Alzheimer's

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Disease (AD) can be distinguished from NC with an 86.30% success rate. This result was obtained despite the fact that there was inadequate imaging evidence to back it up.

Keywords Convolution neural network · Fully stacked bidirectional · Long short-term memory · Deep learning · Recurrent neural networks

1 Introduction

If you recognise the warning signs of Alzheimer's disease, you can take preventative measures. If not treated, the disorder will progress to Alzheimer's disease, another type of dementia that impairs memory and cognitive function. This country is an extreme example, especially when it comes to the proportion of the population that is at least 65 years old. Both categories are sometimes referred to simply as "MCI." Some people are likely to use the term "MCI" to describe both groups. These two types of moderate cognitive impairment were recently added to the list of potential impairments (pMCI). It is expected that the costs of caring for those with Alzheimer's disease will have increased by a factor of four by 2030. Alzheimer's disease is estimated to cost the global economy one trillion dollars over the next few decades. The tendency of Alzheimer's disease symptoms to worsen over time is one of its distinguishing features. Extensive research has been conducted to develop automated methods for detecting structural and functional irregularities in brain regions associated with Alzheimer's disease [1–3]. Several of these discoveries have been the focus of articles published in scholarly journals. Currently, most of these investigations are carried out using traditional approaches to machine learning. The image's qualities can be changed by changing elements such as the location of voxels and the size of their individual pixels [4]. The first strategy focuses on hypotheses about the causes of observable changes in the structure or function of the brain. For example, it is possible to obtain precise estimates of the grey matter volume, hippocampus size, and cerebral cortex thickness of the human brain. One of the major drawbacks of using such feature extraction algorithms is the requirement for extensive preprocessing steps and clinical domain knowledge [5]. This is one of the primary reasons for the underutilization of such algorithms. Another disadvantage of these plans is that they require a time commitment from the planner to be implemented. Furthermore, ROIs cannot accurately capture the size and complexity of the neural network that makes up the brain. The region of interest (ROI) extraction process employs compression, which results in significant data loss. Even though image volumes can contain millions of voxels and appear to be enormous in size, they can only store a limited number of samples. This creates the impression that the clothing is too constricting. Even though it is time-consuming, prone to human error, and highly individualized, manual feature extraction is still widely used in traditional machine learning systems. This is true even though traditional machine-learning systems heavily rely on it. You have the strength to overcome challenges like these and emerge stronger

on the other side. Those looking for a citation are given this, which recommends using shallow 3D-CNN networks [6]. Because 3D-CNN segment feature maps are never displayed in 2D, any attempt to flatten the data results in the loss of contextual information. As a result, any such attempt would be futile. Several attempts have been made to address this issue using CNNs by substituting another component for the fully connected (FC) layer. Some of these efforts have been fruitful. This entire endeavour is an attempt to get around the usage restrictions CNN has placed on this content, but it will fail. Given that state vectors are an essential component of RNNs, the conclusion reached makes perfect sense. According to recent research [7], recurrent neural networks (RNNs) may be able to analyse sequence data and derive trustworthy conclusions from it when conducting structure analysis. The findings of the studies appear to support this. LSTM, or long short-term memory, is mentioned. This is made possible by the numerous gates that regulate and enable information flow. LSTM based on bidirectional learning can consider both the current context and the context to come [8]. In contrast to more traditional LSTM methods, the bi-LSTM algorithm allows users to start collecting data before deciding on a scanning direction. This provides bi-LSTM with a significant advantage over competing methods. As a result, the LSTM may be able to solve the problem by analysing the spatial data contained in the 3D-CNN feature maps. When iterating the results back into the inputs, recent inputs are given an excessive amount of weight because they are given more relevance because they are more recent. As a result, the FC layer can strengthen the link between the numerous SBi-LSTM output nodes, resulting in increased accuracy [9]. As a direct result of these findings, we were able to create a cutting-edge deep-learning network capable of precisely diagnosing Alzheimer's disease. Because of the use of a fully stacked bidirectional LSTM and a 3D-CNN, this network can combine and process data from a variety of sources. In contrast to the traditional FC layer, the FSBi-LSTM method can extract meta-level semantic and spatial information. This is made possible by the method's emphasis on temporal memory. A subsequent diagram depicting the FC layer lends some support to this claim. The FSBi-LSTM method ensures that the spatial information of feature maps created using data from various data areas is maintained by associating one pixel from each feature with its corresponding position at each step. This ensures that the spatial information on the feature maps is correct. These feature maps were created because of extensive research and information gathering, as mentioned in the preceding sentence. After the data processing is finished, the SBi-LSTM sends the results to a feature extraction layer [10]. For the LSTM to function properly, it must be trained in this manner. It can only be trained by exploiting the strong correlation between the output and input of neighboring nodes. As a result, the results of one phase of the process are heavily dependent on the results of the next phase. After the MRI and PET scan features have been combined, a SoftMax algorithm is used to classify the combined data. This is done to make the combined data usable.

2 Proposed Work

Several studies [11–13] have investigated the use of traditional machine-learning techniques to make automatic algorithms that can track the structural and functional neuronal lesions that are linked to Alzheimer's disease. This was accomplished using standard machine learning approaches. To achieve this purpose, standard machine learning approaches must be employed. To categorise data, this method employs a similarity score generated by a random forest classifier. The most efficient approach to accomplishing this is to combine relational regularisation with multimodal data. Using information that is already accessible, this technique makes forecasts. However, for these tactics to be effective, many manually produced qualities as well as a large amount of computational power are required. Both features are unappealing, and replicating the craft can be difficult. Techniques Several recent studies [14–16] used this technique, which was inspired by deep learning systems. This was done as part of a larger attempt to remove the constraints that had previously stymied the advancement of machine learning. This strategy could be used to locate Alzheimer's disease patients. MRI data can be separated into three planes using this technique. Before reviewing the aggregate outcomes of all simulations, researchers assessed the findings of the final diagnosis using three distinct 2D DenseNets. The MRI scan findings will be linked with demographic information to help the researchers achieve their goals of clinical score regression and brain disease classification [17]. Then, using a data-driven approach to identify the landmarks of discriminative anatomical traits, they extracted several picture patches from the MRI data. They were then able to conclude their research without any further complications. They were able to identify the landmarks because of this. Because the feature map is flattened before adding the FC layer, any spatial information in the feature map is disregarded [18–22]. A bidirectionally gated recurrent unit with a two-dimensional convolutional neural network. This was necessary to fix the current problem. Because the FC layer can only analyse data in one dimension, the flattening layer is typically placed after the CNN in current CNN-based processing algorithms. Because the CNN layer is the only one that can handle multidimensional data, this is done. Based on the information that is currently available, this is the only reasonable conclusion. This method employs MRI and PET neuroimages; Fig. 1 depicts it in broad strokes. For example, "P222" shows 222 pooling layers, each of which is 202 bytes in size, but "15@333" shows 15 filters, each of which is represented by a 333-byte string. We employ a three-dimensional convolutional neural network to try to identify the essential components of the MRI and PET inputs. High-level semantic and spatial information can be retrieved from 3D-output CNNs by bypassing the traditional FC layer in favour of the FSBi-LSTM. Before being delivered to the SoftMax classifier for disease diagnosis, the collected features are first consolidated into a single set. It contains a detailed analysis of the suggested technique.

Using the MIPAV software (https://mipav.cit.nih.gov/), we resample the MRI data and reorient it. This is done in conjunction with adjusting the anterior and posterior commissures. To do a more detailed analysis, we reformatted the MRI data into a grid

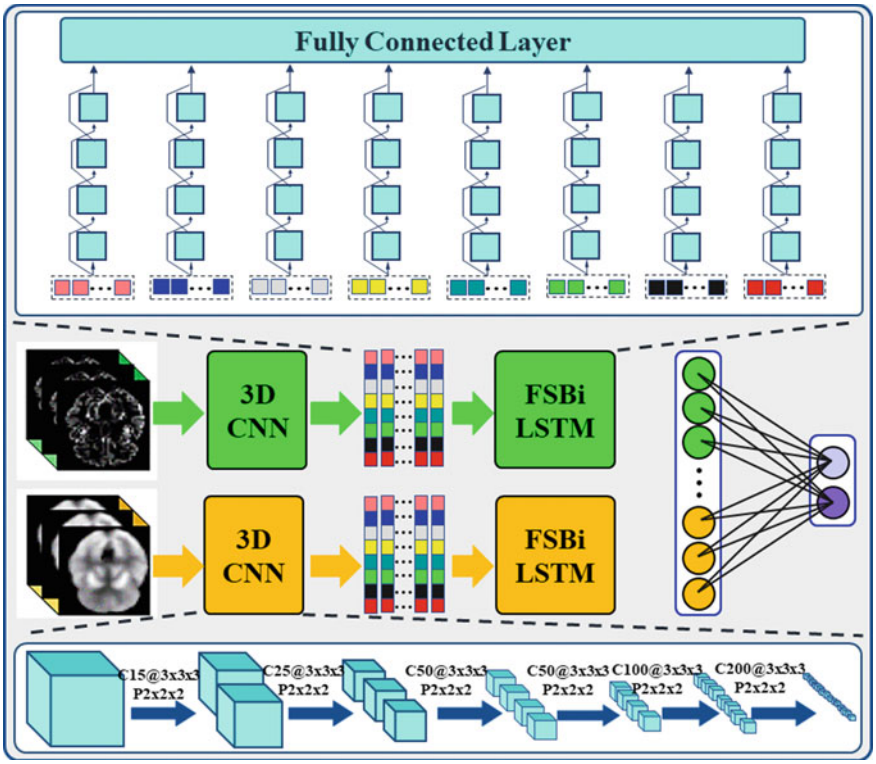

Fig. 1 The proposed method architecture

with 256 cells above and 256 cells below. The skull is then dismantled, the cerebellum is removed, and the uneven distribution of tissue intensities is rectified with the N3 algorithm. There is a considerably stronger association between GM and AD/MCI than between WM or CSF. This is the case because genetically modified (GM) is a genetic marker [23]. As a result, we opted to use masks that had been genetically modified. Before beginning the PET process, the subject must be properly positioned on the MRI scanner in a risk-free way, which has the extra benefit of preserving tissue integrity. This must be completed before beginning the PET process.

This type of network is well-known for its image-processing efficiency. 2D-CNN structures, on the other hand, were developed exclusively for the purpose of analysing 2D photographs due to their inability to successfully extract the spatial information inherent in 3D medical images [24–27]. This was done because 2D-CNN structures can only analyse two-dimensional pictures. As a result, we decided to use a 3D convolution kernel rather than a 2D one. Because of this, we may develop the 3D convolutional kernel. This paves the path for the construction of the 3D convolutional kernel. In conclusion, we should emphasise that the CNN model gives us access to feature maps. It is critical to share this knowledge [28–30]. This is done to design

features that are both useful and take up little space. Additionally, the use of a max-pooling layer allows the characteristics to be more focused from low to high levels. This occurs as the user progresses from the lower to the upper level. This results in "resilience," which is resistance to some changes. We avoided having a top layer that required a very specific set of skills, which is why we did it. This section expands on the information presented in the previous section about Fig. 1. The model is augmented with six new layers during training, each of which combines stacking convolutional and max-pooling operations. Following that, the model will be given two FC layers and a SoftMax classifier. After that, the model will be completed. The FC layers condense all the characteristics into a single-dimensional vector to make analysis easier. Following the completion of the FSBi-training LSTM phase, we will begin feeding it data by utilising the feature learned in the layer preceding the max-pooling layer. This will occur following the completion of the FSBi-training LSTM phase.

In a typical CNN, the FC layers are in charge of managing high-level analysis that is done in a data network. This is because the feature map serves as their primary repository. This is due to the FC layers' sole purpose of connecting neurons. Figure 2 depicts the geographic information and shows how the feature maps and raw data are related to one another. It is feasible to see a connection between the two types of data. It is abundantly clear to both of us that the output of each model in our 3D-CNN network includes a total of 200 features, with each dimension assigned a value of 222. Figure 2's black boxes represent the rows, which each represent a particular aspect of the brain's overall organisation [31, 32]. This is the location where you can find the desired number. Then, within each column, a more detailed explanation of the characteristics specific to the individual brain areas is provided. If we used a red box to intercept a row-by-row feature map, we would be performing a sectional examination of the brain. RNNs and other networks with functionalities comparable to RNNs, as demonstrated in previous studies, are critical in the process of merging multiple architectural styles [33, 34]. This was done so that we could achieve our goal in the most efficient way possible.

But gradient rise and disappearance problems, which are common in these kinds of networks, make it hard for traditional RNNs to work well. Each of these issues now has a significant impact on the global population. These two issues are among the most common that people face. If this is not done, the device will not function. Only one of the gates, marked "forget," can be shut. These gates oversee both high- and low-frequency processes, depending on the situation (ht and ct). Given that the sum of the input xt weight (Wxi), output cell weight (Whi), and input gate bias is four, the correct answer is (Wxixt + Whiht1 + bi). Wxixt + Whiht1 + bi is the correct response (bi). Determine the value of the input gate using an expression of the form (Wxixt + Whiht1 + bi) = (Wxixt + Whiht1 + bi). You can use this to determine the value of the input gate. The sigmoid function has its own symbol in mathematics. The forget gate's equation is ft = (Wxfxt + Whfht1 + bf), which is very similar to the previous equation. As a result, we can determine the modulation mode in which the input signal is currently operating. It can be calculated using the formula gt = (Wxcxt + Whcht1 + bc), where xt is the input weight, Wxc is the tanh

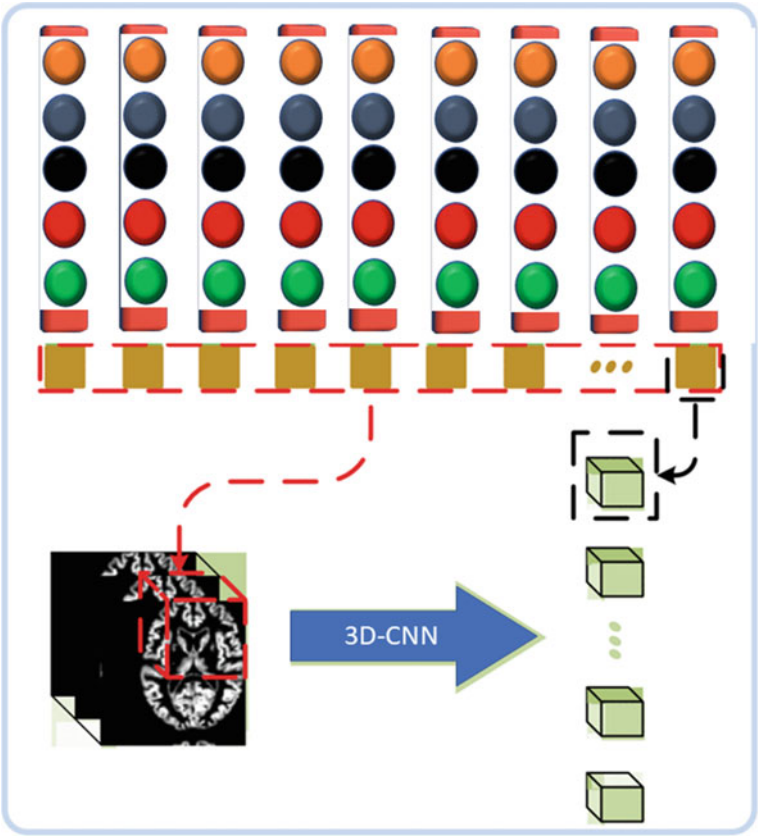

Fig. 2 The possible connections between the feature maps and the primary data

function symbol, Whc is the final cell's output weight symbol, and bc is a constant. Once this information has been gathered, gt can be computed.

A computation requires an input, and the cell's present state acts as that input. The forget gate, which is associated with the previous unit state, multiplies the element to start. The input gate that corresponds to the input unit's current state then multiplies the element. The final step is to combine the outcomes of these two independent processes. Mathematically, the long memory is defined as ct = itgt + ftct1, where the symbol stands for element-wise multiplication. A table can also serve as an illustration of this equation. If our efforts are successful, we will establish a new unit state by fusing the current memory's short-term memory with the LSTM's long-term memory. We have control over the "forget gate," which allows us to choose which aspects of our past we want to remember and which we don't. We might also reject aspects of the past that we do not wish to recall. We won't have to worry about the memory filling up with unnecessary information if we keep control of the input gate. The model is depicted below. The letter H stands for an LSTM cell,

to be more precise. To be processed appropriately, it is expected that a training sequence must be fed both forward and backward via two LSTMs in the context of the bi-LSTM architecture. This is because it is believed that doing so will allow the sequence to be properly digested. The output layer oversees establishing connections with two LSTMs. Because of the way this information is organised, each data point in the output layer can give context for both the information's more distant context and the data's immediate context. The output yt is calculated because of this method. After superimposing a basic LSTM cell on the outputs of the bi-forward and backward LSTMs, the method is completed by applying an FC layer to the FSBi-output LSTMs. In fact, once the fusion stage of processing characteristics has been completed, this could be the very last step of the process. Brain structure feature maps, on the other hand, were used, and each feature on the map is related to every other feature throughout the map. We may be able to build a common brain structure with strong connections between its components using all the SBi-LSTM cells. We will be able to use the FC layer to describe "trait" data that is consistent across all participants by using this structure. This information would be used to replace previously extracted data about the structure of the brain. The FSBi-LSTM computing method is one way to conceptualise this huge method. Figure 3 depicts the structural aspects of several fusion processes. We concluded that FFS would be the best integration strategy to utilise because FSB must integrate both forward and backward LSTM. As a result, we can avoid the performance decrease that the FSBi-LSTM suffers when modal fusion is applied. As a result, it is possible to do so. The SoftMax classifier analyses the data after it has been integrated to reach a conclusion.

Figure 3 shows a few examples of the many different types of fusion processes. There are four possibilities: A modal merging of the two brains; B modal isolation; C modal separation; and D modal separation.

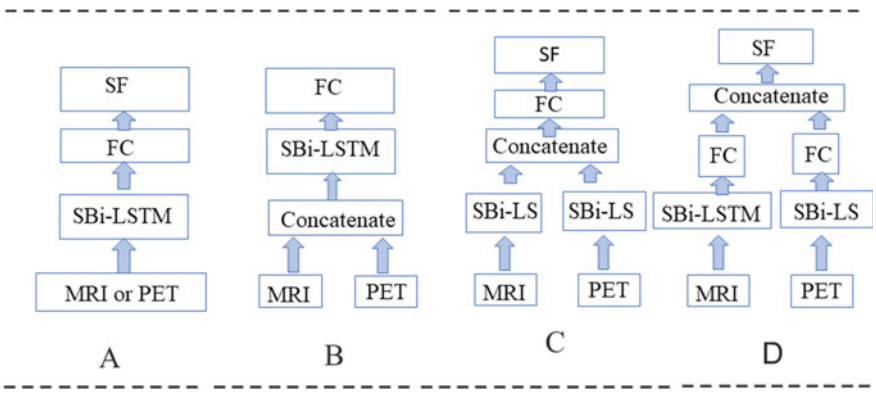

Fig. 3 A few examples of many different types of fusion processes

3 Results

For the experiment, we used Alzheimer's disease neuroimaging. We compared those with sMCI to those without the disease to examine the cognitive differences between those with and without the condition. The results of all these comparisons were used to evaluate our model's accuracy. All these comparisons are being made to see if our model is reliable (NC, pMCI, and sMCI, respectively). When healthy and sick people are compared side by side, it is much easier to identify pathological characteristics that could be useful in the diagnosis or treatment of a disease. We use a set of duals that correspond to each modality to generate feature maps. We can significantly reduce training time by using SoftMax as the classifier in conjunction with two FC layers. During the training phase of the 3D convolutional neural network, 10% of the neurons were randomly removed. This was done to keep the network from becoming too precise. To solve the 3D-CNN segment optimization problem, we decided to use the Adam optimizer, and we determined that category cross-entropy would be the best loss function to use. Because of the recently entered numerical values, the programme has been updated. Following training, an extracted 3D-CNN feature is fed to an FSBi-LSTM right before the layer that pools the most data. This happens just before the previously trained layer. As a result, the module could be trained in less time. The neural network was trained using 30 batches, 25 epochs, 103 learning rates, a 0.9 rho, and 108 fuzzy points. To obtain more precise data, we divided the entire sample collection into ten equal-sized groups. Each group was given the same number of samples. Each test is performed on a computer running the Windows operating system and outfitted with a graphics card from the NVIDIA Titan Xt product line. Tensorflow is the engine of the system and the base on which the experiments are built. Keras is used to do the experiments themselves. How well do people retain fully structurally linked memories and long-term memory (LTM) as they get older? This allowed us to assess how much the depth of the data affects FSBi performance. LSTM's As a result, we were able to determine how much the data's breadth influences performance. As a result, we were able to investigate the extent to which the depth of the data influences the performance of the LSTM. We created multiple SBi-LSTM layers and compared their results to see how much the FC layer affects system performance. Our tests included a single FSBi-LSTM layer (FBL1), a single Bi-LSTM layer (BL1), two FSBi-LSTM layers (FSBL2), three SBi-LSTM levels (SBL3), four FSBi-LSTM layers (FSBL4), and four SBi-LSTM layers. The models were tested using the following configurations: Two FSBi-LSTM layers, two Bi-LSTM layers, three FSBi-LSTM layers, three SBi-LSTM levels, four FSBi-LSTM layers, and four SBi-LSTM levels. Using the identical CNN feature maps, we successfully predicted the outcomes of each experiment. A confidence interval with a value of 0.001 shows that our results are statistically important.

Experiments were performed on an FSBi-LSTM with various FC layer to LSTM layer ratios. Figure 4 depicts the results of using the suggested method in various contexts and then using it to complete a variety of classification tasks. These outcomes are demonstrated to be the result of employing the suggested technique. Despite this,

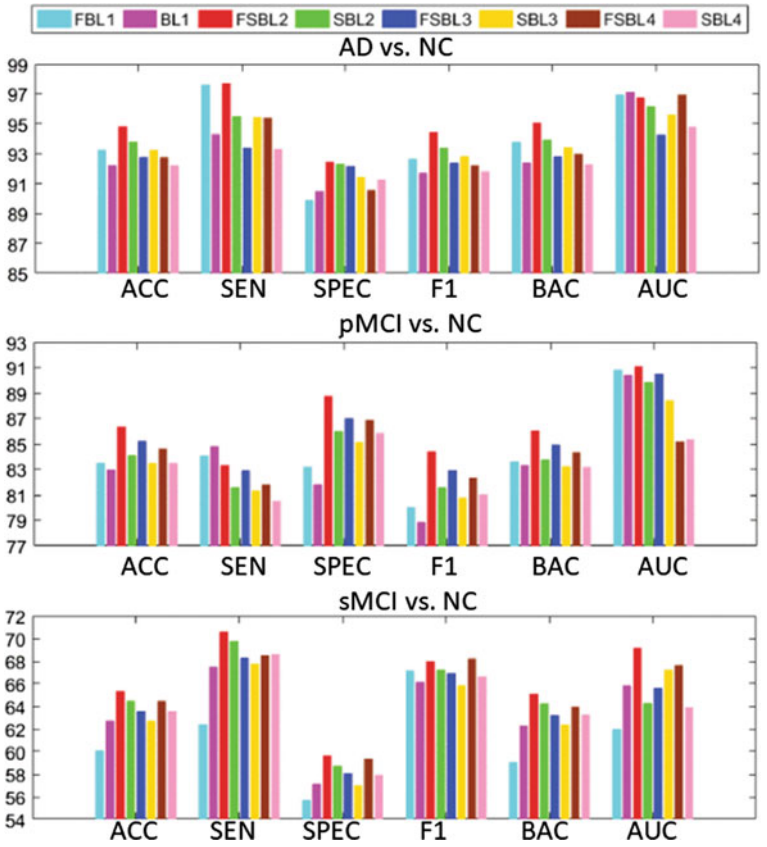

Fig. 4 Number of layers used in the SBi-LSTM and FSBi-LSTM models influences their performance

there are a few notable exceptions. As the number of LSTM layers increases, a model may become more effective. According to our findings, the best performance configuration consists of two LSTM layers that can communicate with one another. When using models from the FSBi-LSTM family with fewer than two layers, deep feature extraction from data is difficult. This is because it is difficult to extract practical, deep features from data. Gradient vanishing is a problem that begins to appear in multi-layer networks. This problem worsens as the network's depth increases. When a network has more than two nodes, its performance begins to suffer, and the performance loss becomes more pronounced as more nodes are added to the network. This is due to a phenomenon known as "overfitting," which occurs when a model produces predictions that are too accurate for their own good. Considering the situation, we will call the model the FSBi-LSTM. It will consist of two layers: long-term and short-term memory. This is necessary due to the circumstances. FSBi-LSTM outperforms SBi-LSTM in terms of performance after feature extraction because it retains more

of the unique characteristics of the initial input. This allows it to model the data. This is because feature maps, which are abstract representations of the brain's structure, include interconnected features. This is because the feature maps contain interconnected features. The presence of this factor explains the current situation. This is due to the way LSTM was designed to work. This is due to the way LSTM was initially conceived in its early stages. The FC layer has the potential to express "trait" information that is consistent across individuals by combining information from various SBi-LSTM cells, each of which represents a related brain region. Using the FC layer could allow people to share information about traits they share. If we followed these steps, we would be able to use the FC layer to express information about characteristics. Once that was completed, we would be able to move on to the FC layer of the protocol. As a result, in terms of performance, FSBi-LSTM outperforms SBi-LSTM.

It is talked about how important it is to coordinate different strategies. According to data from the scientific literature, the accuracy of the final classification seems to depend a lot on the fusion procedures used and the modal choice options chosen. The 95% confidence interval for the statistical significance of the link is set at 0.001, and our findings show a statistically significant connection between the two components once more. Our research and experiments, which focused on different types of fusion, were based on CNN's feature maps. Table 2 and Fig. 5 show how the fusion processes affect the operation of the FSBi. In my opinion, the most important discoveries have been put in bold because of how they fit into the bigger picture.

According to the study's findings, MRI outperforms PET in terms of effectiveness. This is because MRI is better prepared to acquire structural data from diverse brain areas. Furthermore, studies evaluating the efficacy of various fusion procedures suggest that FFS produces the best results. This page summarises the most often claimed justifications by others. When FFC is present, mode fusion, forward LSTM fusion, and reverse LSTM fusion all encounter interference from one another.

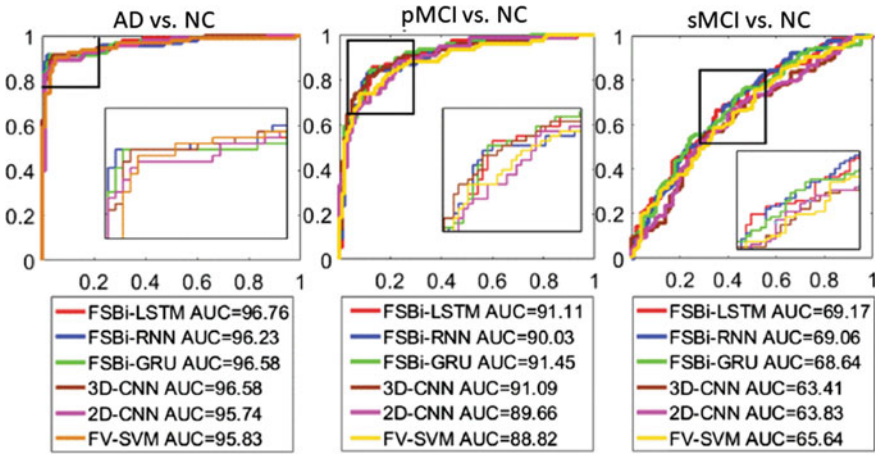

Fig. 5 ROC curves to show how well each information extraction model works

In other words, each of the three types of fusion will have problems. When FSB is used, fusion can occur at the feature map's edge; however, this leads to an unnecessarily large input size. If the feature map were to merge along one of its sides, the new size of the map would be 200 by 16, rather than the existing size of 16. The MRI is used as the input for the SBi-forward LSTM, but the PET is used for the reverse input. As a result, the MRI is used as input. These inputs will have an impact on the fusion technique, but the impact will be bidirectional. Fusion Techniques. In this section of the study, we will compare the FSBi-LSTM approach to several other extensively used feature fusion strategies. To facilitate comprehension, fusion answers can be divided into three major kinds. The first method proposes substituting LSTM cells with standard RNN cells or even generalised recurrent units. These are just two of the many names used to describe this approach. This strategy is also known as the support vector machine in some circles. A t-test will be used to see if the data has any statistically significant meaning. When the 0.001 threshold is applied to the confidence interval, the results show that the proposed relationship between the two variables is statistically significant. That fits in perfectly with our previous discoveries. The results of the evaluations performed by the various feature fusion algorithms are compared to create a performance hierarchy. Each algorithm uses the same CNN output feature map to accomplish this. The accuracy of a study can be increased by using more feature fusion algorithms, as shown in Fig. 5 and Table 1. Everyone has access to Fig. 5, which displays the ROC curves for each model as well as other data. Based on these results, the FSBi-LSTM model seems to be more accurate than the FSBi-RNN and FSBi-GRU models.

Table 1 Compares the Classification Accuracy Attained by Several Feature Fusion Approaches

Method	Accuracy	Sensitivity	Specificity	F1 score	Area under curve
FSBi-RNN	95.41	97.60	93.49	94.03	97.34
FSBi-GRU	94.37	95.55	93.34	93.01	97.69
3D-CNN	93.34	93.40	93.19	92.90	97.69
2D-CNN	92.20	93.33	91.30	91.82	96.85
FV-SVM	93.86	95.49	92.46	93.42	96.94
FSBi-LSTM	97.47	94.44	99.67	95.53	98.48

Table 2 Classification algorithms: a comparison

Method	Accuracy	Sensitivity	Specificity	Area under curve
Deep multi-task multi-channel learning	75.15	74.18	78.42	78.16
3D convolutional neural network and stacked bidirectional recurrent neural network	75.58	81.54	59.52	78.25
Proposed method	76.46	81.60	71.74	78.28

The LSTM cell's superior performance over the simpler RNN cell can be attributed in part to the fact that it has three gates to deal with gradient growing and gradient vanishing problems. This is true because the LSTM cell can handle these issues. In this situation, there was a critical factor to consider. By doing so, it distinguishes itself from the other options, making it stand out. As a result, the network can now be trained more quickly, but the accuracy of the results suffers. When it comes to maintaining a time log, keeping the time is not as important as keeping an accurate time log for our network. As a result, we avoided using the GRU in favour of the LSTM. This is the situation when we want to extract information. When using convolution kernels to identify useful features, the FSBi-LSTM with progressive scanning can outperform the FSBi-LSTM alone. If you use it, FSBi-LSTM can even outperform progressive scanning. In contrast to CNN structures, LSTM structures can provide one-dimensional features. As a result, they can avoid the data reduction that flattening requires. Given that 2D-CNN ignores 3D data, it's possible that 3D-CNN will outperform it. Because our method can pull out deep features, the FSBi-LSTM may, in theory, work better than other machine learning methods.

As part of the visual analysis, we ran two separate experiments: one to visualise t-SNE features and another to look for disease-related clusters in the data. The information was used to conduct these two tests. Based on the information gathered, these two experiments were carried out. These various tests are being carried out as part of the investigation that we are currently conducting. We also give you the feature maps that were made when you used each of the different models and methods. A portion of the brain's many areas, each of which oversees a particular set of jobs and functions, are only tangentially related to Alzheimer's disease. As a result, as part of our efforts to better understand brain disorders, we try to employ the strategies we described by looking for relevant ROIs. To conduct a "mock" experiment, we shall use all our mental faculties. Then, for each of the 93 unique regions of the brain, we construct 93 distinct types. Table 2 illustrates how securing particular brain areas can increase classification accuracy. As shown in Fig. 6, we also selected the top ten brain areas that had the greatest impact on the accuracy of an Alzheimer's, moderate cognitive impairment, or severe cognitive impairment diagnosis. This article has more information about these parts of the brain. The list starts with the part of the brain for which there is the most evidence that it is linked to Alzheimer's disease and goes down from there.

In the next part of this essay, the suggested method is compared to the methods that many other deep learning models use to evaluate it. We made sure that our comparison was correct by giving more weight to models that had already been used successfully with the same data. We were confident that the parameters we were evaluating were comparable using this method. Table 2 shows the comparison of classification algorithms.

As Tables 2 and 3 show, our method can give more accurate results than the current methods [30], which use 2D convolutional neural networks to pull attributes from image slices for analysis. Finally, researchers relied on these distinctive characteristics. Following that, the images were labelled using a cascaded SBi-GRU that took into consideration the inter-slice connections' properties. This was completed for

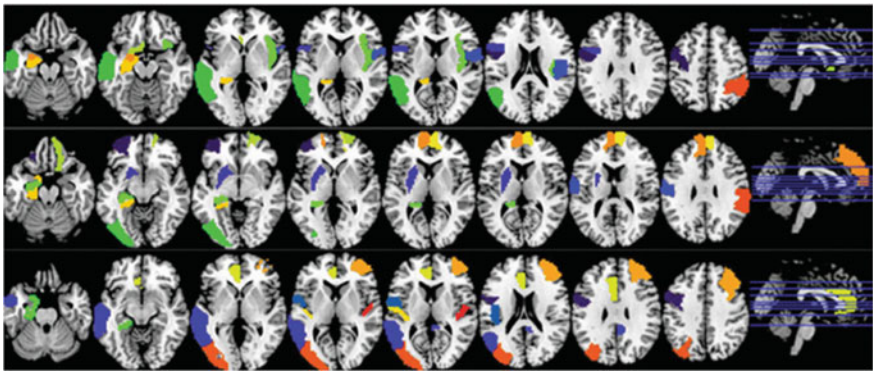

Fig. 6 Recent research has linked a loss in any of ten different brain regions

the photographs to be correctly placed. In several instances, this strategy falls short of the one we use. Despite GRU's capacity to restore 3D data, the 3D-CNN still has the advantage when it comes to storing spatial information because it can do so in considerably greater detail than 2D slices. This comprises geolocation information, velocity information, and acceleration information. As a result, the FSBi-LSTM employs a method known as "progressive scanning." This is because, given the 3D features of CNN's maps, a 2D-CNN network may not retain as much 3D spatial information as a 3D-CNN. This is because our down-sampling method generates fewer training parameters than the approach of dividing the input data into multiple blocks. Unlike other approaches, this one does not divide incoming data into multiple blocks. Our previous research showed that the LSTM's success in mitigating the gradient vanishing problem was due in part to its ability to control information flow through several gates. We can get even more information from the SBi output with the help of the FC layer.

Table 3 Classification algorithms: a comparison of pMCI and NC

Method	Accuracy	Sensitivity	Specificity	Area under curve
Deep multi-task multi-channel learning	93.06	92.19	95.42	97.54
3D convolutional neural network and stacked bidirectional recurrent neural network	95.77	94.67	96.55	91.74
Proposed method	97.47	94.44	98.89	92.42

4 Discussions and Limitations

The current idea for this architecture is that both the FSBi-LSTM and the 3D-CNN could be used as parts of the framework. This design's future applications are being considered. In contrast to other, more traditional types of computer processing, the characteristic extraction in our method does not rely on any prior human experience. As a result, it is now possible to eliminate the inherent bias present in the algorithms used by conventional computers. To accomplish this, it is necessary to determine whether the data may be used in other ways. One technique is to examine whether further data applications are conceivable. Finding out if CNN is capable of learning to do more with the data will help achieve this. The network would benefit from this because it would increase its capacity. As a result, we present a comprehensive examination of all the aspects that, to varied degrees, can influence how well the model works. In real-world applications, CNN retrieves structural and functional brain data as sequences, which FSBi-LSTM then evaluates to provide higher-level spatial data. This technique is repeated until more sophisticated spatial information is received. Following that, this data is accessed. Also, FSBi-LSTM has 27,938 parameters, while FC layers have 57,578. This suggests that FSBi-LSTM may speed up the process of convergence.

The fact that our method outperforms both (namely, SBi-LSTM and SBi-GRU) serves as proof of this. This is because every feature is linked to every other feature. This is one of the primary causes of the current scenario. This means that the results of each iteration are constantly taken into consideration throughout the process. One benefit of adopting this network is that each LSTM output node is more relevant to the present node. This is only one of many advantages of having network access. Once we have established this layer, we will be able to aggregate the input from all the SBi-LSTM cells that are relevant to a certain brain structure. These findings could hint at more consistent information about the individuals, referred to as "traits," rather than information about the structural makeup of each participant's brain. It is critical to emphasise, in order to reach a conclusion, that the results of our experiments using this methodology are consistent with those of previous studies. The suggested technique has shown some promising outcomes, but it is not without risk and should not be used blindly because it may produce difficulties. The first disadvantage is that, despite significant advances in obtaining high levels of accuracy for tasks comparing AD to NC and pMCI to NC, sMCI diagnostic performance remains confined. This is true whether these tasks have been meticulously recorded or not. This is most likely since the anatomical changes caused by sMCI are so minor that their entire impact is hidden. This is just one of the countless explanations. This is just one of several possibilities that could explain this phenomenon. Second, our method is unable to analyse the morphology of the brain injury by simply upsampling the data or deconvoluting the information using CNN and LSTM in a cascade. Both processes must be completed to directly examine the morphology of the brain lesion. Instead, to know where to look, you must first discover which portion of the brain oversees housing it. Third, because we did not use longitudinal MRI data, we did not include that information

in our research. This information would have helped us better understand how the disease progresses. As a result, the course of the disease was not considered in our findings. Even though we are now focusing purely on voxel features, it would be helpful to leverage cutting-edge technology to combine computer vision approaches for the visual elements of the problem. Even if we solved most of the problems, this would still be the case. We can use the structural data that has been stored in the brain to perform processing on that data. If we succeed, clinical diagnosis and prognosis will be substantially simplified. We might come across data that is comparable and shared across multiple attributes. During our next study, we will not only investigate these discoveries and warnings more, but we will also try to figure out what they mean.

5 Conclusion

In the proposed work, the 3D-FC CNN layer is replaced with a separate LSTM network architecture to keep things simple. This will directly lead to improved accuracy. By employing our technique, we can preserve as much data as possible while preserving as much of the spatial information presented on the feature map as possible and establish a fully linked soft-max network while preserving as much of the spatial information presented on the feature map as possible and establishing a fully linked soft-max network. To keep things simple, we propose that the 3D-FC CNN layer be replaced with a separate LSTM network architecture. This will directly lead to improved accuracy. We can save as much data as possible while maintaining as much of the geographic information presented on the feature map as possible by employing our technique. This enables us to store as much data as is reasonable. In comparison to a standard SBi-LSTM, the FSBi-LSTM may collect data on brain structures that are surprisingly similar across all SBi-LSTM nodes. This is superior to the standard SBi-LSTM. This SBi-LSTM is significantly more complicated than a standard one. In contrast to information concerning the subject's brain anatomy, the FC layer may represent stable data about a person's "traits." Kids must be able to grasp this level at all times. We can illustrate the value of the ADNI dataset by conducting a series of tests on it. CNN is employed to aid us in identifying label assignments, which is one of the reasons our method beats our competitors' tactics. Additionally, by conducting brain shielding research, we can strengthen the therapeutic foundation for deep learning.

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Yoga Practitioners and Non-yoga Practitioners to Deal Neurodegenerative Disease in Neuro Regions

Amar Shukla, Shamik Tiwari, and Vinh Truong Hoang

Abstract The ultimate goal of the research study is to determine if regular practice of yoga has any beneficial effects on brain functions and neurodegenerative diseases. To this end, advanced imaging techniques such as the grey matter volume and cortical thickness will be employed, along with machine learning algorithms to evaluate cognitive performance. Furthermore, it will help assess the neuro-regions, white matter, and cortex which affect the brain age and compare it to their actual age. The results of this study can provide a better understanding of how much yoga can benefit day-to-day behavior and life cycles. A further implication of this study is that it could also contribute insights into the role yoga plays in the prevention of neurodegenerative diseases.

Keywords Grey matter · Machine learning · Brain age · Cortex measurement · Free surfer

1 Introduction

Yoga is an ancient practice that has been used for centuries to help improve and maintain physical and mental health. It has recently been shown to have a positive impact on reducing the risk of neurological diseases such as Parkinson's, Alzheimer's, and multiple sclerosis. Research has found that yoga can help to protect and improve the function of the cortex, white matter, and grey matter, which are all essential for healthy brain function. By strengthening these areas, yoga can help to reduce the risk

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of developing a neurological disease. Furthermore, yoga can also help to improve the overall quality of life for those living with neurological diseases, as it helps to reduce stress, tension, and fatigue. By incorporating yoga into a daily routine, individuals can benefit from its many health benefits and improve the quality of their lives. In the Neuroregion which is affected by the disease is cortex. Cortex is an essential and structural quant of brain structure in human body where this cortex is represented like a vertical structure alias with the thickness over the plain of the human body, which varies from 2 to 4 mm in human body. While the measurement of the plane of the cortex of 1 hemisphere covers an area about 1000 cm^2. Cerebral Cortex is the thin layer of contents where is surrounded by the outer portion of the brain to function in the brain adequately. The cerebral cortex is a very complex creature and it's really hard to distinguish the functional performance of the cortex in the different modes. The cerebral cortex contains different lobe section in the brain which is first known as frontal lobe, parental lobes, temporal lobe and occipital lobes, so these lobes contain the different functions and operation on the basis of the action perform by the human body.

In the cerebral cortex, the group of rigid lines is known as the gyri and the single rigid is known as the sulci, and the thicker line which is represented between the lobes that are known as the fissures. The behavior and the functionality of the cerebral cortex perform the different functionality with different features, it takes the complex info processing where it contains the various performances of the cerebral cortex lobes. Sensor and the motor function of the human body are consisting of the cerebral cortex is performed by the Frontal lobe, which is the most and the essential function of the human body. The Visual information and the somatosensory information which is constituted by the Parental lobe of the human brain and it is the most receptive part of the brain which contains the attributes and the other visualization (Fig. 1).

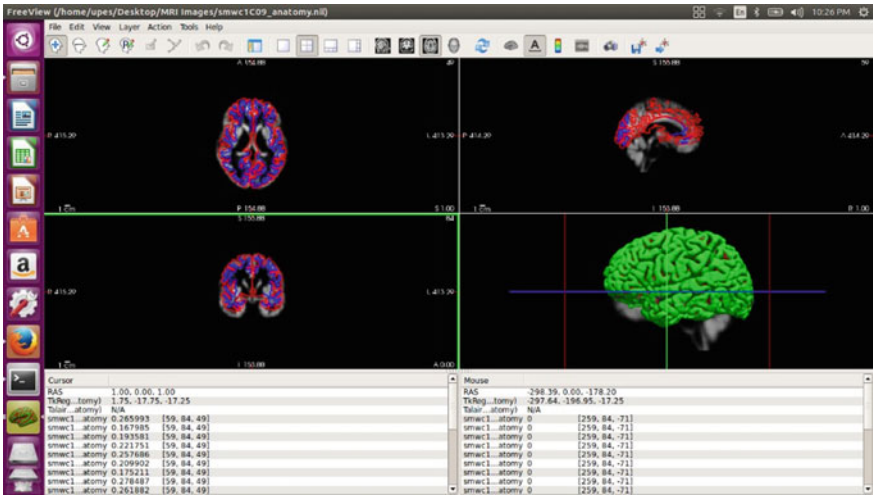

Fig. 1 Brain cortex measurement in all the lobes

The visual information is led by the occipital lobe which is the important and functional attribute of the human brain, so these are basic functionality which is attained in the cerebral cortex. When coming again to the cerebral cortex it is divided into the further classification that is the primary cortex and the association cortex, where the primary cortex lead towards the basic sensory motion and the motor functionality in the human body which constitute the various leads in the various functionality in the human body.

In the cortex the thickness variation always have an unpredicted nature where it is not streamlined in the uniform pattern and also there is certain fundamental that the cortical layer does not contain the same behavior as the cortical thickness sustain due to this variations in the cortical thickness led to many diseases like Alzheimer's disease, Huntington's disease, etc.

Well, when we see the T1-Weighted MRI images it contains the regress process to take out the anatomical features but this too much weightage phase of study cannot distinguish the cortical thickness only it can conclude the volume of the cortical thickness of the MRI Image data.

As the discovery says the thickness of the cortex can only calculated when the parameter like grey, white and the pi surface must contain, so then only the thickness of the cortex can be measured, there is interesting studying that in the postmortem study this measurement of the cortex is done for the condition of the dead body which is present. As from the slice, data pattern the information can only see for the changes in the cortical, whether it is large or small, but in order to commute the actual measurement of the thickness of the cortex we must require the orthogonal projection for the measurement. The measurement between the grey and white matter of the cortex with respect to the pile data gives the actual measurement of the cortical thickness.

The measurement of the cortical thickness is based upon the two methods which are associated that are first based on the surface and the other is based on the voxel. For the measurement of the cortical thickness the segmentation of the white and the grey matter and the cerebrospinal fluid which constitute the measurement of the cortex in a specific manner. The parameter, which affects the cortex sizes are Grey matter volume, White Matter Volume, Cerebral fluid, Curvature Surface pattern.

2 Grey Matter Volume (GM)

The significant concept of the central nervous system is grey matter volume where it contains numerous cell bodies, which is most fundamental part of the structure of the grey matter volume. Contents of the grey matter volume is available in the various sections of the human brain that is the stem of the brain, brain and all the part of the spinal cord.

The grey matter includes regions of the brain involved in muscle control, and sensory perception such as seeing and hearing, memory, emotions, speech, decision-making, and self-control. The grey matter contains the motor control, sensometry

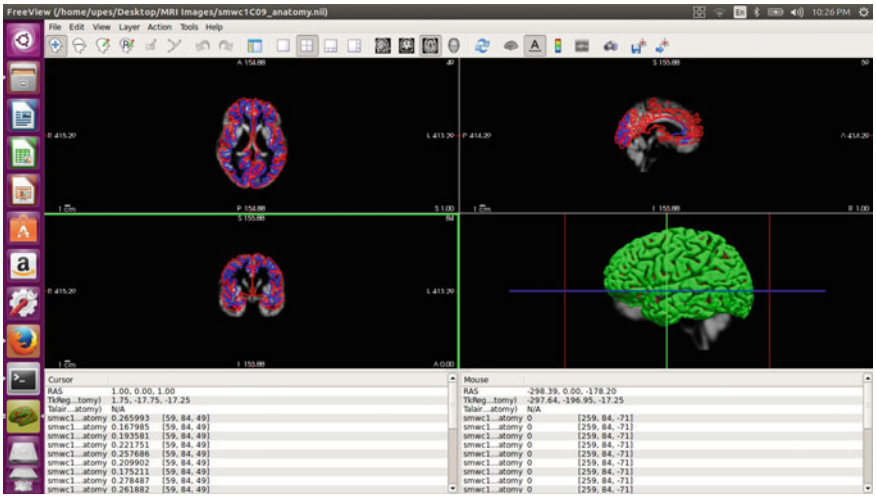

Fig. 2 Grey matter in the functional MRI

characteristics, hearing, sensing, and intellectual decision-making which contains the specific characteristics of the different parts of the human body (Fig. 2).

2.1 White Matter Volume (WM)

White matter volume contains the central structure of the nervous system, which are made up of axons. The basic function of the white matter is learning. White matter contains the myelin, which is the central nervous system of the brain where it is worked as an insulator. The main function of the white matter is to send the messages or the signals to the grey matter associated tissue in it. White matter volume is generally responsible for the cognitive issues, functional disability of the body, death neurologic problem; these are the main area of concern, which is constituted in the presence of the White matter volume (Fig. 3).

2.2 Cerebral Fluid (CF)

It is also a major concern for the measurement of the cortex, on the availability wise the cerebral fluid does not have any color, and this plays an important role in the measurement of the cortex by which the prediction of the different disease scenario can also be done easily (Fig. 4).

Measurement of the cortex is not much easier job; the characteristics of the cortex is not uniform, and it is really hard for the measurement of the cortex, so on the basis

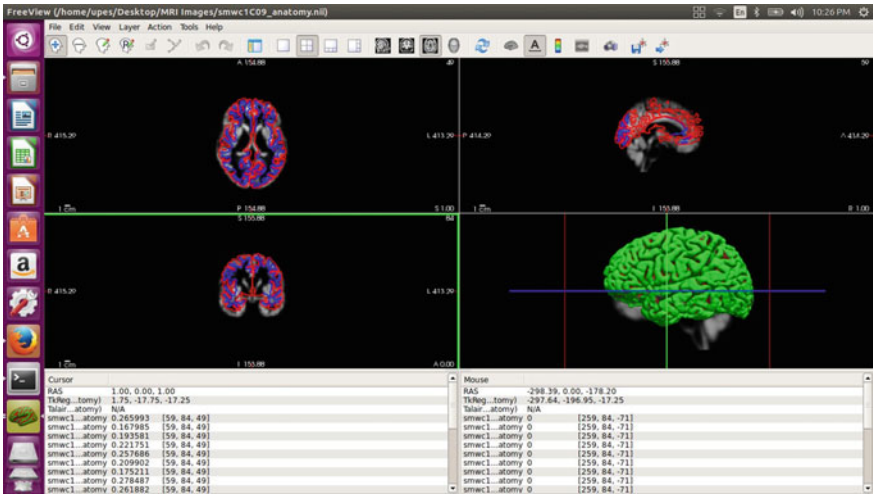

Fig. 3 White matter in the FMRI brain image

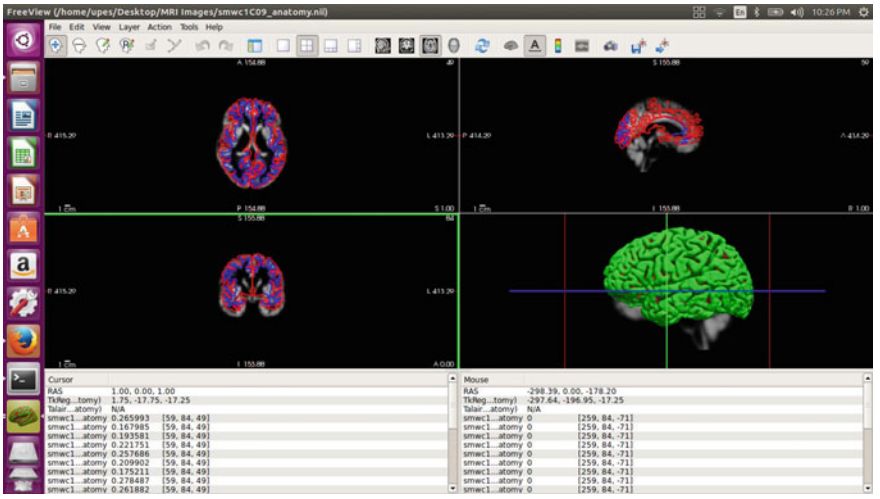

Fig. 4 Presence of cerebral fluid in the cortex

of the white matter, grey matter and the cerebral fluid we can actually measure the cortex sizes. There are different methods, which are available for the measurement of the cortex are Free Surfer Method.

2.3 The Free Surfer Method

Hence, these are the different method, which are available for the measurement of the cortex, (a) Free Surfer method contains the basic approach for the measurement of the cortex that are as follows: Talairach Registration here it contains the transformation of the high performance image to the matrix form, which means with the help of the gradient approach the to strengthen the relation with the volume of the one with average volume. Then the second step is to proceed for the normalization of the intensity, which contains the various steps of setting histograms, then eliminating the noise packs, then finding out the peak mechanism, then outliers should be getting discarded from the white matter intensities, spline fitting, interpolation of the coefficients, read adjust the intensity values.

Stripping of the Skull is another process where it allows segmentation process of the white matter from the brain cortex, and to remove the content of the noise. Generation of the different cortical shape and surface is done, here in this shape, surface is divided into the different planes, and the minimal area of the cross-section is identified with the Talraich process.

Then generation of the different connection component takes place, where it contains the representation of these components of white matter, to distinguish the characteristics can be done. After this process the Surface tessellation of the components, refinement of those components and deformation of those components is done. Laplacian method is one of the lineup approaches where the identification of the various parameters like GM (Grey Matter), WM (White Matter) and CSP (Cerebral Spinal Fluid) for the measurement of the cortex, there are different steps for the measurement of the cortex they are. In the Laplacian method the probabilistic segmentation of GM, WM and CSF performed, resampling of the probabilistic images. Taking out the white matter for at least one voxel side, then Laplace's equation is solved by checking of the boundary, so this step concluded the thickness of the cortex and the measurement also.

3 Yoga

Yoga has been practiced in every part of the countries and they are also coming in the practicing session of different ages of the people, as the study determine the people who are doing yoga are getting benefitted from the different functionality of the pranayama and the kriya and the meditation which constitute the several aspects of growth in the human body, which constitutes the changes in the living standard of the people and in the thinking of the common people. Yoga is dominated by the various passion thing field which can be characteristics into the different patterns like while practicing yoga tends to be safe and very much responsive, good health creatures. Countries are now moving in the different research trends in the yoga

which constitute the scientific proof of the study of the yoga tends to the specific parameter of the yoga term in the field of medical science.

MRI based study, ECG based studies are trending in the field of yoga, which constitute the significance changes in the cortex where each can determine the specific growth of the cortex which attain the proper channelizing approach for the proof of the study.

Yoga has been taken in the number of institutes which can signify the better practicing of the yoga which results in the major trends in the field of the yoga where all the practices are done in the specific and better way, there are multiple assessment method for practicing yoga checks the self-efficiency where the performance level of the people in the field of yoga. Yoga has now taken in the course curriculum of the students, graduate students and the university student in order to have the specific constraints so that the life of the people can be strengthened to attain the proper strength in the stress full world. There is also a barrier in the yoga when there is no knowledge depth of the yoga, which can cause severe attainment in the body of the human being and can cause severe changes in the human body. There are a lot more benefits which carrying in the field of yoga which contains the physical flexibility of the person who is performing the yoga, it contains the better movement of the spinal and the functioning of the muscles in the better and accurate way so that it contains the specific order which specify the stregnthenization in the body of the human body. The practicing of the yoga contains the person stronger and more expressive, which constitute the specific dormitory where the people can easily collab with the people so that it can sustain the greater changes in the human body.

The yoga is also intensified, it has the creatures of the parental studies where it has many beneficiaries which constitute the proper attainment of the body in the particular sensory order which constitute the specific changes in the body of the human. Yoga is also one of the important aspects of improving the psychological disorder which constitutes the major problem in the real world, there is no significance control on dealing with the physiological attainability of the human body, but the yoga found the successful approach for the redemption of this problem and it is successfully attainable. Yoga also helps in the traumatic improvement in the human body which constitutes in the better propagation of the traumatic condition in the human body, it also helps to improve the anxiety disorder where it contains the specific channelization in the detail of the human body, it also decreases the depression level in the human body the person who is practicing yoga. Overheating of the body is also channelized who is doing yoga in the particular and regular manner which constitute the result in the greater absorb in the human body.

Coming to the cardiac scenario the person who is doing yoga will be beneficial on the subject who is affected from prehypertension, hypertension, blood pressure, so these are the things where the human can be cured, cholesterol affected people will also have the right scenario when they are practicing yoga. In the pain section like arthritis, knee pain, neck pain, headaches so many of the pain-related issues are also cured by the yoga, which will be helpful for all the stems of the yoga scenario.

4 Magnetic Resonance Imaging

MRI imaging is the boom in the medical field for the finding out the various bodies dis-functioning issues, which occurs, MRI imaging contains the magnetic effect, powerful radio waves which produces the various results of the screening of the various parts of the human body. It also differs in the usability of the modern technology like X-Ray, it is very different from the X-Ray or the tomography, which constitutes the better, visualization of the various infected regions in the body. MRI imaging signifies the treatment level of the doctor which is constituted with various features occurs in the human body, its feature guides the doctor to respond to the patient according to the report generated by the MRI, and also signifies how well the patient is responding to treatment.

There are various MRI of the various parts and tissues of the body is done, like, brain injury, blood vessel damage, cancer, multiple sclerosis, spinal cord injuries, stroke, blocked blood vessel, damage caused by the heart attack, heart disease, the structure of the heart, Cancer, damage to joints, disk problems in the spine, neck or low back pain with nerve signs, breasts, liver, kidneys, ovaries, pancreas, prostate. Functional magnetic resonance Imaging (FMRI) is a quick way of the observation of the various problems occurs in the human body and it also contains the various significant approaches to segregate the various issues is affecting the human body, but when we are adding to the concept of the FMRI.

FMRI contains the various significant approaches of the for analyzing the pattern, which constitute the control observation of the various diseases which affected specially in the brain area, FMRI contains the most prominent feature of analyzing the pattern on the basis of that pattern, it can be easily identified the infected region which is causing the problem or the region is creating the change in the human body (Fig. 5).

FMRI constitutes with the active participation of the cortex region on the brain which constitutes the increase or decrease of the cortex region. FMRI can standup with various important features to distinguish the relation of the different sizes of the left cortex or the right cortex whether it occurs in the various lobes. FMRI contains the finer evaluation of the disease with the detail tradition of the disease, which rises in the human body. It resulted in various significant approaches in the detail attention of the disease which is occurring related to brain or the strokes rise in the human brain. It also modulate the different modalities characteristics of the activities of the brain, which signifies the better result in the treatment of various diseases.

5 Brain Age

Brain age can also be predicted by the various techniques which are available in the real world, but it constitutes the various methodologies to segregate the structure and creatures of the brain which can constitute and lead the various and the significance

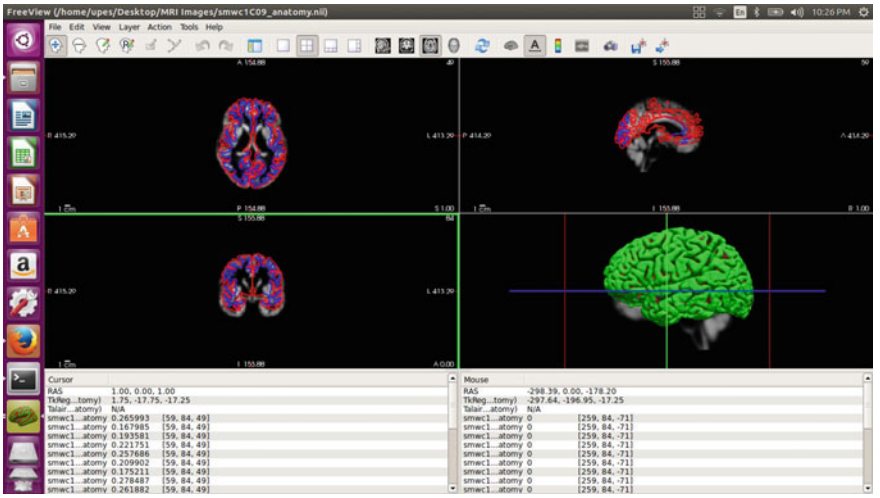

Fig. 5 Use of FMRI image for grey matter, white matter and cerebral fluid

approaches for the finding out the various brain age predictions. This can also correlate of the better function of the brain by how much it constitutes all the observation of the activities in the human body. Measurement of the cortex and finding out the specification of the cortex can also constitute the age prediction; by applying, the different technique to constitute the data in the appropriate manner, which will be, quantified the significance of the brain age and leads the various significant changes in the brain anatomy. Actual possession of the brain age can be determined by the structural quantization of the cortex and it can also be stating the health condition of the brain for the future working and the prediction of the brain status.

Brain anatomical measures can lead to various estimation and the prediction of the brain ages, which directly implies to the human age, these measures contains the various significant observation of the different people, which lead to the various estimation of the prediction of the group. This age prediction can constitute the various observations on the median, mode, standard deviation which further result in the finding of the accuracy, this prediction also depends on the different parameter like various sizes of the brain which constitute and lead to the volume of the cortical brain, thickness of the brain, area, subcortical volume, cerebellar volume, so all these significant feature lead to the various observations and the prediction of the ages.

Some morphological features also lead to the various trends in the human brain and constitute the various and the significant approaches in the human brain for finding in the various ages of the brain, cortical surface pattern also implies the various significant aspects of the changes in the human body constitute the various predictions of the ages. There are various prediction techniques based on the anatomical data which lead to the accuracy of the particular features and lead to the significant observation of the data by applying different methodologies like regression, selection,

discriminant analysis, so all these techniques constitute the various observations and the prediction of the old age of the human brain.

6 Mechanism for Cortex Measurement

Cortical measurement is one of the major aspects of finding out the consistency of the brain functioning and finding out the various subsequent anonymity of the brain, which results in the proper function of the brain. There are various tools, which are available for the measurement of the brain, which helps in the finding out the measurement of the cortex and finding out the volume of the cortex, so some of the tools are Free Surfer, SIENA, SPM, MIPAV, and VOLBRAIN. Therefore, these are the tools, which are available for the measurement of the cortex:

FREE Surfer: Free surfer is the open source tool which is constituted for the analyzing the various features of the brain, whether it constitutes with the thickness, volume, cortical reconstruction, subcortical reconstruction, FMRI analysis, and it's also an open source tool. It also contains the various deficiencies in the result and the analysis of the cortical section with noisy values.

SIENA: Siena is also another tool which is helpful for the brain cortex measurement and led to the various aspects of the analysis of the cortex, like reconstruction and the measurement of the cortical thickness and the volume of the cortical thickness, here it also defecated in the end result which contain the less accuracy level and also the noisy contribution in the Image which contains the cortical structures.

MIPAV: MIPAV is the tool which is stated for the medical image processing and visualization, it also contains the visualization in the field of various medical data, and analysis of the data which is termed as MRI, CT, PET. It helps to quantitative analysis and the visualization of the various effects, which is shown in the various data types, and conclude to the specific result.

SPM: SPM stands for statistical parametric mapping, which leads to the various parametric mapping and the statistical analysis of the data, it also helps in the various analyses of the FMRI studies, which constitute the better significance for the infected region of the disease in the MRI images. It is demonstrated by the means of the signal and the noise.

VOLBREAN: It also contains the method, which constitutes the better evaluation of the structural construction of the brain with reference to the human brain and lead to the significance approach. It constitutes in fully automatic manner, it has limitations to accept the data for the evaluation and measure, due computational issues.

Ancova: Ancova modeling is also the tool which depends on the some of the factors and prediction on the basis of that factor, it stands for the analysis of variance, it contains the different level of analysis is which constitute the various parametric studies in the different levels of the data.

6.1 Normalization of MRI Data

Normalization of the data is the essential part of the medical image processing or normal image processing; Normalization of the data is required to strengthen the intensity of the image through various mathematical models in order to make the significant features of the selection.

Normalization of the MRI data contains the spatial normalization where there are many normalization techniques which is constituted for the adoption of the different features, like Gaussians Normalization technique, Z score normalization technique, Statistical Normalization technique, histogram based normalization technique. Hence, these techniques help to quantify the pixel value according to the condition of the problem, so that a significant feature can be extracted from the particular state of the problem. These normalization techniques are the data validation constituents with the standard score, students statistics, students residual, standardized moment, coefficient of variation min max feature scaling.

Gaussians distribution normalization technique follows the distribution technique which constitutes the better involvement of the data, whether it is above the mean value or below the mean value, so these constituents lead to better significant approaches in the normalized the consists of the data. Z Score normalization technique is also one of the important techniques for the betterment of the various integrated information on the basis of the mean value the value which comes below the mean will be result as negative and above the mean will be regarded as positive, the determination of the size is determined by the standard deviation which constitutes the significance part in the calculation of the data points.

Min Max Normalization is also attempting the significant features of the normalization of the data and it constitutes the various parameters for the adequate chances in the growth of the data, her it contains the maximum value tends to the 1, and the minimum value tends to the 0, this is how the normalization of the data has been containerized for the various processes of the problem.

Histogram based standardization is also setting the unique feature for the normalization of the data, so there for this technique is also state the dependencies in the intensity value of the data which constitute the actual observation of the normalized data which is available for the feature selection. Histogram based standardization that is directly pinpoint the intensity level of the Image and constitutes the better performance of the data for the various absolute process and make it assure for the processing of the data according to the variance of the problem.

6.2 Noise in MRI Data

In the MRI data, you will find out the various noise content but most common noises are Salt and Pepper, Speckle, Gaussian and Poisson Noise. In order to restore the images by removal of these noises, this is also termed as the image restoration. This

is important because we can increase the quality of the images by removing of these noises.

Gaussians Noise: when we go for the Gaussian noise, which is constituted with the Gaussian probability distribution. PDS function is equating with the statistical parameter base noise therefore, it is stated as Gaussians noise. This noise can be removed by the various smoothening techniques so that the quality of the image can be traced for the optimality of the image.

Salt pepper Noise: Salt pepper noise is also one of the important noises which occurs in the low-level intensity in the images, the Image which is perceived where the black intensity of the pixel is surrounded by the white pixel and the white pixel intensity is surrounded by the black pixel. So in order to remove this noise we have to consider the generation of new points in the region of infected portion and use the various median filter in order to remove the noise.

Speckle Noise: Speckle noise is also one of the severe noises, which attain in the MRI images; it contains the various wave formation when the various magnetic resonance processes occur. This noise is contained in the SAR images and MRI Images. This Noise is caused due to various data transmission process which occurs and which tends to the deformation of the images.

Poisson Noise occurs on the occurrences of the various light factors attaining in the image containing the different sources of energy in the images, which makes quantifiable in order to give preference to the image, also degrade the contents of the images.

Blurred Noise: Blurred noise is also due to the light intensity and the outward factors which termed the combination of various noises in the images. The photo also comes in the blurred pattern and the noisy pattern degrade the image quality.

These noises can be removed by using various filters and the techniques like median filter, Wiener filter and Gaussian Filter. Removal of noises will basically enhance the quality which is really attainable for taking the better decision of the problem, and it will also quantify the better performance in the result so that the accuracy of the attainable algorithm for the image modality will lead to the best limits.

6.3 Feature Selection

When the entire process of the frame work is decided, the feature selection methods play an important role for the betterment of the learning techniques. Selection of features makes an important role in order to contain the various performance factors of an algorithm to perform better. There are various parameters in which the feature selection process continues to better the continuity of the algorithm.

In the feature, selection process the parameter has to be selective in order to optimize the certain algorithm according to the state of the problem. This process also contains various prediction adaptability on how to make the features prominent

as well as to select the new features which are accountable to improve the learning techniques in the reference of data to be better.

It better learning techniques and also make it easier for the production of an object. It also checked the overfitting of the data points learning process it also makes the better improvement in the learning techniques, check the accuracy level of particular algorithm on the particular data sets.

It contains the various selection techniques like filter methods, in which the filter method contains the group of features, and then selecting the best subset of the features, then the learning process from those features and then after this checking the performance. In this method the contiguous and categorical are the two factors where the ANCOVA, Pearson correlation comes under the contiguous and LDA and chi-square comes under the categorical. Another important method which is substituted for the various significance of the process is Wrapper methods, in the wrapper methods, selecting all the features, then selecting the best subset, in which it contains generating subset and learning algorithms both comes under the selecting the subset, then testing the performance of the particular algorithms. Some of the examples of this process are forward selection, backward elimination, recursive feature elimination, so these are the techniques which constitute the better feature selection process in which it is constitute the various performance parameters also.

Embedded methods are also prominent feature selection techniques. It is mixed up with the behavioral performance of the wrapper and filter methods. In this method, it also contains the group of the data where it selects the best subset, where it contains the learning algorithm and the performance in the second process itself. They use the lasso and the ridge regression techniques for the selecting of the features (Table 1).

Table 1 Quantitative difference between the filter and the wrapper methods

S. No.	Parameter	Wrapper methods	Filter methods
1	Features	It checks the usefulness of the features	It checks the relevance of the features
2	Execution	Wrapper is quite slower as compared to filter process	Filter process is quite faster as compared to the wrapper process
3	Statistical	Wrapper does not use the statistical approach for the selection of features	Filter process uses the statistical approaches for the selection of the feature
4	Cross validation	Cross validation of the process contained by the Wrapper Feature Selection Process	But when we talk about the filter process, it does not contain the cross validation
5	Performance	Wrapper method always produces the best subset of the feature selection process	Filter method does not provide the best subset of the feature selection process

7 Recent Study

Controlled group of the yoga practitioners woman who all are carrying out the yoga for the last three years, there were accessed for 6 min walk to test the access fitness a, psychological and demographic questionnaires and MRI imaging to measure the Fat Suppression in the dorsolateral prefrontal cortex in yoga practitioners [1]. Methodology used for the data Analysis are they have used software tools (FMRIB software library), FSL Brain Extraction Tool, MCFLIRT. From results, they have not found the measure difference in terms of the demographic analysis but in the cortex, they have found the difference with that in yoga.

ADHD [2] is one of the major neurodevelopmental disorder that affects about 5% of the children in the whole world and Author mentioned the varieties of the symptoms, which is regenerated in the new cases repeatedly. So in order to test the findings of the disorder the author has taken the group of controlled subjects, which are suffering from disorder, and uncontrolled subject, which are not suffering from disorder. In this, also they have found that that the right hemisphere of the brain was superior frontal gyrus was thinner in subjects who are suffering from the disorder as compared to the controlled group. Methodology they have the T1 weighted MRI Images, and processed in the free open source software "Free Surfer" for the analysis of the image and the data analysis. In [3], the controlled group of the twenty-three experienced yoga practitioners, they are 5 to 26 years of experience in the field of the Sahaja yoga and have scanned, taken structural magnetic resonance imaging and comparing the grey matter volume using Voxel based Morphometry was chased using SPM12 Software (Statistical Parametric Mapping Software). In order to further process they have found that the GM, WM and CSV (Grey matter, White Matter and Cerebrum spinal fluid) volume is larger in the person who is doing Sahaja Yoga Meditation for longer duration. Whereas, the person who is not doing yoga in any terms are having the less GM, WM and CSV (Grey matter, White Matter and Cerebrum spinal fluid) volume as compared to the controlled group. ANCOVA analysis has been used for the analysis between (GM, WM, and CSF) and TIV. Yoga is the essential part of day-to-day life in the real world [4]. In this, the author has taken the constraints of 21 women who were regularly practicing yoga in which they have practiced hath yoga at least for 8 years and the other yoga exercise is continuously. In order to see the comparison study author has taken T1-weightage MRI images, where they have taken the MRI modalities in order to see the changes in the cortical thickness of brain images by applying some data analytics techniques using free surfer analysis.

But comparison of control and uncontrolled groups, they also had a question and test like back depression inventory and mini mental state examination. In this, the author has found that the cortical thickness of the women who are doing yoga from last 8 years has been large greater volume as compared to the women who are not doing yoga. The author is found in the left prefrontal lobe cluster in the yoga practitioner brain MRI images has greater volume as compared to the controlled group. Image processing techniques on how to solve the consent of thickness identification of cortex

[5]. In this, the author introduces various image processing technique multiscale analysis to find out the detection of the grey-white region in the MRI images. In order to make the curvature smooth, the author has used Gaussian, curvature technique in order to have an accurate comparison of the white grey regions in the images. Again, in the author has used gradient Descent approach for surface deformation. Similarly, numerical integration has also been taken part in the concern for the calculation of the cortical thickness in the camera images. In this, sample of 30 subjects where 17th army and 13 are females and found the measurement of thickness in the cortical region of the brain.

The memory test and resting test, functional connectivity before and after yoga intervention [6]. In this, the verbal memory contact and the cortex size improvement when the person is handled with yoga. In this, Hopkins verbal learning test ostrich Complex test for the person who is indulged with yoga and meditation. In the yoga intervention, various time slots have been divided for Pranayama Kriya breath meditation and they have gone through extensively 12 weeks for regular practices. In this, MRI image modality is used for checking of the cortical thickness. In order to process this image various readymade tool FSL melodic used for the various data analytics and noise removal functionalities to segregate the white grey component in the MRI images. In this group, the studies happen to find out the cortical thickness and visual-spatial memory performance, as a result, there is a significant change in the thickness of the cortex and the memory performance people who are doing yoga for consistently in many years. The neuroimaging studies, which constitutes that, the meditation increases the blood fluid in the prefrontal cortex [7]. They have taken the various spectroscopy (fNIRS) to evaluate the changes in PFC. In this, the author has taken 25 samples of suggested participants who are particularly doing meditation in order to that all the participant's 12-month experience in the yoga, in this context the author wants to see that changes in delta HBO, delta HBR, and delta THC prefrontal cortex. RM ANOVA involved in the three factors of testing first session's second PFC right and left and the third is States after performing the test of Ancova [8]. It has been found at the present quantity of HBO HBR and THC this on the measurable greater side on the prefrontal cortex whether it is right or left in the person who is doing yoga latest years remained less as compared to the person who is not in the yoga practices, in which the author has taken the reconstruction of a surface and the segmentation of a surface on the basis of various different method has been used first Talairach registration, intensity normalization, skull stripping, matter labeling, cutting planes which constitutes segmentation of a particular MRI modality of the infected reason after segmentation the surface tessellation refinement.

This technique used for the smoothening of an image after the segmentation the author has taken the validation of a particular surfaced and validation of a surface geometry. In this, as finding out the structural analysis of features of the cortex in MRI images. In addition, reconstruction of the complex task such an intensity normalization skull stripping filtering segmentation and surface deformation.

Various study groups of the yoga practitioners who are doing Yoga from many years more than 10–15 years which itself define the comprehensive task [9]. According to it studies that have mentioned the activation likelihood estimation

to make an analysis of PFC in the MRI images while doing meditation and yoga. In order to the studies, the author has found there is appreciable changes in the CORTEX of the brain and The White grey matter in the MRI images case present. The longitudinal study four different subjects, which constitute of some females and some males who are regularly practicing yoga [10]. Today's the subject usually practicing yoga for 60 min in 12 weeks where it has been found that on the parameter of blood flow to the cerebral cortex frontal lobe and midbrain suggested that there is a continuous decrease in blood flow of amygdala increases then activation of FLC. This suggested that there has been an enormous change in the continuity of a yoga practices person in the structural references. Institute yoga and meditation practice practices yeah it has done the cross-sectional studies of yoga techniques [11].

The author has taken the various subjects which constitute of 14 number 7 people there train with yoga practices and 7 is untrained with yoga practices. Hatha yoga was the major key concern in the intervention in this to find out the flow of blood to the cerebral cortex frontal lobes and midbrain. This LPC onto the greater volume and lens distortion in the white grey ratio of the cortex in the MRI data set it also suggests that with greater efficiency in the volume practices the enormous growth in the behavior structure of the yoga practitioners. Yoga's and the Pranayama, which constitute of the longitudinal studies of the various pranayama and the yoga techniques, which constitutes the significant changes in the control group studies in order to find the better practices of the yoga [12]. Here, in this 7 subjects where trained in the various and the yoga practices which constitutes of the 5 healthy males and 3 healthy females. In this subject practice yoga for the 5 days per week for the three months and three months without instruction which constitutes the various changes, and which justify the changes in the periodic change in the structural behavior of the subject while performing the yoga. Here, it trends out the grey white volume indexes in the cerebral in the cortex on the large scale, which constitute the better performance of the person who is performing the yoga.

The 14 subjects for the various types of yoga and Pranayama example post-facto and others are the constituents study type [13]. In this, at least 2 years of study of the yoga practitioner who are doing yoga consistently by doing some various image constituent studies MRI. It has found that it has been found that the white matter connectivity is onto the greatest strength the person who is practicing yoga which has the greater pain tolerance as compared to the others who are not practicing yoga [14]. Nostril Yoga techniques for the experimental where it has found that he 20 subject males have the increased scores in the later cancellation test while performing the nostril yoga breathing and uni nostril yoga breathing, which constitutes the behavioral changes in the yoga practitioners in the right direction. In [15], 108 subjects healthy children where the author has found the enormous scores in the left nostril breathing which constitute in the change in the behaviors' performance of the subject who are partitioning yoga again and again. Here the uni nostril and alternate nostril breathing has been taken as the type of yoga. Further in [16], 51 subject which consists of the 25 males and 26 females where it contains the unilateral forces' nostril breathing for the 30 min. Here is it has been measuring that there is a great change in the scores of the verbal task test, here it contains the high score in the verbal task test. This

justifies the greater extent in the behavioral concern in the cross-sectional studies of the breathing. Longitudinal study of the 8 subjects in order to intervene the Santi Kriya Yoga is done in [17]. In this intervention the subject where practicing yoga for the 50 min for the 30 days, the parameter of the intervention is done on the basis of the Peak Amplitude and frequency of the Alpha Wave activity, which is to be concern in the practice of the analytics part of the yogic science. Here, in this, intervention is practice a lot according to the duration mentioned and lead to the conclusion that the alpha wave activity of the yogic person is increased for the duration which entitled the better performance capability of the yogic person.

In [18], the alpha wave activity and the peak amplitude for the parameter of the yoga technique. In this, the author has taken 18 subjects where 8 belongs to the female and 10 belongs to the male orientation. They all are experienced and practicing yoga for the 2–20 years, which is the consistence performance of the yoga practitioner. The significant changes in the alpha waves which led to the better performance of the yogic person [19] the sahaj yoga, which is the cross-sectional studies. Here, it contains the 9 healthy subjects and these are experiencing the major depressive disorder, and the 10 subjects which are the healthy. They are going to intervention of the training of the 30 min, from 4 to 5 weeks, in order to have this intervention during some test, the conclusion that is termed that there is an increase in the alpha activity of the yoga practitioners. In [20], various yoga practices and the various cross-sectional studies among the 80 subjects, here in this intervention are as an, pranayama, asan pranayama group and control group. Here they are practicing 4 days a week for the 6 month, in which the parameter of the concern is peak amplitude and the frequency of alpha wave activity. As the result, it is found that the alpha activity is increased in the asan and asan pranayama group and the theta power is increased in the pranayama and asan pranayama group.

In [21], 19 healthy subjects, who are partitioning the yoga more than 1 years, and they followed this sudarshan kriya for more than the one years and here the observation is Yoga Practitioners who are doing yoga are having the increased beta activity. In [22], constituents of the cortical thickness measurement of White grey matter in the MRI Images of the body deficiency with Alzheimer's, HIV AIDS to see the changes pattern in the cortical thickness of the body. In this, the author has taken the computation of linear integral, through a point, possess a minimum integral through a line as a thickness, and uses the binary probability map and Continuous probability Map. The author has taken the calculation of each voxel to find the thickness by choosing the minimum integral value. In [23], to measure the sample MRI T1 weighted images which consists of the white grey matter in the cortical and to measure its thickness the author has used the FIRST and Free Surfer Tools.

As while validating its data in FIRST and Free Surfer and comparing their result, after comparison the author has found that the result is advanced in the free surfer as compare the FIRST. It concludes that the FREE Surfer for the better data analytics and processing the MRI data in real time. The concept of the cortical thickness measurement, where it contains the generation of CSP that is cortical surface pattern, which constitutes the variety in the volume separation and the measurement of the thickness of the cortex [24]. They also used the RVR techniques for the prediction

of the data from the certain classification methods. They used the basic technique of relevance vector regression and constituted from the IXI database where 360 healthy subjects, which are aging from 20 to 82 years and some, are aging from INDI database that is 303-subject aging from 7 to 22 years. In this assumption, they have attempted to reach the mean difference of the age calculation of 4.57 years, and in further classification, they have approached the 97.77% accuracy.

The age based on the cortical images from the MRI datasets, Author is saying the prediction of the age of the certain features which is extracted from the MRI data sets. Further, the author has described the local feature extraction method and the local feature normalization and building up the classifier [25]. In this, author has taken some tools for processing of the data that is statistical parametric mapping SPM2 and uses the Voxel based Morphometry 2. For the further classification the author has taken the SVM based classifier, LDA and RVM which is proposed by author and they compared the result obtain. In this, the author has found the MAE of 4.498 using RVM classifier. In [26], author has done the prediction the brain age by using the different anatomical features. They have used different techniques for the prediction of the ages from those anatomical features. They have used the different technique like K-nearest neighbor, linear discriminant analysis, multiple linear regression, and in the machine-learning dimension, they have used the neural network, ridge regression, relevance vector machine and voxel based morphometry. They have used the free surfer tool for processing the data can continually take out that concern anatomical features, which can be categorized based on the cortex area, cortical thickness, and cortical grey matter volume. In this, after applying this all the technique they have used the neural network approach is the best approaches compared to others. This technique [27] detail out the anatomical features where it contains the brain age estimation and uses the various algorithms for the prediction of the age estimation, it also possesses the neuro-cognitive disorder. In this, the author has used the Free Surfer tool for the measurement of the cortex and taken the various significant features. In this, author has taken the local outlier factor, SGL technique for the prediction and the Gaussian process regression, then it also uses the Neural network technique for the estimation, and the author has also applied to the process of the hybrid techniques SGL + GPR, SGL + RVR and has the mean absolute errors 0.004 and 0.003. In this, author has taken the mean absolute error difference of 4.05 errors, which constitute the best MAE in the process of the prediction.

The estimation of the brain age where it contains the prediction of the actual age of the brain age that is termed as delta age [28]. They have used the correlation and relation techniques for the estimation of the data; they have also reform to delta approach.

In order to make the static variation of the data being non-image. However, prediction of the actual age cannot guarantee but the author suggested the systematic approach for the prediction of the age of the human body from the brain image. In order to reduce the features, the author has used the side technique so that selected features can be traced from the source brain imaging. Therefore, this technique led to the significant approach to the study of the different image age contribution. In [29], the field of deep learning where they constituted the process of selected features

and training them to use deep learning approach. In this, the author has taken the open source database where it takes the MRI images from the database, taken out the features applied the convolution neural network. By those feature the author has predicted the age of the brain, with the mean absolute error of 4.08 years with comparison of the different set of the features' combination.

In [30], Bayesian characteristics for taking out the sparse result from the correlation, regression and the classification approaches. In this, author has taken the relevance vector machine and the support vector machine for the better classification and the prediction of the data to analyze the strength of the various methods, which is described. In this, the author has taken the benchmark datasets which contain the Since, Friedman, Boston housing, Piama diabetes, USPS, in which various classification techniques has been applied to get out some useful observation. In [31], segmentation of the MRI Images and contain the different features, the author has developed the CAD system for finding out the features. Author has applied the probabilistic neural network for training the classification of the data set, taken the approach to the probabilistic neural network, and uses the edge detection techniques for the detection of the brain tumor detection using neural networks.

In [32], support vector network for the various classification of the linear set of data, containing the classification of the linear algorithms to attire the benchmark study for the optical character recognition. This continues the better practice of the data formation for the prediction of the character recognition. By this methodology, the OCR states the better performance by applying this technique, which constitute the better recognition. In [33], SVM procedure from the Statistical learning theory. In this, the author has taken the better segmentation approach, which constitutes the multi class classification where the segmentation part of the MRI image becomes easy and significant. This direct fundamental to the proper classification of the images where it constitutes the proper estimation of the infected region, which can cultivate the better feature classification of the MRI data.

Various specifications for the feature extraction from the MRI images where it catches the significant approach for the detection of the MRI images [34]. Here it contains the specific categorization based on the stages, namely, feature extraction. They use the discrete wavelet transform, which contains the specific and the better approach for taking out the features of the MRI brain images. The detail analysis of the Cortex Measurement done in the various research studies for the cortex measurement.

Table 2 describes the various constituents of pranayama and yogic kriya which facilitates the various function of the body describe various parameters which effects the brain, it can be easily be found out the sample unit which it describes the person who is doing yoga for many years and the person who is not doing yoga. Responsible factors which affect the brain and the parameters helps to measure the cortical thickness.

In Table 3 the researcher comes into contribution that what are the factors responsible for the estimation of the age. So, the factor like GM, WM, Cerebral fluid in the different part pf the brain, and to measure the thickness of the cortex, which will give some features, on the basis of those features the estimation has taken out.

Table 2 Analysis on the cortex measurement in the yoga practitioners

Author	Data set	Objective	Methods	Result
[3]	23 controlled group and 23 meditators from the Sahaja Yoga Meditators	Finding out the grey matter volume in the MRI images of the Mediators and the Yoga Practitioners	They have used MRI Images, Voxel Base Morphometry	In the predator the presence of the Grey matter volume is large as compared to the Nin mediator or the Yogic Person
[7]	23 mediators and the Yogic person participated with having Twelve months experience minimum in the swami Vivekananda yoga research foundation	Finding out the increase of oxy hemoglobin and deoxy hemoglobin and the reduction of the hemoglobin in total hemoglobin	They have used the FNIRS techniques	They found the increase of the delta hbo, and the decrease of delta hbr in the total hemoglobin
[6]	29 where the yoga intervention and 26 were in the memory enhancement training	Finding out the relation between memory test and resting state after and before yoga	They have used the FMRI images and applied on the FSL software and data analysis in the MELODIC	In the group, they found the better connection between the cortex region and the default mode network
[35]	No. of participant 376 and the mean age 20, with the 16 week course of the Yoga	They are finding out the individual boundary of change of the state and change in the body appreciation of doing yoga	They used the latent curve growth model	They found the level of the state mindfulness is high and medium level of trait mindfulness in the means of Comparative fit index, slope, and mean, and standard root mean square
[36]	The number of participant where 61, excluded 29 not meeting the requirements, uses n = 10 for movement capability, awareness n = 14 and pain n = 8	Finding out the effect of yoga in the brain	They have taken the ECG based method and the FMRI based cortex measurement method and the EMG based method	In this method, they have found the yoga has cover all the aspect of awareness, stress decreasing, sensory awareness and interception
[4]	21 woman who is doing yoga (Hatha) and 21 woman who is not doing any yoga or meditation	Finding out the cortical thickness in the yoga partitioning woman and non-yoga partitioning woman	They have used the MRI images and the free surfer approach and the general linear model for the measurement of the cortex	In the result they have found the larger grey matter volume in the context in the prefrontal lobes and there is major changes in the age, education and questionaries'

(continued)

Table 2 (continued)

Author	Data set	Objective	Methods	Result
[37]	There is the 20 group of the Extreme meditator and yoga practitioners, and 14 where the non-meditation	Finding out the size increase d of the cortical thickness	They have used the MRI based approach for the detection of the cortex	They have taken the Kolmogorov Srinov approach and the apriority approach for the determines of the thickness and found the increase of the cortex in sensometry region of the cortex
[38]	Yoga consisted practitioners 25 patients and where men 11 and 14 women where they are suffered with the tetanus	Finding out the surface orientation using MRI, TFI index also which is based on the sleep, sensing, relaxation auditory	They have used the MRI images, and the practicing of the yoga for 6 months	The results were positive when practitioner the yoga the on the presence of white matter in the brain cortex and the TFI score was improved

It also describes what are the approaches that author has taken out for the prediction of the age and the estimation of the age, like deep learning, regression model etc. There should be significant approach for the measurement of the thickness of the cortex, and also there should be proper and specific features are required to take out for the measurement of the cortex because the area of the cortex surface is not uniform, so cross-sectional observation and measurement is required for every section. There should be the specific features should be taken by the measurement of the cortex, which should help for the proper analysis for the knowing the condition of the anatomical behavior. There should be an efficient model for the prediction of the age so that the MAE of the efficient sample who is practicing yoga must not deviate too much from the validation.

8 Conclusion

This review article has demonstrated the different state of the art methods that can be used to find the cortex in different regions of the brain that are practicing yoga. MRI scans of these regions can then be evaluated using various cortex measurement methods such as machine learning and deep learning technologies. These technologies provide clear insights into detecting white and grey matter. The chapter has detailed discussion about the machine learning and deep learning technologies are discussed, which are generally used for the classification of yoga and non-yoga practitioners. This helps to identify which areas show increased activity due to yoga practice or not. These methods are useful for understanding the impact of yoga practice on the brain and its cortical regions. The chapter also proposes some measures

Table 3 Analysis on the brain age estimation methods

Author	Data set	Objective	Methods	Result
[39]	Taken the two project where it contains the male 561 and female it contains 591 and tsurgaya where it contains 176 total and there 84 male and92 female	They are calculating the brain estimation by using the local features from the data	They are using the statistical mapping tool for the feature extraction and voxel based morphometry and using the ML techniques implementing on SVM, LDA and RVM	They have estimated the age of the with the MAE of 4.498
[26]	Taken the various open source group for that is from 100 projects like ABIDE, ADHD2000	They have chosen the prediction of age on the basis of anatomical features	They are using the volume, area and thickness as the features for the prediction of the age	They are using the volume, area and thickness as the features for the prediction of the age
[27]	They have taken the 2911 group of people whose age between 45 and 91	They have also done the prediction of the age with the cortical thickness	They have applied the processed image in the manifold harmonic transfer for features and they have applied Sparse group lasso and Gaussian Process registration and they also proposed the hybrid approach SGL + GPR, SGL + RVR)	They have also estimated the brain age with the MAE of SGL + GPR with 4.053, SGL + RVR with 4.094, SAE + GPR with 4.063, SAE + RVR with 4.135
[24]	They have choose the IXI database with 360 healthy subjects and INDI database	They are estimating the Age using Surface pattern combination	They are using the surface based feature extraction through free surfer and uses the RVM based RVR regression techniques	They have the estimated the age with MAE of 5.97 with thick U surf area, 4.57 with thick U 2 Curv and 5.06 thick U surfArea
[29]	They have taken MRI of N = 5121 samples ages from 4 to 96 age and taken Computed tomography of age 1 to 97 with the count of N = 1313	They are using the anatomical features and predicting the age	They are using the estimation of the age by using the convolution approach deep learning	They have estimated the age of MAE of 4.08 years

(continued)

Table 3 (continued)

Author	Data set	Objective	Methods	Result
[40]	They 78 subjects where men are 37 and women are 41 for the process	They are finding out the age of the tissues and cerebrum and cerebellum	They are seeing the loss of the of the grey matter due to age, critical volume loss and loss of white matter in cerebrum and cerebellum	They have found the grey matter reduction in cerebral cortex almost every region, white matter increased and CSP also increased

such as neuro feedback that can be used to monitor changes in cortical regions due to different yogic practices. Moreover, it provides an insight into how this data can be used for further studies in order to understand the effects of yoga on cognitive performance and mental health. Therefore, this chapter offers a comprehensive overview of the various methods used for measuring cortex in different areas of the brain and how machine learning and deep learning technologies can be used to classify yoga practitioners from non-practitioners.

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Machine Learning Models for Alzheimer's Disorders

Automated Electroencephalogram Temporal Lobe Signal Processing for Diagnosis of Alzheimer Disease

Sarika Khandelwal, Harsha R. Vyawahare, and Seema B. Rathod

Abstract Nowadays early diagnosis of cognitive disease is a challenge because of lifestyle and stressful life. It is not easy to differentiate stress and Alzheimer condition from mere observation of personality. Detection of Alzheimer at the early stage is crucial to avoid later issues that include memory loss, person getting bedridden etc. The existing methods to detect Alzheimer is mostly expensive and requires laborious analysis which may result in delay for the start of actual medical treatment. Even some of the methods are invasive too. Hence there is demand to automate the detection of Alzheimer at the early stage using some noninvasive methods. In this chapter, the authors have suggested a strategy for the cognitive study of brain signals with Electroencephalogram (EEG) device. Collection of EEG signals are noninvasive and not much expensive. In our study, we have conducted experimentation for the temporal lobe. EEG signals originating from temporal lobes are down-sampled to 5 bands of varying frequency and further used as a dataset for the classification model. Five datasets were created from 5 different bands are used for training and testing purpose in proportion of 70–30 respectively. We have achieved praiseworthy accuracy for theta band for diagnosing of Alzheimer disease at early stage. We have achieved 98% accuracy by using deep learning model with 8 layers and activation function ReLu.

Keywords Electroencephalogram (EEG) signals · Alzheimer disease · Activation function · ReLu · Temporal lobe

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1 Introduction

Alzheimer's disease (AD) is a neurological malfunction-oriented disorder and is found to be the most common untreated disorder at an early stage thus lead the sixth most common cause of mortality in the United States and the most expensive therapy. As per survey rate of patients suffering from this deadly disease going to increase exponentially in next 50 years [1]. Patients with AD undergo a steady decline in several cognitive functions, including memory, orientation, and reasoning, to the point that it affects their ability to carry out daily tasks. Although this condition was first noted in 1906, its cause is still unknown, and a definitive diagnosis may only be made at a brain autopsy [2]. According to the research, however, amyloid plaques and neurofibrillary tangles are two key characteristics that appear before the impairment is apparent [3]. Protein deposits known as amyloid plaques build up around the neurons after they lose their usual structure. The fibrils that around the neuron nucleus are thickened to form neurofibrillary tangles. MCI (mild cognitive impairment) is frequently described in this context as a condition that occurs between normal ageing and AD. Patients with MCI have unexpected memory declines given their age, but these do not affect how they go about their daily lives. Nonetheless, MCI patients develop AD more quickly than healthy people of same age. Even though there is currently no cure for AD, early detection can slow the disease's progression and prevent cognitive impairment [4].

The goal of AD detection methods is to identify the disease's cognitive and physical signs. Traditionally, medical procedures and neuropsychological testing were used to do this. Neuropsychological tests are intended to assess cognitive domains such as memory, language, and orientation that are impacted early in the AD course. Despite the widespread use of neuropsychological testing, prior research has shown that they are insensitive and highly variable. On the other hand, medical techniques work to reveal the harm done to particular brain areas. Cerebrospinal fluid (CSF) analysis is the most dependable of these methods. But, lumbar puncture, an invasive medical procedure with known risks, is used to remove this fluid. Instead, functional or static images of the brain can be produced using medical imaging techniques. The most advanced techniques include single photon emission computed tomography, positron emission tomography, and magnetic resonance imaging (SPECT). Despite the fact that these methods produce precise answers, they have certain disadvantages, such as lengthy waiting lists and analyses that are frequently relied on visual inspection [5].

There are other multiple ways to diagnose this deadly disease at an early stage like MRI, brain test survey, EEG signals. Table 1 shows the comparison of Alzheimer disease diagnosis method. Like other disease cancer, AD also traverse from first phase to deadly phase, in medical terms the phases are categorized as 1. Mild Cognitive Impairment (MCI) and in this phase though affect is not at all to alter life but if remains untreated can progress to the next level. As per the survey the ratio of minimum 6–25% affected population traverse from first to subsequent phase and which is alarming digit. Some of the commonly observed symptoms of phase 1 are trouble in doing

Table 1 Comparison of Alzheimer disease diagnosis method

Method	Diagnose AD	Progression	Non-invasiveness	Cost
MRI	Yes	Yes	Yes	High
PET	Yes	No	Yes	High
Bio marker	Yes	Yes/No	No	High
EEG	Yes	Yes	Yes	Low

Fig. 1 Stages of AD

mathematical calculations, persistent enquiries, mood swings and loss of memory [6]. Second stage is known as Mild and Moderate AD, which starts exhibiting symptoms in the form of cognitive deficit and increasing dependency thus need of caretaker arise in this stage. This stage also exhibits the symptoms like being unable to pick up new skills, having trouble in identifying the known ones like family and friends, prone to delusions, paranoia, impulsivity, and hallucinations. The third and last stage of AD is severe AD where the person completely becomes bedridden and dependent. It also exhibits symptoms in the form of complete personality deterioration [6]. The three different stages of AD are shown in Fig. 1.

Thus, to prevent progression from first phase to subsequent phases; early diagnosis is the only key [7]. Early diagnosis helps patient and family member with ample amount of time to restrict progression from mild to severe AD. It also gives enough decision window time to decide about financial planning of future and care taking schedule for the patient. Even though medication which start at later phase has capability to delay deterioration of personality but it is effective for defined time window only, so only key is to diagnose early so that medication has larger window size as compare to medication started at later stage. Now the key question is how to make sure that patient is well informed and well aware about disease at early stage only, as it initial trigger point is cognitive impairment in mild way. Various approaches are available like blood test, neurological test, Physiological test, color troop test, various imaging techniques are popularly used methods to diagnose the disease [8]. In this chapter we have proposed approach for diagnosis of Alzheimer disease on the basis of medical studies which shows that maximum time the origin of disease is identified as receiving neurological signals from brain are deviated from what it actually should be and not in synchrony mode as per expectation [9]. Thus, correlation is the major cases of brain damage and receiving irrelevant signals from different parts of brain. Inaccurate correlation and decreasing correlation between

arising brain signal is the key to diagnose disease at early stage [10]. Thus, methods which directly intervene with brain signals and fetch exact correlation arising from different lobes of brain is the best fit technique for early diagnose of the disease. We have proposed electroencephalogram (EEG) study of temporal lobe of patients suffering from AD [11]. Proposed approach is invasive approach and if portable device being used for signal capture can be use in real time as well while subject is performing some cognitive activity, in field signal capture gives more precise information about correlation deviation of signals in brain. It helps to screen large population in less time window and inexpensive approach is affordable by maximum population. Though electrodes can be placed at various mounting points varies from frontal, parietal, occipital and temporal lobes [12] along with left and right ear lobe in connection with reference node, we have studied temporal lobe signals to dip dive into correlation/deviation of brain signals in case of patients suffering from AD as well as healthy category.

In an electroencephalogram (EEG), electrical currents produced by a collection of specialized pyramidal cells in the brain that track neuronal activity are monitored [13]. Brain electrical activity (EEG) has a very complicated nature with pronounced nonlinear and dynamic characteristics. The electrodes are applied to the subject's scalp to assess brain activity. The 10–20 International Electrode Placement System specifies where electrodes should be placed [14]. The cerebrum, cerebellum, and brainstem are the three anatomically significant regions of the brain. The right and left hemispheres of the cerebrum are separate hemispheres. The frontal, parietal, occipital, and temporal lobes make up each of the four divisions of each hemisphere. Each component is linked to the brain's cognition, movement, emotion, and motor activities. Each part's responsibility is depicted in Table 2.

The brain signals are a combination of different base frequencies. These broad frequency ranges have been divided into several subgroups, called EEG rhythms or frequency bands. Each frequency band reflects a different state of mind or cognition in the brain and in depicted in Table 3. Types of rhythms such as theta, delta, alpha,

Table 2 Responsibility of major portions of brain [14]

Region	Responsibility
Cerebral cortex	Higher order cognitive tasks, such as problem solving, language comprehension, movement and processing of complex visual information
Frontal lobe	Personality, emotions, problem solving, motor development, reasoning, planning, parts of speech and movement
Parietal lobe	Sensation (e.g. pain, touch), sensory comprehension, recognition, perception of stimuli, orientation and movement
Occipital lobe	Visual Processing
Temporal lobe	Involved in dealing with the recognition of auditory stimuli, speech, perception and memory
Cerebellum	Motor control, sensory perception and coordination, voluntary muscle movements, fine motor skills, posture and balance regulation

Table 3 Brain rhythms [14]

Rhythm	Frequency range (in Hz)	Regions	Activity
Delta (δ)	0.1–3.5 (< 4)	Mostly in thalamus	Deep sleep, continuous attention tasks and unconscious
Theta (θ)	4–7.5	Hippocamtus	Creativity, intuition, recall, imaginary dream
Alpha (α)	8–13	Occipital and parietal	Relaxation, drowsy
Beta (β)	14–30	Parietal, somatosenonsory, frontal and motor areas	Memory, problem solving
Gamma (γ)	30–100	Cortex	Cognition, information processing, motor functions, higher mental activity

beta, and gamma can be observed in the brain waves depending upon the different functional states of the brain. Any small changes to these waves' frequency patterns help identify neurological conditions [13].

AD detection methods that are currently used are expensive and upsetting. Electroencephalography (EEG) is a quick, low-cost, and non-invasive method to collect brain data, but its interpretation necessitates a visual examination, which takes a lot of time and differs depending on the level of skill. Moreover, lengthy EEG recordings necessitate lengthy manual reviews that run the risk of making mistakes due to distortions in the signal. Another non-invasive method of collecting brain data is using Magnetic Resonance Imaging (MRI). Manual examination of both of these methods requires a lot of time and expertise hence there is a need to develop an automated diagnosis of brain signals for the detection of AD [15]. Other imaging techniques for screening of AD include Computer Tomography (CT) scan and Positron emission tomography-Computed Tomography (PET-CT).

The general steps to implement computer-aided brain diagnosis includes following steps.

1. Collection of brain signals: Either MRI or EEG or any of the cost-efficient and non-invasive method of collecting brain signals can be used.
2. Preprocessing of brain signals: This step is used to preprocess the signals to remove the noise and to enhance the signal quality. This can include filtering algorithms [16]. The preprocessing is necessary to get better feature extraction results. Preprocessing of signals are broadly classified into three categories that includes downsampling, artifact handling and scaling. Downsampling is done to save the space and time of processing the signals. It ensures range of the signal to particular rate. Downsampling the signal at any rate varies from application to application. Artifact handling ensures removal of noise from the signals. Feature scaling is done to ensure normalization of the data.
3. Feature Extraction: This is used to select the optimal feature using any of the feature extraction algorithms. Feature extraction can be done using Discrete

wavelet transform (DWT), Discrete cosine transform (DCT) or any of the optimal algorithms.

4. Dominant Feature identification: Dominant features can be selected from the p-values obtained through different test. Various test to obtain p-values include Standard normal distribution, Student's t-distribution, Chi-squared distribution, F-distribution etc. A higher p-value denotes poorer evidence supporting the null hypothesis, while a smaller p-value implies stronger evidence opposing it. If the p-value is less than 0.05, there is less than a 5% probability of getting the observed result if the null hypothesis is true, and it is improbable that the result is the result of chance. This is the conventional threshold for significance. It's crucial to remember that the p-value is only one type of evidence, and that it should be interpreted in light of the sample size, study design, and other elements. It ought to be analyzed in light of the sample size, study methodology, and other elements.
5. Classification of signals: Implementation of any of the classification algorithm to classify the brain signals. Classification algorithm that are used in literature includes support vector machine (SVM), K nearest neighbor, Multilayer perceptron (MLP), Random forest etc.
6. Validation and testing of developed classifier: The performance of the designed classifier can be measured using the performance metrics like accuracy, precision, recall, F1-score etc. The general framework for implementation of brain signal diagnosis is shown in Fig. 2.

The details of EEG signal processing are shown in Fig. 3.

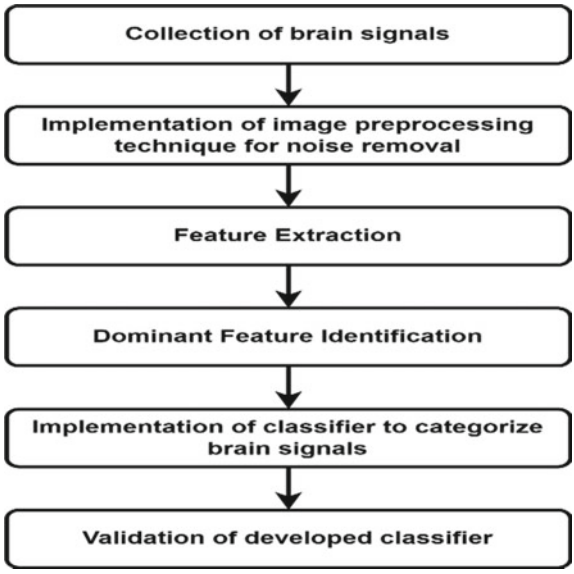

Fig. 2 General framework of implementation of computer aided brain signal diagnosis

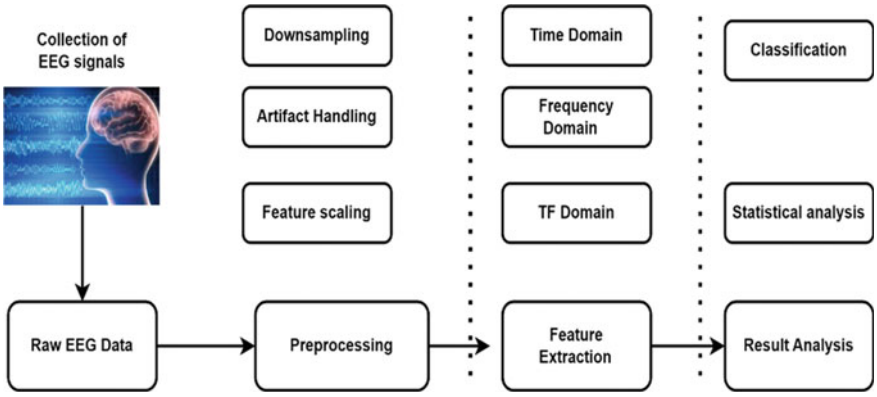

Fig. 3 EEG signal processing details

2 Related Work

Achraya et al. in [16] have devised an automated method to detect AD using MRI images. Authors have used Shearlet Transform (ST) for feature extraction. ST has outperformed for AD detection compared to other methods. KNN classifier is used in addition to ST. For dominant feature identification, authors have used Student's t-test. The reported accuracy with this KNN + ST is 94.54% and 98.48% with benchmark MRI dataset.

Kulkarni et al. in [15] have utilized complexity based nonlinear feature of EEG for detection of AD. Authors have shown that the use of these complexity features can enhance the accuracy of AD detection. Authors have used non ERP (Event Related Potential) EEG recordings for computing the features like spectral entropy (SE), spectral roll-off (SR), spectral centroid (SC) and zero crossing rates (ZCR) is used for classification of AD using those features. It is observed that combination of complexity feature provide better accuracy compared to individual nonlinear feature. The accuracy of 96% was reported for complexity feature using SVM, proving that complexity based features are more accurate for AD classification.

Trambaiolli et al. in [17] have used EEG sub-band modulation for AD detection. EEG signal are first decomposed into five sub bands namely alpha, theta, delta, beta and gamma depending on the frequency range. Onwards Hilbert transformation is used to compute the temporal amplitude envelope for each of the sub-band. Modulation energy features are used to train the classifier. Authors have used SVM, Logistic regression, regression tree and Neural network for classification of AD. It is evident form the achieved accuracy that Neural network outperforms with the accuracy of 91% when used with modulation energy features than conventional spectral features.

Bairagi in [18] have used EEG signals for detection of AD using spectral and wavelet features. EEG signals are first preprocessed using third order Butterworth band pass filter. Those EEG signals are then are divided into sub-bands and spectral

features like relative power (RP) and complexity features are then passed to classifier. The accuracy of 94% is achieved to diagnose AD using spectral and wavelet features.

Perez-valero et al. in [5] have use EEG signals for classifying the AD. They have used binary classifier to classify two classes of AD namely mild AD versus control and MCI-Non-AD Vs control. They have first prepressed the EEG signal using FIR filter to filter the raw EEG. Autoreject algorithm is used for artifact removal. Blink artifact are removed using independent component analysis (ICA). Three features namely relative power (RP) in the five main EEG bands, Hjorth complexity (HC), and spectral entropy (SE) are extracted. Authors have used Chi-square test for feature selection. Classification is performed using SVM classifier and Logistic regression (LR). SVM has outperformed over other classifier.

3 Methodology

As shown in Fig. 4, datasets 1 and 2 are included in an experimentation. Signals in dataset were captured from various mounting positions frontal, parietal, occipital, and temporal lobes. We have considered signals from temporal lobe only from both the dataset and other mounting positions were excluded. As signals were captured at sampling frequency of 200 Hz in first dataset and 128 Hz in second dataset, we have down sampled signals to desired sampling frequency 60 Hz. 50 Hz signals are also excluded as it is assumed to be signals generated from electrical power supply to device while performing an experimentation [19]. Down sampled signals from both datasets are further divided into bands by using wavelet transform with mother wavelet. Division of bands from both datasets are merged together to create dataset to classification model. Thus 5 datasets of different bands are created from 2, datasets with band division of 0–4 Hz, 4–8 Hz, 8–16 Hz, 16–32 Hz and 32–60 Hz [20]. Classification model used in this study is deep learning model. Proportion of records used for training and testing are 70–30 in proportion. 70% records are used for training and rest 30% are utilized for testing.

4 Dataset Used in Experimentation

We have studied EEG signals captured from AD patients from 2 different datasets. Third dataset (http://adni.loni.usc.edu) we have excluded from study because it has captured signals from only frontal lobe and not relevant for inclusion in our study as we are studying temporal lobe impact of AD and non-AD patients [21].

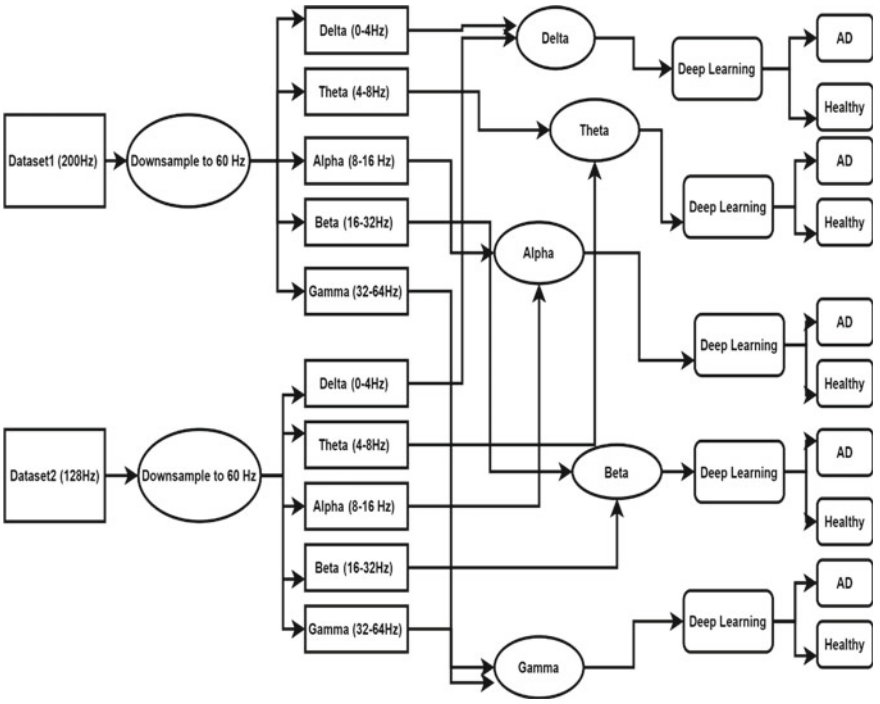

Fig. 4 Proposed approach for classification of AD

4.1 Details of Dataset 1

It consists of two groups controlled and non-controlled sets. Controlled set consists of population count 25 with suffering from minor cognitive impairment that eventually leads to mild Alzheimer's disease. To capture EEG signals while EEG signals are at peak, test which has conducted is mini mental state exam. To clearly distinguish about inclusion and exclusion of subjects in MCI category solely based on score of mini mental state. The average score of all subjects who have participated in test was 26 with standard deviation of 1.8 and criteria to decide about MCI suffering or not was set to score received by subject is 24 or more. Subjects with less score were excluded from further study. The age criteria for this category are 71.9 ± 10.2. For non-controlled category age criteria was 71.7 ± 8.3. Here subjects have not reported any cognitive impairment. Ag/AgCl electrodes (discs with a diameter of 8 mm) were positioned on 21 sites in accordance with the 10–20 international system for the experimental setup, with the reference electrode on the right earlobe and frontal lobe. The Biotope 6R12 (NEC San-ei, Tokyo, Japan) was used to capture the EEG at a sampling rate of 200 Hz [22].

4.2 Details of Dataset 2

It consists of 24 healthy subjects (in age category of 69.4 ± 11.5) and 17 affected subjects (age: 77.6 ± 10.0 years old). Affected subjects have traversed through multiple tests like mini mental state including animation effects, color test, verbal pronunciation test, retention test as well as memory recall test. 19 electrodes were used with placement standard of 10–20 system with sampling rate of 128 Hz. Time taken to record EEG signals in both datasets is approximately 5 min in awake state while subjects were actually performing screening test with eyes open and resting state in between is of 2 min with eye closed state.

5 Deep Learning Model

Model used in this study is deep learning model with 8 layers and ReLu activation functions. In the hidden layers of deep neural networks, the ReLu function is now a common option for many neural network architectures. ReLU provides nonlinear mapping while keeping the positive values unchanged. Other activation functions are sigmoid and hyper parabolic tangent. But Relu is most preferred option because it is faster to compute compared to other activation functions. Because of hyper parameter and base parameter tuning capability of deep learning model it serves as best fit for our experimentation. We have experimented with 5–8–10–13 layers by keeping input fixed and achieved good accuracy with 8 layers thus findings of records from other layers are excluded from inclusion in this chapter. Total iteration taken for entire experimentation is 5 with various parameters values being fixed in each iteration to reduce loss of values [23].

As shown in Fig. 5, two datasets are used for AD classification. A proposed model classifies the EEG signal into AD and healthy one.

6 Results and Discussion

We have experimented with 5 band datasets. For every dataset type the structure of the classification model which has achieved good accuracy is 8 layers only though we have experimented with 4 different layer size. While experimenting with delta band signals which are originated from the temporal lobe, we have not received any prominent differentiation between healthy and non-healthy (Alzheimer suffered) patients. We have manually studied the signals for the identification of peak values, but no prominent distinct behavior has been exhibited for delta band thus model has not achieved good accuracy and we have concluded in our finding that on temporal lobe delta band signals doesn't serve the purpose of early diagnose of Alzheimer patient. Same is applicable for alpha, beta, and gamma bands. While experimenting with

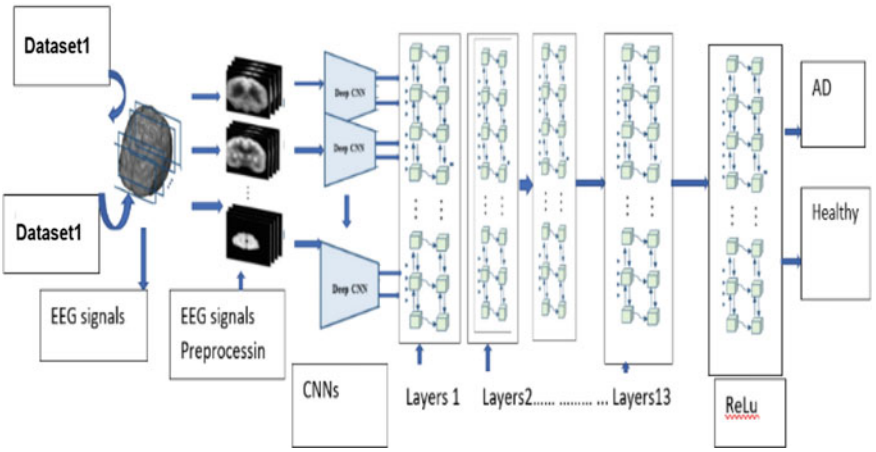

Fig. 5 Proposed approach for classification of AD using CNN layers and Relu activation function

theta band model has achieved prominent accuracy of 98% which is praiseworthy as compared to other studies which are carried for temporal lobe of Alzheimer patient [24].

Performance metrics used in an experiment are given in Table 4. Accuracy and F1-score are used as performance metrics in this work. From the table it is evident that Theta band gives highest accuracy and F1-score. Delta as well as Beta band gives same performance in terms of accuracy and F1-score. Alpha and Gamma band gives moderate accuracy and F1-score.

Accuracy is defined as the number of correct predictions to the total number of predictions [25]. It can be mathematically given as Eq. (1). F1-score balances between recall and precision as given in Eq. (2).

$$Accuracy = \frac{True\ Positive + True\ Negative}{(True\ Positive + False\ Positive + True\ Negative + False\ Negative)} \tag{1}$$

$$F1\text{-}Score = \left(\frac{Recall^{-1} + Precision^{-1}}{2}\right)^{-1} = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{2}$$

Table 5 shows the comparison of the proposed work with sate of art work available in the literature. It is evident from the table that the proposed solution gives praiseworthy accuracy for AD classification.

Table 4 Performance analysis of proposed work

Lobe	Delta		Theta		Alpha		Beta		Gamma	
Temporal	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
	67	56	98	98	78	67	67	56	76	67

Table 5 Comparison of proposed work with state of art literature

Reference	Signals used	EEG signal preprocessing	Classification algorithm	Feature extraction	Accuracy (%)
Acharya et al. [16]	MRI	Median filter	ST + KNN	Shearlet transform (ST)	94.54
Kulkarni et al. [15]	EEG	–	SVM	DFT (SC, ST, ZCR, SR, complex)	96
Trambaiolli et al. [17]	EEG	An infinite impulse response low pass filter	Neural network	Hilbert transform	90
Bairagi [18]	EEG	–	SVM	DWT (spectral and wavelet features)	94
Perez-Valero et al. [5]	EEG	FIR filter, autoreject algorithm	Logistic regression (LR), SVM	Relative power, Hjorth complexity, spectral entropy	96
Proposed	EEG	Down sampling the signals	Deep learning model with Relu activation function	Empirical mode decomposition (EMD)	98

7 Conclusion

EEG signals are proven to be reliable and robust indicator of measuring electrical activity arise in brain and thus helpful approach to diagnose any disease which originated from malfunction activity of electrical signal emissions. As EEG signals can be captured from various mounting points, in this chapter we have carried intensive study of temporal lobe behavior in case of controlled and non-controlled category. Temporal lobe has proven to exhibit distinct pattern of signals for the band theta in category of AD patients while in case of no AD patient's theta has not exhibited any distinct behavior. Thus 4–8 Hz frequency signals are mostly affected in case of AD patients. While mild patients have exhibited prominent theta behaviors for middle range of 4–8 Hz and severe AD patients are more inclined towards end of theta band. Thus proposed EEG study of temporal lobe is more promising for early diagnosis of Alzheimer patient before it progress towards severe AD. As we have experimented with limited subjects, vast study is required with large population set. This study is also applicable for various other disorders of cognitive in nature and easily be mounted for real time scenario study.

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Machine Learning Models for Alzheimer's Disease Detection Using OASIS Data

Rajesh Kumar Shrivastava, Simar Preet Singh, and Gagandeep Kaur

Abstract Early Prediction of Alzheimer's disease is a challenging task for researchers to contribute. Dementia is the simplest symptom of Alzheimer's disease. Nowadays, most researchers apply Artificial Intelligence to discover mental disorders like Alzheimer's, which mostly affect the old age population worldwide. In Alzheimer's disease, the brain is under neurodegenerative changes. As our population ages, more people will be affected by diseases that impact memory functionalities. These repercussions will profoundly affect the person's social and financial fronts. It is difficult to predict Alzheimer's disease in its early stages. The Medication given early in Alzheimer's disease is more effective and has fewer minor side effects than treatment given later. To find the optimum parameters for Alzheimer's disease prediction, researchers used a variety of algorithms, including Decision Trees, Random Forests, Support Vector Machines, Gradient Boosting, and Voting classifiers. Predictions of Alzheimer's disease are based on data from the Open Access Series of Imaging Studies (OASIS). The performance of machine learning models is tested using measures such as Precision, Recall, Accuracy, and F1-score. Clinicians can use the proposed classification approach to make diagnoses of these disorders. With these ML algorithms, it is extremely beneficial to reduce annual Alzheimer's disease death rates in early diagnosis. On the test data of Alzheimer's disease, the proposed work demonstrates better results, with the best validation average accuracy of 80%.

Keywords Machine learning · Healthcare · Random forest

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1 Introduction

Alzheimer's disease is a degenerative neurologic condition in which the brain shrinks (atrophy) and brain cells die. Alzheimer's disease is the most frequent form of dementia, defined as a progressive loss of cognitive, behavioral, and social abilities that impair a person's capacity to operate independently [1, 2]. Proper treatment helps the patients to reduce the disease symptoms temporarily. Correct medicines can assist patient by preserving their independence and mental functionality. Alzheimer's disease is known as no cure disease it effects patient's brain. In this illness the patient suffers loss of memory that can lead to mortality in the advanced stages of illness.

Alzheimer's disease has its characterization by loss of memory. Early identifications of this disease include recalling recent events or discussions [3]. Memory functionality also get effected as the disease progressed. A person suffering from Alzheimer's may notice difficulties in remembering things and managing thoughts. These changes in the brain are caused following problems:

1. Memory: This illness cause badly memory loss, making the infected person difficult to operate at work or home. An Alzheimer's patient may experience the following symptoms:
    - Replicate statements and queries as needed.
    - Remember about discussions, appointments, or events and remember about them.
    - Frequently misplaced belongings, keeping them in strange places.
    - Family members' names and ordinary objects are eventually forgotten.
    - Facing problems in recognizing items, express thoughts, or in conversations.
2. Reasoning and thinking: The disease of Alzheimer's impairs concentration and thinking, especially when abstract notions like numbers are involved [4]. Multitasking is particularly difficult, including managing finances, paying payments on time, and cheque books balancing can be a difficult task. This all is because a person who is suffering from Alzheimer's disease may eventually lose the ability to recognize and cope with the numbers.
3. Making decisions and judgments: Alzheimer's disease impairs a person's capacity, making sound assessments and decisions in everyday situations becomes very difficult. As a result, a person can make bad or unusual decisions that lead to social encounters or improper dressing that is inappropriate for the present weather. Even responding successfully to ordinary situations like a stove on fire or unexpected driving conditions seems very difficult to a person suffering from this disease.
4. Organizing and carrying out routine activities: Over time, the person with such a disease starts facing problems with daily routine that involve normal tasks, such as playing games, kitchen work driving etc. Extending this, in the advanced stage of Alzheimer's disease patient forget daily work like bathing, dressing, etc.

5. Personality and behaviour change: As Alzheimer's disease causes changes in the brain functionality, this impacts the mood and behaviour of a person. Such a person shows the following issues.

Apathy, Depression, Social isolation, Mood Swings, Others' mistrust, changes in sleeping patterns, Aggressiveness, irritability, Wandering, lost inhibitions, and Delusions.

The daily diagnosis of an Alzheimer's patient is difficult. But the patient needs daily monitoring, and the family members are also curious about the patient's status. Earlier detection of Alzheimer's disease was difficult. In most cases, it is diagnosed after death. But with the help of artificial intelligence, it is possible to detect Alzheimer's disease in its early stage. This chapter compares various methods to detect Alzheimer's using Machine Learning (ML) techniques.

Brain images are not good for Alzheimer's disease. It is mostly used to study strokes, trauma, or tumors to understand cognitive change. This chapter uses Magnetic resonance imaging (MRI) data from the Open Access Series of Imaging Studies (OASIS) [5–7]. MRI provides detailed image of brain. MRI take help of radio waves and a magnetic field to capture brain status.

This work helps in the early detection of Alzheimer's patients. This is very useful for recovering the disease at its initial phase itself. The work in this paper explains various machine learning algorithms [8–13]. In addition, the work evaluates different machine learning algorithms on MRI data to identify Alzheimer patients, and each algorithm shows its accuracy in the identification process. As a result, parameter tuning has been carried out by considering the machine learning approach with the highest accuracy to be the best optimal feasible solution for the dataset.

2 Related Work

Bari et al. [14] described the problem of Alzheimer's disease very well. We also used the same dataset (OASIS) used by the author. The Author used various ML techniques and compared the result. The data set Bari et al. [14] used s small but contains useful information that we reuse in our proposed work.

Moradi et al. [15] Experimented with Moderate Cognitive Impairment (MCI) to use MCI as a bridge between age-related cognitive decline and Alzheimer's disease. The Authors demonstrate the usage of a machine learning-based MRI biomarker. According to the paper, their aggregate biomarker attained a tenfold cross-validation AUC score of 0.9020 in differentiating between progressive MCI (pMCI) and stable MCI (sMCI). The Author used semi-supervised learning to implement sMCI/pMCI classification on data from AD patients and normal controls rather than MCI patients. Regularized logistic regression was used to choose features. To avoid possible confusion between changes owing to AD and those related to normal aging, they eliminated aging effects from MRI data before classifier training. Finally, they created an

aggregate biomarker using a random forest classifier by first learning a distinct MRI biomarker and then merging age and cognitive data from MCI participants.

Zhang et al. [16] focused on Eigen brains and machine learning; this research suggests a new computer-aided diagnosis (CAD) approach for MRI brain imaging. They employ critical slices from the 3D volumetric data acquired by the MRI to generate Eigen brain pictures based on EEG data in their method. After that, they used kernel support vector machines with several kernels trained using particle swarm optimization. Their polynomial kernel (92.36%) was more accurate than their linear and radial basis function kernels (91.47% and 86.71%, respectively).

Magnin et al. [17] suggested a method based on support vector machine (SVM) classification of whole-brain anatomical MRI to distinguish patients with Alzheimer's disease from old controls in this publication. The researchers parceled three-dimensional T1-weighted MRI data from 16 patients with Alzheimer's disease and 22 elderly controls into regions of interest (ROIs). The grey matter properties of these ROIs were subsequently used to classify participants using an SVM algorithm. The classifier has a mean accuracy of 94.5% based on their findings. The fact that they should have accounted for age-related changes in the grey matter and worked with a tiny data set could be one of their technique's drawbacks.

Khan et al. [18] reviewed the four most common deep learning and machine learning methods for brain disease identification. Some significant insights into modern ML/DL approaches are revealed in his paper. The most difficult part of the analysis is feature extraction, identification, and classification techniques using ML/DL methods. He also discussed methods to increase classification precision. The author also focuses on the quantity of training data that must be increased. The author used hybrid algorithms and combined supervised learning with ML and DL. Khan et al. [18] also identified the shortcomings of current ML/DL-based methods in identifying different types of brain disorders. The article offers a debate centered on a collection of open research problems to create efficient AI-based medical systems Incorporation of XAI methods is the ultimate goal for applications. This will aid healthcare workers in developing self-assurance, and AI-based solutions will become a treatment for individuals with neurological diseases (Table 1).

Saratxaga et al. [19] proposed a method using balance accuracy calculation. They achieved 88% of accuracy. The author deployed BrainNet 2d and BrainNet3D techniques for classification; both methods belong to deep learning. The author used OASIS-1 and OASIS-2 datasets for training and testing purposes. The authors used 2D and 3D architecture in this paper and applied a subject-level approach using transfer learning. But this approach needs more resources and high computing power. The result could be promising better. There is a scope for modification in the method used.

Sudershan et al. [20] discussed the problem of Alzheimer's disease and the nonavailability of drugs. The authors also discussed the importance of early detection of disease and the problem with the available datasets. The authors experimented with mild cognitive impairment, structural magnetic resonance, import vector machine,

Table 1 Related work

Author	Method	Dataset	Accuracy (%)
Khan et al. [18]	Machine learning and deep learning models	Image modality	85
Saratxaga et al. [19]	Deep learning and image processing technique	OASIS dataset	88
Sudharsan et al. [20]	Machine learning models	ADNI dataset	75
Helaly et al. [21]	Convolutional neural networks	ADNI dataset	93
Shakila Basheer et al. [22]	Deep neural networks	OASIS dataset	92
Martinez-Murcia et al. [23]	Deep learning using convolutional autoencoders	ADNI dataset	84
Prajapati et al. [24]	Deep neural network binary classifier	ADNI dataset	85

and support vector machine. They achieve 75% of accuracy in validation. The experimented models are novel in this dataset but there is a scope for improvement because of poor accuracy.

Helaly et al. [21] discussed the importance of early detection of Alzheimer's disease. The authors used a convolutional neural network (CNN) for their work. They classified Alzheimer's disease into four broad categories. The authors used 2D and 3D brain image data for classification from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Once the classification is done, the authors applied transfer learning models, for example, VGG19. The authors achieved 93.61 and 95.17 for 2D and 3D multi-class classifications and 97% of accuracy in the VGG19 pre-trained model.

Shakila Basheer et al. [22] investigated the MRI images dataset and used a large set of features for processing. As per the research, they conclude that age is the most important feature of Alzheimer's disease. They achieved 92.39% accuracy with the CNN model. There is a scope to improve the result by applying more validation to external data, and researchers also apply the same model to different datasets.

Martinez-Murcia et al. [23] experimented with a deep convolutional autoencoder that helps decompose a large dataset. The author uses conventional features and neuropsychologic variables to get the result. They achieve 84% accuracy, which is acceptable with the image data. But there is still scope for improvement, and researchers can improve accuracy.

Prajapati et al. [24] perform binary classification using a deep neural network. The author used an ADNI image dataset with three hidden layers and a k-fold combination with the fully connected network. They achieved 85% of accuracy with the scope for improvement.

3 Understanding of Data

3.1 Data

In this chapter, we used the Open Access Series of Imaging Studies (OASIS) data [25–27] from Kaggle. With the help of this MRI data, we will find the various categories of dementia. This dataset contains 60–96 years of patients with longitude values. This data is also balanced in nature. It has 72 nondemented and 64 demented patients' information. Each patient was scanned exactly once. Fourteen patients were found nondemented earlier but later were found demented.

3.2 Initial Data Analysis (IDA)

Before starting our analysis, we try to understand the nature of the data with a few statistical analyses. We try to establish correlations between features that help us better understand MRI data and dementia [28].

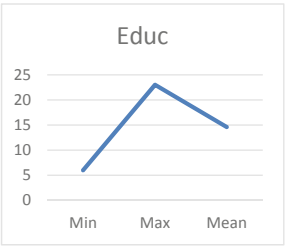
Figure 1 uses the numeric features to represent their minimum, maximum, and average values.

While observing the value of the dataset, we can infer the following.

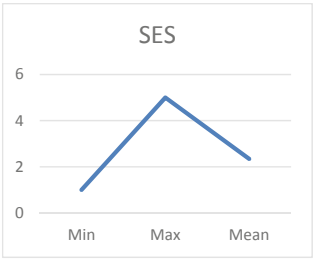
1. Men are more prone than women to be demented, as in Alzheimer's disease.
2. Demented patients had fewer years of education than healthy people.
3. Compared to the Demented group, the Nondemented group had a larger brain volume.
4. Compared to Demented and non-demented patients, demented have a higher proportion of people in their 70 and 80 s.

3.3 Data Pre-Processing

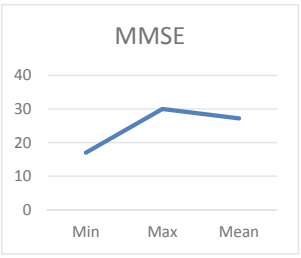
Table 2 represents the sample dataset used in this chapter. This dataset had some values that needed to be added. We have two choices: leave the entire record of the missing values or fill in a value in the missing space. We used Imputation as a method to fill in missing values. After that, we compare our model with our benchmark parameters, such as accuracy, AUC, and recall. We divided the data set into two parts one for training purposes and the second for testing purposes. We divide the dataset into a 7.5:2.5 ratio, i.e., 75% of the data is for training, and 25% is used for testing.



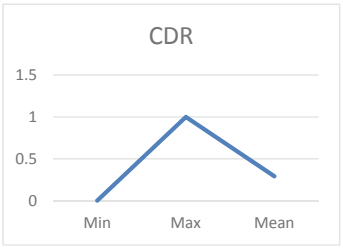
Education Years (EDUC)



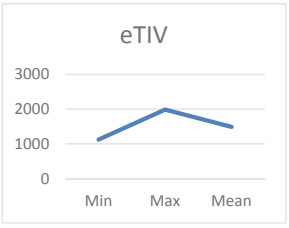
Social and Economic Status (SES)



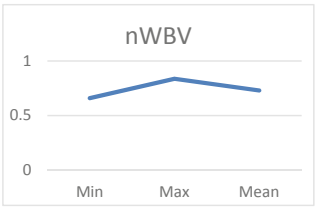
Status of Mini-Mental Examination



Ratings of Clinical Dementia



Estimated Total Intracranial Volume



Normalize Whole Brain Volume

Atlas Scaling Factor

Fig. 1 Representation of minimum, average, and maximum values of every feature for graph implementation

Table 2 Sample dataset

MRI ID	Group	Visit	MRDelay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2	27	0	1987	0.696	0.883
OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2	30	0	2004	0.681	0.876
OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23	0.5	1678	0.736	1.046
OAS2_0002_MR2	Demented	2	560	M M	R	76	12	NaN	28	0.5	1738	0.713	1.01

4 Performance Evaluation

4.1 Evaluation Metric

Our focus is on the early detection of Alzheimer's patients. We mainly focused on true positives and false positives. We wish to increase the true positive rate and decrease the false positive rate. So, we effectively detect Alzheimer's patients. For this purpose, we used AUC, Precision, and recall. In the Machine Learning (ML) method, if we have a labeled dataset, then two possibilities occur [29]. The either experimented result matches with the original result, i.e., True event, or not matched i.e., false event. On this basis, we can divide these true or false positive events into the following categories.

Table 3 represents the confusion matrix. Our statistics are based on TP and FP mostly. We try to increase TP and reduce the FP. This confusion matrix helps us to determine precision, recall, and accuracy as follows:

$$Precision = \left(\sum TP\right) / \left(\sum (TP + FP)\right) \tag{1}$$

$$Recall = \left(\sum TP\right) / \left(\sum (TP + FN)\right) \tag{2}$$

$$Accuracy = \sum (TP + TN) / \left(\sum (TP + FP + FN + TN)\right) \tag{3}$$

Equation 1 talks about a condition where we have a ratio of actual Alzheimer's patients and positive patients found by our algorithm. This situation is known as precision. Equation 2 represents a ratio of total positive (patients) out of the total number of people tested correctly. Equation 3 informed us how many correct results we achieved from the total experiments.

Table 3 Confusion matrix (Ma et al. [30])

	Experimental result		
Label in dataset		Positive	Negative
	Positive	TP	FN
	Negative	FP	TN

where *TP* True Positive, i.e., we got the same result as stored in the dataset, correctly identified Alzheimer's patients
FN False Negative, Result is opposite to the dataset result. i.e., we missed an Alzheimer's patient
FP False Positive; we wrongly mention a healthy person as an Alzheimer's patient
TN True Negative; our analysis finds a healthy person as a healthy person. i.e., we worked correctly

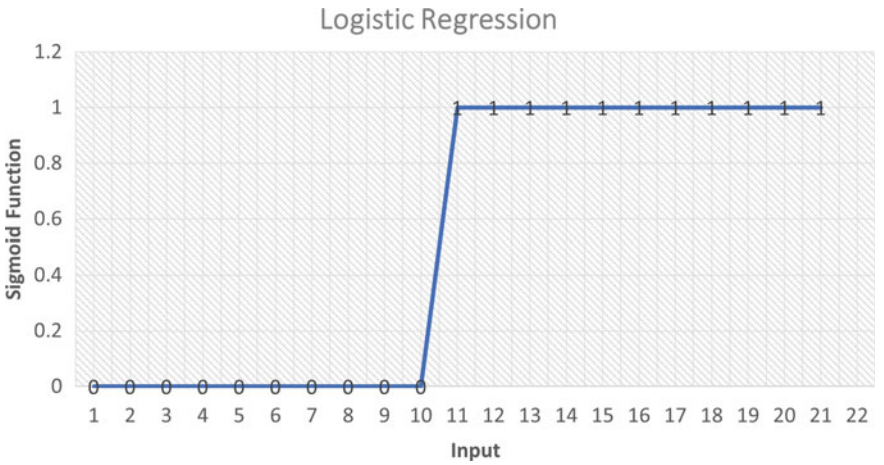


Fig. 2 Logistic regression

4.2 Algorithms

We Applied the following machine learning algorithms.

- Logistic Regression (LR): LR is a binary classification method [31]. It is used with supervised ML models. This model is best suited if we classify data in a yes/no format, such as whether the patient is suffering from Alzheimer's or not. The LR algorithm uses the following mathematical function.

$$Logistic\ function = 1/(1 + e\hat{}(-x)) \tag{4}$$

- This function is also known as the sigmoid function. This LR function uses the likelihood function (conditional probability) to calculate the loss. Figure 2 explains the behavior of the logistic regression function. The values are categorized into two segments. Values move toward positive infinity, represented as 1, and values move toward negative infinity, represents by 0. This model gave 75% of accuracy in a testing environment. We received the following results with LR algorithms.
- The max accuracy at the time of validation is 75%
- The value of the regularization parameter is 10
- Test accuracy is 78%
- Value of recall at the time of test is 75%
- AUC shows 79% score

4.2.1 Support Vector Machine (SVM)

SVM is a supervised classification method [32]. This method uses the kernel function for calculating the distance. This method is best suited for binary classification and

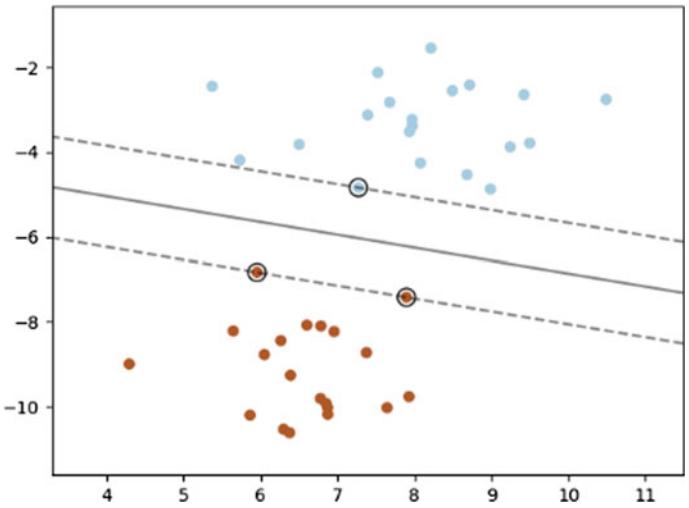


Fig. 3 SVM Model

outlier detection. It uses subset distance (support vector) for classification, making it memory efficient. But, if the number of features exceeds the number of samples, this method must be more balanced. SVM works effectively due to its core mathematical function, i.e., quadratic programming problem solver, but its space and time complexity increases rapidly.

In our experiments, we found the following result with the SVM model.

- We achieve the best accuracy with 77%
- The value for parameter 'C' is 100%
- The value for gamma we achieved 0.1
- Correct prediction with AUC is 81%
- Highest recall value is 70%
- Test recall (with the best parameter) is 82%.

Figure 3 explains the working of the SVM model. The SVM uses a hyper-plane model for classification or regression purposes. The larger separation of two planes is possible due to this hyper-plan function.

4.2.2 Decision Tree

A decision tree is another powerful algorithm in ML, as shown in Fig. 4. It is used for classification and regression. This method returns a true or false decision on an input. As the name suggests, it is a binary tree structure. It may grow internally in a binary tree manner. This method helps us in the question-answering pattern. For example, it takes features like patient age. If the age is greater than 50, then this

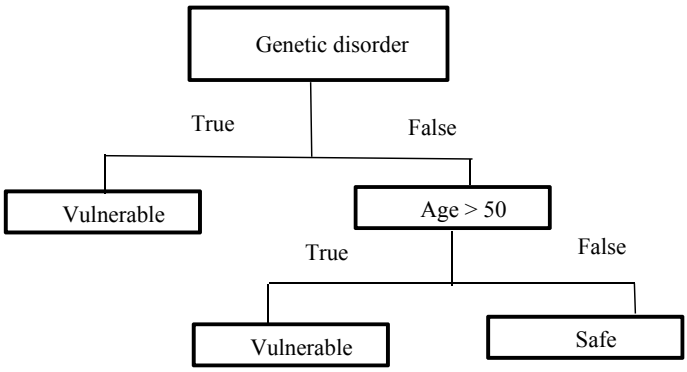


Fig. 4 Decision tree

method gives a positive answer, and the patient may be vulnerable to Alzheimer's disease.

We receive the following result with decision tree algorithms.

- The best accuracy (on validation set) computes as 77%
- Best parameter (for the maximum depth) comes out as 2
- We achieve the best accuracy with 81%
- Highest recall value is 65%
- Correct prediction with AUC is 82%.

4.2.3 Random Forest Classifier

Figure 5 shows the working of the random forest random. A random forest classifier is a collection of various independent trees. It is an ensemble machine-learning technique. As the name suggests, it is a forest of several decision trees.

We received the following result with a random forest classifier.

- Best accuracy (on validation set) computes as 80%
- Best parameters (of M, d, m) comes out as 14 5 7
- We achieve the best accuracy with 84%
- Highest recall value is 80%
- Correct prediction with AUC is 84%.

ML algorithms help us to analyze data and classification. We achieve good accuracy and result with SVM. If data is labeled, supervised learning is the best way to classify the data.

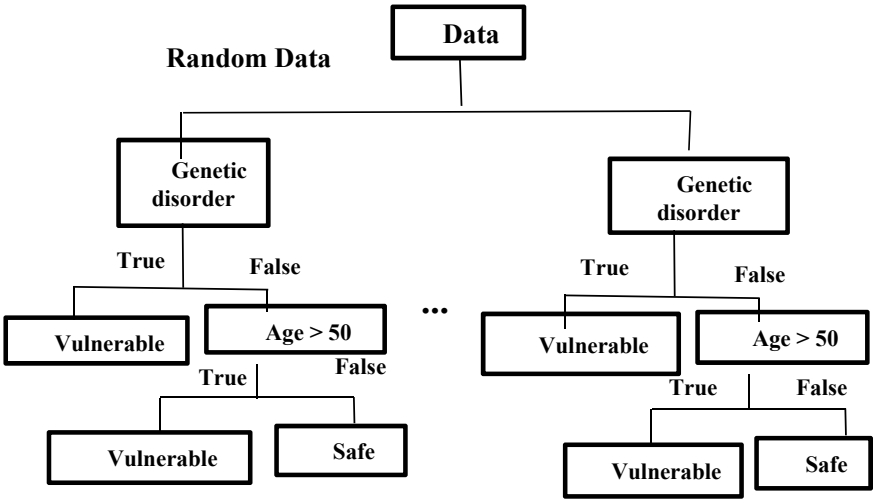


Fig. 5 Random forest

5 Result Analysis

To verify our results, we experimented with different ML methods like SVM, Decision tree, LR, Random forest, etc. The result we get is verified with a confusion matrix. The confusion matrix is the standard method to verify the experimented result. Our primary focus in this research is to avoid a false negative. Because if we start drug with a patient who has not suffered from this disease and we start medicins, it is too dangerous for the patient's health. To avoid this scenario, the AUC is the best option for a performance metric. We also experimented with accuracy and recall to verify our results. We compared the results of all ML algorithms. Figure 6 shows all results. That Random forest is best for AUC. Best accuracy we achieved through SVM and Random forest. But recall is higher in random forest and Logical Regression methods. Since data is labeled and the random forest is an ensemble learning algorithm. So, it gives better results in comparison to all algorithms.

6 Conclusion and Future Directions

In work mentioned, we applied the most common ML techniques and got better results than early researchers. Due to the data size, we are restricting ourselves to employing a more complex model. Since data is labeled then, supervised ML methods are best suitable for this dataset.

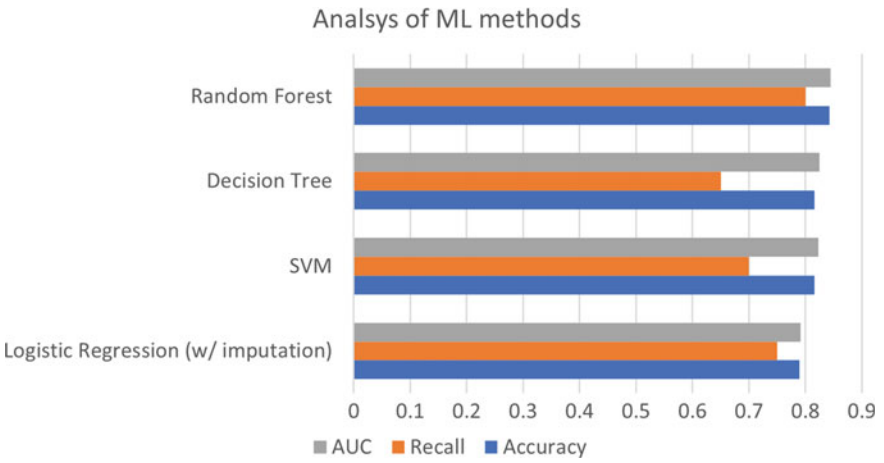


Fig. 6 Result generation and comparison of AI methods

The future direction of this research is to collect more data with a variety such as images and other patterns. With the voluminous data, we can go for deep learning approaches.

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Electroencephalogram Analysis Using Convolutional Neural Networks in Order to Diagnose Alzheimer's Disease

David Benavides López, Angela Díaz-Cadena, Yelena Chávez Cujilán, and Miguel Botto-Tobar

Abstract Recent technological advances have made it possible to collect biomarkers in the same geographic areas where a disease's earliest symptoms occur. Recent technical advances have enabled the collection of biomarkers in areas where early symptoms co-occur. This goal, which is important for finding Alzheimer's disease and its symptoms quickly and accurately, could be achieved in a way that is helpful. It is critical to attain this goal to have a way to treat Alzheimer's disease and its symptoms. It is critical to recognize Alzheimer's disease and its symptoms accurately and immediately, while also maintaining a high degree of diagnostic accuracy. This goal's significance cannot be overemphasized. This severe impediment must be overcome to go forward. It will be critical to monitor the postsynaptic potential of hundreds of neurons grouped in the same spatial orientation to progress in this direction. This enables the calculation of the entire amount of time that the electrical activity happened during the measurement. This is since the total length of time may be calculated. Time-dependent power spectrum descriptors were employed in this study to provide a differential diagnosis of electroencephalogram signal function. This chapter will be delivered to you as verification of the accomplishments. You will be given this information in the form of a record after the findings have been tallied. Convolutional neural networks will be the focus of the third phase of the discussion on how to categorize people with Alzheimer's disease. Following that, we'll conclude our investigation into this topic. These networks have just recently,

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if at all, been created and placed into service. Analyzing the data indicated that the initiative was a resounding and unequivocal success in every way. The absence of negative outcomes may lead to this conclusion. Look at this fantastic example: When convolutional neural networks are used as the analytical technique, the concept of correctness is accurate to an accuracy precision of 82.3%. This demonstrates that our understanding of the concept is correct. There was a lot of success in terms of obtaining the desired degree of precision. Only 85% of cases with moderate cognitive impairment are fully and totally recognized, compared to 75% of the population that is healthy and 89.1% of cases associated with Alzheimer's disease.

Keywords Alzheimer's disease · Convolutional neural network · Electroencephalogram · Support vector machine · Long term short memory

1 Introduction

Dementia is a word used to describe a group of symptoms characterized by declines in cognitive ability and changes in behavioral patterns. Dementia is distinguishable from other types of neurodegenerations by the presence of typical cognitive and behavioral deficits. In common usage, the term "dementia" is widely used to refer to all these disorders and symptoms. Alzheimer's disease (AD) is responsible for seventy percent of all dementia cases reported in the history of humans. As a person approaches the age of 65, the probability of developing this disease increases [1–3]. This illness exclusively affects adults over the age of 85 when they first exhibit symptoms. Those over the age of 65 have a threefold higher chance of developing these symptoms. Patients with Alzheimer's disease have no choice but to get palliative care because there is presently no medicine that will lessen the condition's symptoms [4]. Patients have the option to get palliative care if that is what they choose. These medicines, on the other hand, can temporarily slow the progression of the disease, which is great news for both patients and caregivers. This is the case, and I can say that with absolute certainty. It is common practice to provide accuracy scores of up to 90% for existing diagnostic procedures such as neurological tests and medical histories. This is due to the accuracy of these procedures. These processes are so precise because they produce such constant results. This section lacks sufficient sources to back up its assertions. The Alzheimer's Association supplied comments throughout the study's development, giving them the opportunity to influence the criteria as they were constructed. This section lacks sufficient sources to back up its assertions, the electrode contacts effects considerably increased the group size between 8 and 10 Hz as shown in Fig. 1. There are certainly more references to this somewhere. It's probable that it's mentioned somewhere in the text. The most recent set of guidelines [5] says that neuroimaging should be used along with biomarkers and cerebrospinal fluid to diagnose Alzheimer's disease in people who are already showing signs of it.

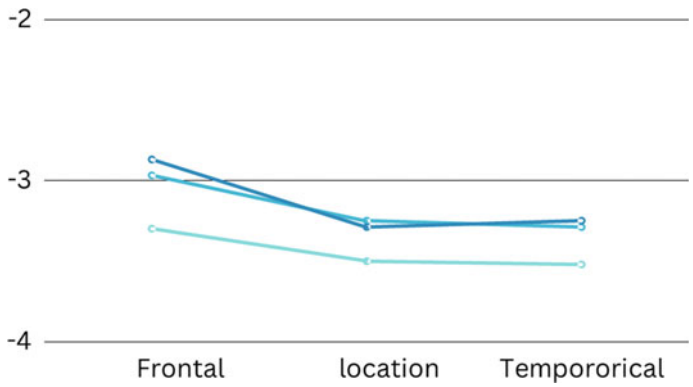

Fig. 1 Electrode contact effects considerably increased the group size between 8 and 10 Hz

The Alzheimer's Association created this exam because it may be accomplished fast and with little effort on the part of the person executing it. Furthermore, these two examinations examine a candidate's ability to fulfill administrative tasks and other job-related activities. On the other hand, the Rey Auditory Fluency Assessment and the Visual Learning Test are meant to test every skill that has to do with taking care of patients [6]. Aside from Alzheimer's disease, researchers have discovered a variety of additional disorders that can contribute to dementia in certain people [7]. This data may be recorded using an electroencephalogram (EEG). This sort of examination is most often known as an EEG. An electroencephalogram can be used to record this data. Electrodes are implanted on the patient's scalp to acquire reliable measurements of electrical potentials. The level of spatial resolution that an electroencephalogram may achieve is controlled in part by the number of electrodes placed on the scalp as well as the precise placements of those electrodes.

These tests were performed to determine which of these illnesses was more likely to progress to dementia. The primary frequency bands in analytics are typically separated into theta, which runs from 4 to 8 Hz; delta, which runs from 0 to 4 Hz; beta, which runs from 12 to 30 Hz; and alpha, which runs from 8 to 12 Hz. Each frequency band has its own specific data collection based on a wide variety of aspects of brain activity and synchronization [8, 9]. These characteristics are as follows: Several studies [10] have investigated the feasibility of employing EEG in the clinical assessment of dementia and Alzheimer's disease, it is more often known, has a high temporal resolution, is noninvasive, is very inexpensive, and may be transmitted (about milliseconds). Patients with frontotemporal dementia and healthy controls were created using sLORETA and compared with this study is shown in Fig. 2. The major purpose of the investigations was to compare electroencephalogram (EEG) recordings of individuals with Alzheimer's disease and healthy control volunteers [11, 12]. To do so, the two sets of recordings were evaluated and contrasted. Alzheimer's illness is well known for diminishing EEG signal synchronous change and complexity. This is one of the signs of the illness.

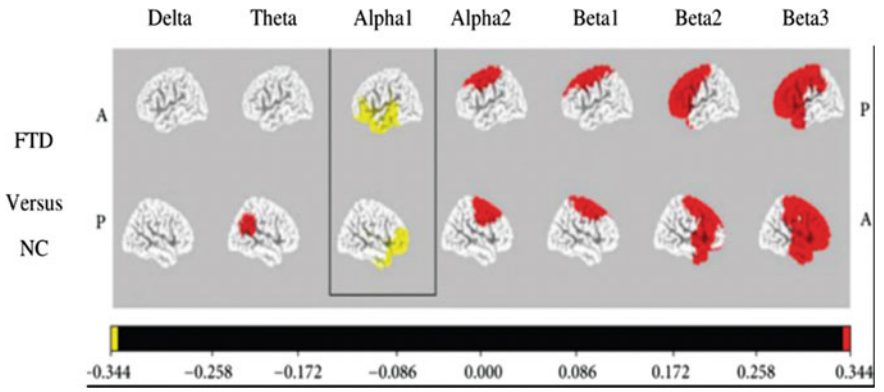

Fig. 2 Patients with frontotemporal dementia and healthy controls were created using sLORETA and compared with this study

These increases have been employed as identifying markers in EEG recordings for Alzheimer's disease diagnosis. Previously impossible, it is now feasible to analyze the intricacy of EEG signals using a wide range of scientific methodologies. This was not always the case. In addition to the first positive exponent of Lyapunov [13], the connection factor has garnered a lot of attention [14]. When compared to the EEG signals of age-matched control people, Alzheimer's disease patients' EEG signals exhibit lower values in several tests, indicating a lower level of complexity. This conclusion was possible because the average age of Alzheimer's patients is much older than that of the study's controls. Other information-theoretic approaches, most notably those based on entropy, are emerging as potentially valuable EEG indicators for Alzheimer's disease (AD). These methods establish a relationship between the intensity of a signal and how much it varies over time. They contend that analyzing signals that behave erratically is more challenging than analyzing signals that behave regularly. To make sense of the data, recent research [15] on epileptiform EEG data offered a variety of potential detection techniques. These methods were created to detect epileptiform activity. The existing seizure detection approaches rely on manually constructed feature extraction algorithms extracted from EEG data [16]. These approaches were developed by utilizing raw data collected during an epileptic episode. As a result of seizure activity, several solutions were eventually established.

A description of the features that were picked because of the feature extraction approach [17] is necessary to accurately identify the various EEG signals that may be collected by utilizing the various types of classifiers. This is done to prepare for the identification of the various EEG signals that will be coming. To gather features, Hamad et al. employed a technique known as differential wavelet processing. The support vector machine was then utilized to teach the radial reference approach. They ended by demonstrating that the proposed SVM Grey Wolf optimizer can aid in the establishment of an epileptic diagnosis [18]. Subasi and his colleagues developed a hybrid model that refines SVM parameters using genetic algorithms and particle

swarm optimization. This was done to enhance efficiency and simplify the procedure. The given hybrid SVM model shows that an electroencephalography is a key tool that neuroscientists use to find seizures [19].

This strategy, however, does not eliminate the factors that influence manual activity selection [20]. This is because a large percentage of the classification's degree of detail is established at this phase. It has been stated that constructing a classification scheme does not necessitate the elimination of potentially detrimental traits. Furthermore, recent advances in deep learning have demonstrated a fresh strategy to overcome this challenge, which is a favorable development. This topic has recently sparked a lot of attention from a variety of sources. Deep learning commands the respect it does now because of its recent success in differentiating itself as a unique discipline within the larger domains of computer vision and machine learning. It would be a better use of one's time to do feature extraction first. However, a significant proportion of recent research [21] did not employ feature extraction and instead used raw EEG data for the deep learning model. These studies did not make use of feature extraction. Unlike most other research, this one didn't use "feature extraction" to get its data. TD-PSD is an abbreviation for a time-dependent power spectrum descriptor. Three different forms of sample testing add to the overall EEG input. The MCI, AD, and HC are the three. These methods are referred to as "approaches. Finally, an example of the architecture of a convolutional neural network, often known as a CNN, is shown here with the goal of categorizing patients with Alzheimer's disease. Since the performance review was given, it can be used to make decisions about the results.

2 Review of Literature

Due to the complexity and nonlinearity of EEG signals, novel machine and signal processing approaches are required [22]. As a direct result of the stunning discoveries in the field of deep learning [23], more difficult abstractive algorithms have been constructed. Now that we have these tools, we can quickly and efficiently delete any data that is no longer needed for our current purposes. This is made possible by the availability of these algorithms. The most recent accessible research on the issue served as a guide for the creation of these methods. These approaches were created because of previous research. The progress to this level has occurred during the last few months. These deep learning algorithms have risen in popularity in recent years, and their applications currently include the generation of video games [24], image processing, audio processing, and natural language processing [25]. Researchers have successfully defined the biological domain using approaches like those described [26]. A deep neural CNN with 13 layers is proposed as a method of distinguishing between "healthy" EEG data, "preictal" EEG signals, and seizure-related EEG signals. A total of 300 EEG signals were analyzed during the study endeavor to achieve the required classification rate of 88.67%. At the time, this was recorded on a computer. Deep neural networks were developed by the same

academic team that developed the first depression diagnostic tool based on EEG data [27]. These researchers also thought that their new technology should be based on a deep neural network.

The success rates in the left hemisphere ranged from 93.5% for healthy participants to 96% for depressed people. This is a whole-brain measurement (right hemisphere). A 13-layer CNN model including information from both healthy people and Parkinson's disease patients yielded an accuracy of 88.25%. Patients with Parkinson's disease and healthy people were picked at random. Long-Term Short-Term Memory. The type of RNN used in this model is called a Recurrent Neural Network (RNN). Before being employed in this study, the pictures were subjected to several preprocessing techniques such as segmentation, registration, smoothing, and normalization. These steps were taken to remove distracting aspects from the photographs, such as the skull.

Visualization of the channels in EEG Linear Data as well as nonlinear data is shown in Figs. 3 and 4 respectively, it is used to categorize features in the model. The model is trained after data preparation by giving it sequential data that has been separated into time increments. This is done throughout the treatment. This is done to guarantee that the model has received an adequate education. After learning this information, the model goes on to provide a projection for the state it will be in over the next six months. While the model is being evaluated, the user gets access to the data for the 18th and 24th months. Once the assessment of these two distinct sets of data is completed, the model will be able to provide a forecast for the subject's status during the 30th month. Analyzing longitudinal data using an RNN approach to identify people with AD and those who are stable. This is accomplished using strategies like those discussed in previous chapters of this work. However, both the input and the function will go through separate preprocessing processes before being exposed to the normalization procedure [28]. When the preprocessing stage is completed, the data will be given to the LSTM and gated recurring units for processing. This will occur after the preprocessing stage is completed. This is done so that the cell can detect the pattern of data flow. This is done to provide the cell with the capacity to understand the pattern of data flow. This is done so that the cell can learn how to recognize data flow patterns.

The effects of nonrecurrent networks, commonly known as multilayer perceptron's, are compared to the effect models of each data arrangement. The Classification Strategy for EEG Signals Based on Machine Learning is shown in Fig. 5. Many of these trainable parameters are prone to overfitting the training data since they need extended training for sequential data. Unsupervised feature learning employs the concept of unsupervised feature learning as a guiding principle, with the primary purpose of defining AD. Sparse filtering has been advocated as a strategy for better understanding the expressive features of brain images [29]. Students are shown how to use the SoftMax regression technique to categorize the scenarios. The first phase includes three steps, the first two of which are training the sparse filter and calculating its W weight matrix. It may extract the local attributes existing in each sample using learned sparse filtering, Fig. 6 shows a straightforward example of a convolution operation in two dimensions.

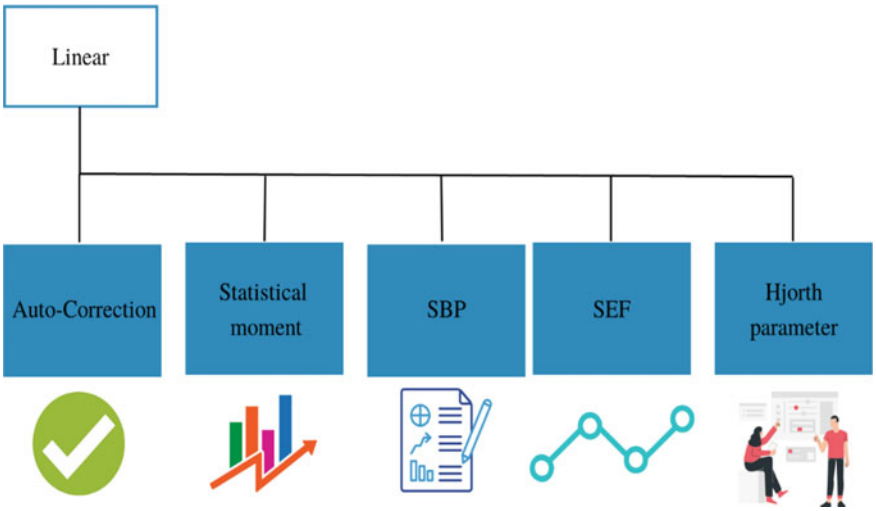

Fig. 3 EEG linear data channels are used to classify data characteristics

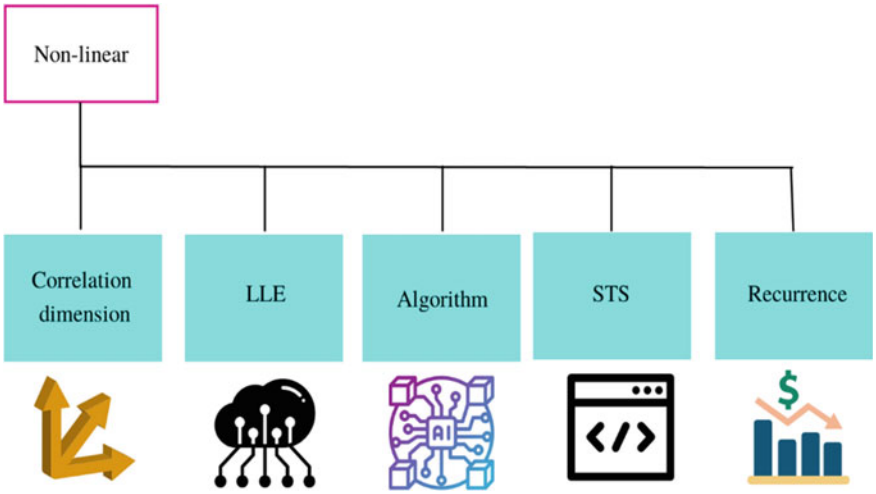

Fig. 4 Channels of the EEG's non-linear data are used to classify its features

The goal of this article is to give a high-level overview of how machine learning is used to analyze EEG data and make clinical diagnoses of neurological illnesses.

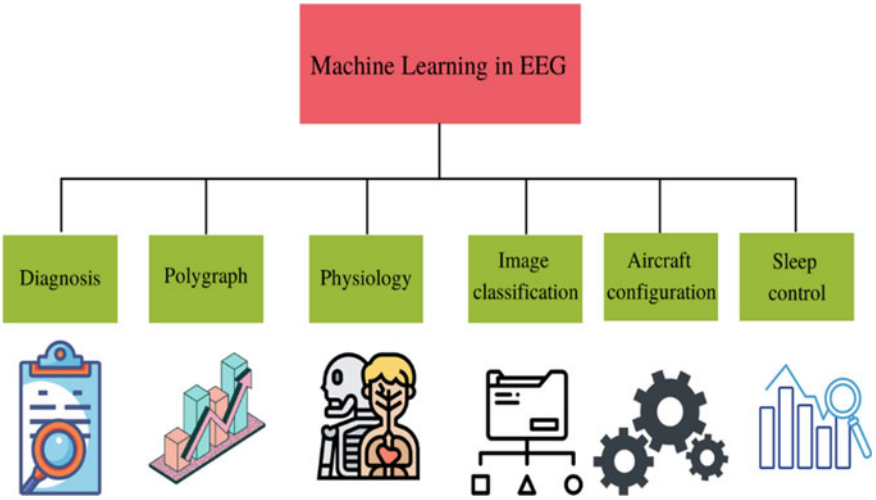

Fig. 5 The classification strategy for EEG signals based on machine learning

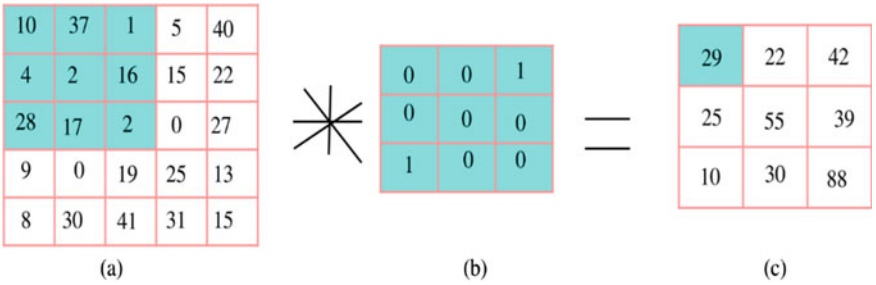

Fig. 6 A straightforward example of a convolution operation in two dimensions, showing **a** the input, **b** the kernel, and **c** the output matrix after the operation has been performed

3 The Proposed Methodology

The EEG data will be used at some point in the investigation, providing a more detailed assessment of the disease's phases than was previously possible. A deep convolution neural network design has been proposed to partition multichannel human EEG signal data into the relevant phases. This might allow for a more precise analysis of human brain function. This would allow a more accurate analysis to be performed [30–32]. If this were done, the amount of productivity that could be accomplished when categorizing things would dramatically increase. The following additional components have been incorporated into the scope of this development.

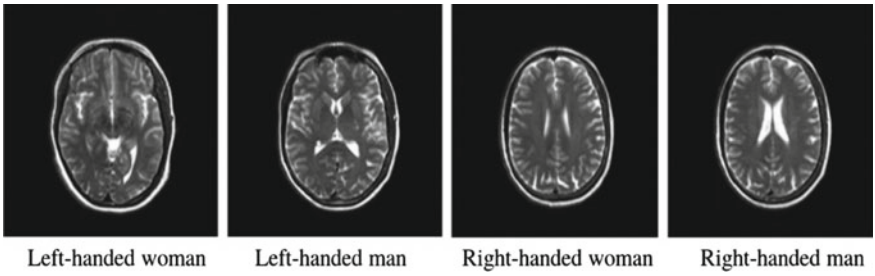

Fig. 7 MRI brain slices are taken from people suffering from Alzheimer's disease

3.1 Extraction of Characteristics

The discrete Fourier transform will most likely be employed to interpret the EEG trace in terms of a frequency function. MRI Brain Slices are Taken from People Suffering from Alzheimer's Disease is shown in Fig. 7. This will be completed after the sampling representation is completed. This is possible since the EEG signal has been sampled. This will be done as a direct and immediate result of the representative sample that occurred. The successful representation of the EEG wave is expected to result in the successful completion of this study [33–35]. According to the Parseval theorem, the "extraction of features" is always the first stage in every transformation. Theorem studies could be helpful in this case because they could give new information about this step in the process. According to this theorem, the full square of the function's transformation and the complete square of the function's transformation are both equal words.

3.2 Proposed Model

This process employs a variety of different algorithms, including KNN, SVM, and LDA, among others. These algorithms are commonly combined with one another. One of the criteria used in the selection process was how well each strategy used machine learning technologies. These elements eventually influenced the decision. This was a critical issue that was examined throughout the decision-making process. According to the data acquired, 51 of the 64 individuals assigned a diagnosis of moderate cognitive impairment had a proper diagnosis identified (MCI). Therefore, the diagnosis accuracy rate is 79.7%. The KNN test, on the other hand, has a sensitivity of 71.9% for detecting whether a person has Alzheimer's disease. The sound samples, which featured the various voices of forty different people, could only correctly identify the people 62.5% of the time. The findings also demonstrate that the correct subgroup of people with MCI is recognized in 63.7% of those who have been diagnosed with the illness. When compared, the KNN method, SVM algorithm,

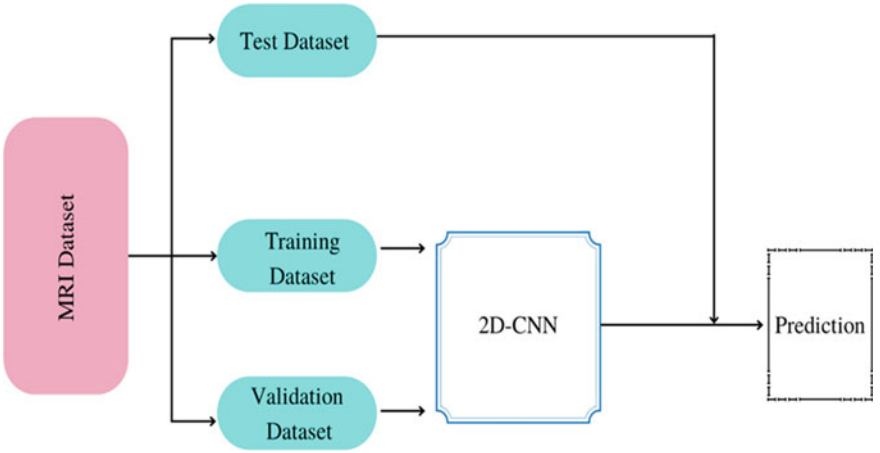

Fig. 8 Schematic representation of the proposed method

and LDA algorithm may attain accuracy levels of 71.4%, 41.1%, and 43.8%, respectively. This is because there are several methods for classification, such as the KNN technique, the SVM methodology, and the LDA algorithm. The proposed model may be shown in Fig. 8.

To put it another way, the degree of precision that can be attained using KNN is significantly more than the level of accuracy that can be attained via the use of other approaches. After this step is completed, a brand-new EEG signal categorization architecture based on CNN will be installed. This architectural style will be implemented. This architecture will help us in the future. It is possible that a correct evaluation of accuracy would be performed 82.3% of the time utilizing CNN's approach [36–38], which predicts accuracy. Because the given CNN outperforms other techniques, the KNN methodology will be the next target pursued as part of this study. This will be completed in order to meet the project's main goal. When compared to other techniques, the CNN presented here performs far better than its competitors [39, 40]. The LDA and SVM got similar values for the area under the curve (AUC) at the same place near the bottom of the spectrum. These are just a handful of the ideas that have been proposed. It has been recommended that the feature extraction technique be modified to utilize a different EEG signal cause for categorization and a reduced number of characteristics. It has also been proposed that training be conducted utilizing the design supplied. These are just a few of the many proposals that have been offered thus far. All of these are recommendations made by various individuals. It's not inconceivable that this will have an impact on accomplishing the stated objectives.

4 Results

Another strategy that might be used is to standardize the zero-order moments of each channel. To achieve this purpose, each channel must first be disassembled into the zero-order moments that comprise it, and then those moments must be standardized. Only then will one be able to achieve this aim. This information is suggested to be critical for each channel in this case. Figure 9 illustrate both the Dropout Rate and The Dense Unit Affect the Proposed Model's Precision. After being utilized as power two times, the spectrum passes through this transformation for whatever reason. For some unknown reason, the spectrum undergoes this transformation twice after being used as power. When you successfully execute this approach a certain number of times in a row, the following will happen: Here's how a power transformer is made, with the goal of making the domain of all moment-based characteristics the same and minimizing the effect of noise on those parameters: For the sake of this experiment, the researchers have decided to employ a significance level of 0.1. We came to this conclusion after much deliberation. Because of this, and taking into consideration each of these distinct characteristics, the top three identified attributes are as follows:

This is because their "sparseness" is determined by how much vector energy may be found in only a few more components. The following are the immediate repercussions of this behavior: A feature is a vector representation that comprises all objects that are comparable to a zero-sparseness index, such as and. The zero-sparseness index, denoted by the symbol, is one example of this. For all other degrees of sparsity, however, a feature must have a value greater than 0. This is because differentiation causes a feature to be represented as a zero-sparseness index for a vector whose elements are all the same. This is one of the sources of the problem.

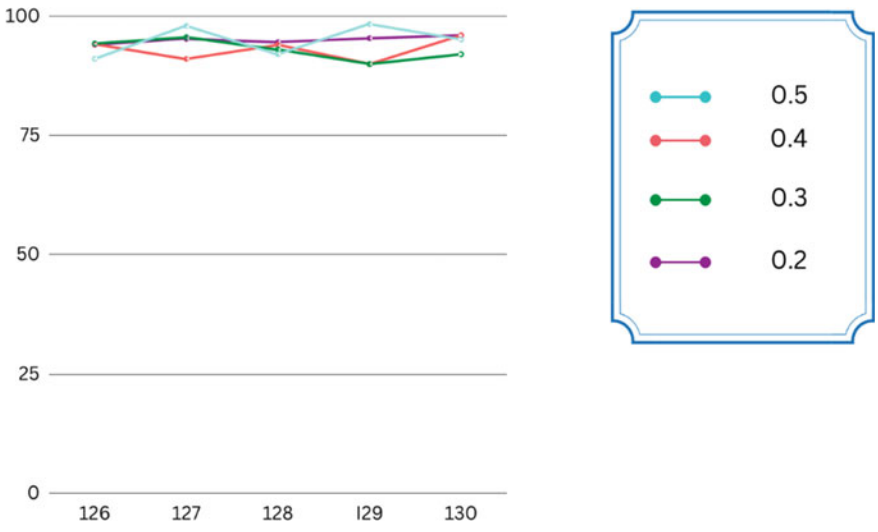

Fig. 9 Both the dropout rate and the dense unit affect the proposed model's precision

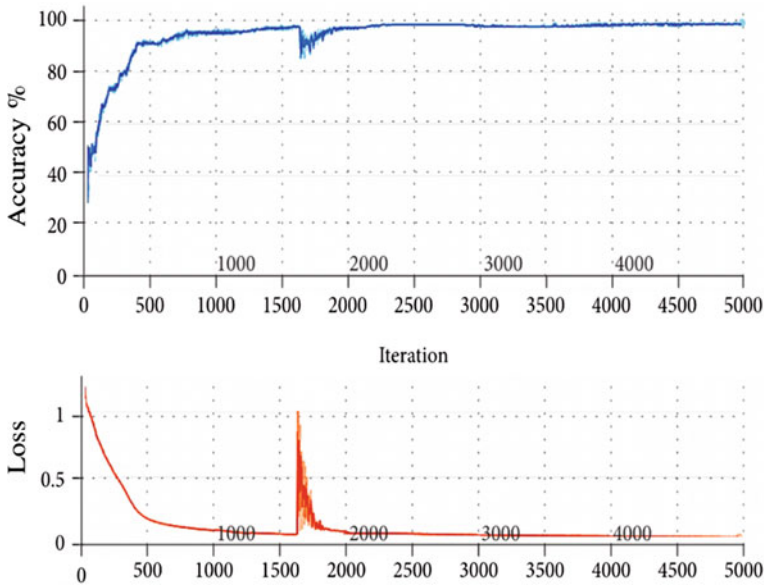

Fig. 10 The presented CNN's accuracy and loss figures during categorization

The following are some of the factors at play in this situation: The entirely linked layers are employed first, followed by the system's hidden layer, which is known for its ability to differentiate signals. This occurs after traveling through the buried layer. The system's next level is reached after navigating the buried layer. When the deep learning layer is completed, the entire linked layer will be built. The final categorization choice is made by this part, which is fully connected to all the other parts. Figure 10 shows the presented CNN's Accuracy and Loss Figures During Categorization.

These curves were used to identify whether a signal was radio noise or not. These curves were utilized at various phases of the investigation to assess if a signal was radio noise or not. Until recently, no one was aware of the relevance of these curves in relation to the procedures used in the medical industry to make choices. This is because these curves were previously unknown. Figure 11 shows the confusion matrix of the CNN approach that is being proposed to categorize Alzheimer's patients. Consider, for a minute, a universe in which there are only two types of people: those who are considered healthy and those who are considered abnormal. It is a screening test that we offer to both ill and healthy people, and the range of findings it generates ranges from zero to an immense number scale. In the following discussion, a higher test result indicates a greater risk of having the condition being tested. The risk of this occurring increases with the severity of the consequence.

This causes the curve to develop as a direct and immediate outcome of what happens because of it. This projection is based on the overall percentage of diagnostic procedures that provide false positive results (FPR). A TPR may also be referred to

Fig. 11 The confusion matrix of the CNN approach that is being proposed to categorize Alzheimer's patients

as the sensitivity, recall, or detection probability by those who are educated in the field of machine learning. All of them are different names for the same object. This is evidenced by the fact that the ROC has shifted to the left. If you want to get things rolling, you should start here. Both issues are taken into consideration and considered by the ROC over the course of the inquiry. After computing the TPR and FPR, it is feasible to build a higher-quality consequent curve. This is made feasible by the computation of the TPR and FPR. This may be accomplished by using an algorithm that fits curves to data. To calculate the TPR, divide the value of the objective by Y. To calculate the FPR, divide the value of the target by the total number of observations. After identifying the value of the aim, any of these computations can be performed alone or together. The answers to both equations may be found in a table just below this one, which can be reached by using this table right here.

To capture numerous channels of EEG data, standard monopolar connections of electrodes implanted on the earlobes were used [34]. Since Fig. 3 is meant to show the standard way of doing things, the electrodes used to make an electroencephalogram are often put where they are shown. The fact that the interviewees' eyes were closed during the process showed that they were sleeping. In this scenario, it's not out of the question that the same hierarchical structure may influence a range of distinct brain regions. This is related to the brain's hierarchical organization. During the recording process, electrodes are put on the head to pick up the electrical impulses that the electroencephalogram makes. We were able to gather data using a signal that was active for 300 s, a total sample size of 300 terabytes, and a sampling rate that ranged from 1024 to 256 samples per second. Each of these aspects has a direct impact on the success of our data collection efforts. For extraction, just the first 180 s of each signal are collected and transformed into 256 samples per second. This restriction was put in place so that we could guarantee the data was comprehensive and correct. The sampling frequency, also known as the sample rate, is the number of samples gathered at regularly spaced-apart intervals throughout the course of a

particular length of time. Another name for this metric is the pace at which samples are gathered.

5 Conclusion

These sample sets were gathered using a random sampling approach. Each of these patient groups supplied a unique collection of diagnostic samples, which were then evaluated. KNN, SVM, and LDA are traditional classification approaches that register both the final features and the impact that these features have on the data that is being recorded. The information is also recorded. This is done as a precaution to guarantee that the results are correct. When doing either of these two actions, it is critical to always keep the context of the data in mind. Performance measurement is used to help provide data that confirms and supports the results. This enabled us to obtain the necessary information. The number of artifacts created by the EEG's background activity can be reduced by initially collecting data for each signal for 180 s (i.e., between 60 and 240 s) and then converting that data to 256 samples per second. This approach must be performed between 60 and 240 times. If you execute your computations at 256 samples per second, you will be able to accomplish this work successfully. This is done to ensure that the results are correct. This is done to ensure that the data is as accurate as is practically practicable. The extraction of features from 256 EEG data sets results in the construction of seven value characteristics. This stage represents the completion of the procedure. The KNN test has a sensitivity of 71.9% for detecting whether a person has Alzheimer's disease. The findings also demonstrate that the correct subgroup of people with MCI is recognized in 63.7% of those who have been diagnosed. When compared, the KNN method, SVM algorithm, and LDA algorithm may attain accuracy levels of 41.4%, 41.1%, and 43.8%, respectively. It is possible that a correct evaluation of accuracy would be performed 82.3% of the time utilizing CNN's approach, which predicts accuracy. KNN methodology will be the next target pursued as part of this study. It has been recommended that the feature extraction technique be modified to utilize a different EEG signal cause for categorization and a reduced number of characteristics.

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Alzheimer's Disease Diagnosis Assistance Through the Use of Deep Learning and Multimodal Feature Fusion

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Abstract Patients suffering from Alzheimer's disease (AD) lose their ability to think and frequently forget what they have learned during their life. There are currently no effective therapies available for this illness. The sooner the disease is recognized, the better the therapy alternatives and the greater the possibility of eliminating Alzheimer's. Computer-assisted diagnosis, or CAD, is a method that integrates neuroimaging with deep learning algorithms trained on multimodal pictures. The CAD system is powered by deep learning algorithms that were trained to function by being exposed to a diverse spectrum of artistic outputs. Each component of the system affects the functioning of these algorithms. In recent years, several multimodal feature learning-based alternative techniques for extracting and integrating latent. We were able to achieve our aim because we devised several novel approaches. Here are some more detailed illustrations of imaging techniques: This diagnostic category includes imaging procedures such as MRI and PET scans. Given the complexities of the procedures utilized, providing a complete assessment of the immeasurable value of the data obtained is difficult. An image-based multimodal fusion approach is proposed as a result, our understanding of the brain's structure and operation has grown significantly. The technique's primary emphasis is the grey matter of the brain.

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We were able to provide more accurate diagnoses to individuals suffering from neurological diseases. To accomplish our purpose, we use the registration and mask coding procedures. This had a direct impact on the creation of a well-rounded theory aimed primarily at the automobile sector. In addition, we put our image fusion approach to the test with a 3D basic convolutional neural network for binary classification and a 3D multi-scale CNN for multiple classification tasks. These two networks are linked by the fact that they are 3D convolutional neural networks. In a three-dimensional situation, both functions admirably. Using the ADNI dataset, researchers revealed that their suggested picture fusion algorithm outperformed cutting-edge approaches for detecting Alzheimer's disease. Furthermore, as compared to feature fusion and single-modal approaches, its overall performance is significantly superior.

Keywords Alzheimer's disease · Computer-assisted diagnosis · Convolution neural network · Feature fusion

1 Introduction

It is a neurodegenerative illness, which means that brain cells progressively and inexorably die over time. People with cognitive impairment are unable to execute daily tasks because their cognitive abilities have deteriorated. As the symptoms of Alzheimer's disease increase, both patients and those who care for them experience a decrease in their overall quality of life [1]. By the year 2020, global spending on dementia-related medical care, nursing home stays, and end-of-life treatments is expected to exceed $305.2 billion [2]. According to the most recent predictions, there will be 115 million Alzheimer's disease patients globally by 2050. This demonstrates the critical need for better therapies and an accurate technique for identifying Alzheimer's disease.

Alzheimer's disease has an unknown aetiology, making it difficult to determine what causes it. The scientific community recognizes that these two pathways play a significant role in both neurodegeneration and synaptic loss [3, 4]. The capacity of a patient to fulfil the diagnostic criteria for that condition determines whether they have normal control, moderate cognitive impairment (MCI), or Alzheimer's disease. Normal control, MCI, and Alzheimer's disease are all terms used to describe the same illness. One of these situations is within "normal control," making it the least perilous of the three. Alzheimer's disease is frequently identified with structural magnetic resonance imaging, also known as diagnostic MRI. The ability of structural MRI to highlight critical parts of brain architecture and its enhanced soft-tissue resolution are largely responsible for this. The cerebral cortex, temporal lobes, parietal lobes, and anterior cingulate gyrus are all part of this group of brain structures [5, 6]. Alzheimer's disease is characterized by an enlargement of the ventricles, which oversee creating cerebrospinal fluid. The hippocampus and other areas of the brain have been revealed to be smaller than they were previously. When brain tissue is scanned using magnetic resonance spectroscopy, sharp, three-dimensional (3D) pictures are produced. These

graphics may help you identify structural issues and have a better understanding of them. While conducting their research, some studies that employed MRI as a clinical diagnostic technique for Alzheimer's disease revealed some unexpected new facts. Trained support vector machines on voxels representing grey matter (GM) to improve their understanding of the features of MR images [7]. Until recently, white matter, grey matter, and cerebrospinal fluid were all thought to be different, independent components of the brain. The researchers could plainly determine that Alzheimer's patients were not identical to healthy controls. When the spatial normalization method was completed, we turned our focus to the GM tissue densities and gave them additional thought because of the strong link between GM and AD, no other approach could have produced this result [8, 9]. On the other hand, when I learned more about cerebral spinal fluid and grey matter, I developed a newfound excitement. Effectively recognized neuroimaging data by using GM volume as a single feature for all 93 ROIs in the annotated MR image. The only methodologies we used to reach this result were GM volume analysis and multiple-kernel learning [10]. This change was made in anticipation of the anticipated favorable impact of the migration on the efficacy with which data categorization may be performed. The findings of these studies suggest that when attempting to diagnose Alzheimer's disease, magnetic resonance imaging (MRI) should concentrate primarily on GM tissue. It is worth noting that this result is consistent with what Zhu and colleagues observed [11, 12].

Functional techniques, which rely largely on this technology, rely on PET imaging's capacity to give a rapid and accurate study of brain-related activity. Functional approaches may thus thrive in conditions such as these. Finally, it has the potential to be utilized to test individuals at high risk for Alzheimer's disease's cognitive symptoms decades before the illness manifests itself in a clinical environment. One technique that may be used to successfully attain this goal is to compare the person's intellect and memory to a standard. FDG-PET is a highly useful diagnostic tool because it can discriminate between favorable and detrimental morphological changes [13–15]. Because the number of brain structures decreases with age, it may be difficult to appropriately assess a person's mental health based just on the morphological changes shown by an MRI of the brain. This is because physical changes do not necessarily influence mental health. This is described because of a person's brain naturally weakening with age (for example, in individuals who are older than 75 years). According to the study's findings, this characteristic is more widespread among elderly people (those aged 75 and over). In cases like these, PET testing may be able to offer a more exact evaluation of the patient's present state of health than more traditional approaches.

2 Background

In contrast to functional PET imaging, which may only highlight metabolic changes, structure-based MRI may be able to illustrate how the structure of the brain has

developed over time. This would be preferable to functional PET imaging. When it comes to pinpointing the exact site of lesions, structural MRI outperforms functional PET imaging. Consider the following example: One strategy for improving the precision of the Alzheimer's disease diagnosis procedure is to combine MRIs and PET scans into a single multimodal approach. In this scenario, a reference is necessary [16–19]. The challenges raised by multimodal learning have been handled in several ways, many of which rely on the integration of many components. This is one of the most widely used methods: These techniques produce high-dimensional semantic characteristics by beginning with a diverse set of unimodal inputs [20, 21]. According to Shi and colleagues' study, two-layered deep polynomial networks may be able to recognize the ethereal properties of pictures such as MRI and PET scans [22]. The inclusion of these attributes into a second SDPN facilitates the integration of data from diverse neuroimaging modalities. We were able to merge data from photographs with different pixel sizes by including a second deep neural network, which was quite useful. A variety of data sources are integrated into a process known as "feature fusion," and it has been demonstrated that this produces more accurate experimental findings than using only one data source [23–25]. This method has been nicknamed "the black box" since it cannot explain why observed outcomes differ from those predicted. Data is collected from a variety of sources using deep learning approaches based on fusion and a multi-channel input network. As a result, the conditions for the total number of model parameters quickly become much stiffer.

The multimodal technique is one of the easiest ways to accomplish medical data fusion. Many independent input pictures are merged to generate a single composite image using this approach. This image can assist medical experts in making a more accurate diagnosis and determining the best course of therapy. If this method is used, the patient is more likely to respond positively to the treatment they are receiving. Feature fusion algorithms, on the other hand, merge information from many pictures to generate a more accurate whole. The integrated visualizations highlight the data's numerous modal features while also providing a more realistic picture of the data. GM tissue, on the other hand, is required for a correct diagnosis of Alzheimer's disease. MRI scans, which are restricted to finding just morphological abnormalities in the patient's brain due to their low resolution, cannot analyze the metabolic rate of the patient's complete brain like PET scans do. A PET scan may be used to assess the patient's whole body. Once all the scan data has been obtained, any genetic differences determined to be of low significance are removed, while any genetic differences deemed to be of high significance are saved for future research. Feature extraction is the practice of removing sections of an image that are deemed superfluous or insignificant. As a result, the viewer will be made aware of the major points of interest in the image.

Our lengthy investigation enabled us to divide the most relevant findings into two categories. Here, an unusual approach for detecting Alzheimer's disease is presented that incorporates a substantial number of photos. We hope that using this strategy, we will be able to improve the information representation capabilities of a wide range of neuroimaging modalities. This is accomplished by contrasting and comparing the capabilities of each of these CNN versions. This is demonstrated by comparing the

diagnostic effectiveness of the proposed fused modality to that of the two CNNs. In this post, we will provide evidence to back up our work. In the next chapters, we will continue to dissect the project into its constituent elements and undertake a much more in-depth investigation of each. In this section, we will go through the dataset we utilized as well as the photo fusion approach we employed in depth. Convolutional neural networks can extract and categorize a wide range of characteristics from neuroimaging data. These studies were carried out to explore if our suggested picture fusion method could be employed in the context of an AD diagnostic paradigm. The purpose of this study is to see how viable the picture fusion approach we presented is within the framework of an AD diagnosis paradigm. There are additional comparisons of AD and MCI to NC. NC and AD can also be contrasted. As a result, there are now four possible combinations in total. The similarity between NC and Alzheimer's illness is one such connection. The fifth subsection of this section contains both the judge's decision and the final ruling. Section 4 contains the argument, which is stated below.

3 The Proposed Method

Unmistakable visible evidence that the components that have been assembled successfully complement one another [26–35]. To do this, the data from the two scans will be blended. As a result of this, the conclusions will be more trustworthy. Combining photos from several sources is one approach that may be utilized to attain this aim. As a result of this, we may have higher expectations for receiving a more accurate diagnosis. The composite picture modality must be sent across a network with only one channel to complete the diagnostic process. Another citation is required in this area of the text. The Alzheimer's Association created the image. It is critical in this process to merge many photographs into a single image, then identify certain components inside the merged image, and finally categorize the resulting images. Which is the full word (PET). Following this, we'll most likely analyze the GM-PET pictures to find the semantic traits they have. All the information gathered about everyone is sent into a two-tiered classifier. These layers are also known as the FC layer and the SoftMax layer. In this instance, categorizing individuals into the appropriate category based on their characteristics will be easier.

Since its inception, multimodal image fusion has been able to integrate complementary data from photographs collected using several modalities. Before contemporary technology, things were done differently. Figure 1 depicts how we utilize the MRI as a mask in our method of image fusion. This allows you to avoid the FDG-PET scan in the whole GM area. This industry is heavily reliant on Alzheimer's disease diagnosis. The MRI scan is used as a mask to achieve this effect. This article will lead you through each stage of the multi-stage picture compositing process.

The following is a list of the MRI processing pipeline stages that we performed in the order that they were done. After removing a portion of the patient's skull, the MRI is registered using MNI152, and the tissue is segmented on the MRI. The

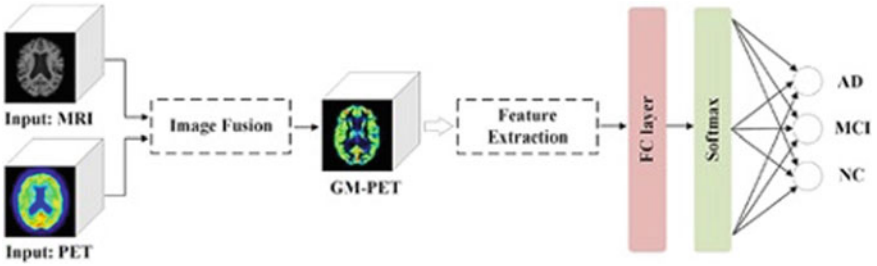

Fig. 1 An approach that incorporates a variety of imaging data sources for diagnosis of Alzheimer's disease

following protocols must be followed to successfully finish the PET technique: The steps of this procedure are as follows: The Origin PET was matched to the MNI's MRI, the MNI's PET to the GM's MRI, and the MNI-GM PET back to the Origin PET.

It has been demonstrated that the FreeSurfer 6.0 program's "watershed" module may be used to skull-strip structural MRI data [29]. This instance is depicted in Fig. 2. To remove surrounding tissues such as the skull and those that aren't part of the brain, the data can be filtered using the watershed segmentation approach. This immediately reduces the amount of background noise and irrelevant data in the research participant's brain volume. It is now known as SS-MRI, and it is expected that this will be the only aspect of brain tissue structure that is maintained. Toxins will continue to be eliminated from various bodily areas.

The affine translation from the SS-MRI space to the MNI152 space is shown in Fig. 2. This transition is a common design for global brain atlases. This strategy may be applied to a variety of additional imaging modalities. Affinity linear transformations are widely used in healthcare. To get the most exact results from the registration procedure, the motions of the participants in the scanner must be constrained as much as possible about a reference frame. This increases the precision of following treatments that segment the tissue. Now, MNI-MRI data that has already been recorded is used as the input mode for unimodal Alzheimer's disease classification tasks.

The FMRIB Automated Segmentation Tool (FAST) module, which is part of the FSL package, is used to extract and segment the GM area. This is done to achieve the planned aims. The fully automated procedure begins with an input picture and ends with probabilistic and/or partial volume tissue segmentation. A variety of criteria can be met by modifying the bias field. Unlike previous techniques that depended on finite mixture models, our approach is dependable and devoid of background noise. Figure 2c depicts the results of the GM tissue segmentation.

It may be possible to fix the grayscale divergence problem that we addressed by co-registering the MNI-GM-PET picture with the appropriate. This approach was used to generate the GM-PET picture shown in Fig. 2. Our method of registration, which simultaneously accounts for and corrects for the divergence brought on by the affine translation, maintains the spatial resolution of the initial PET image. Following

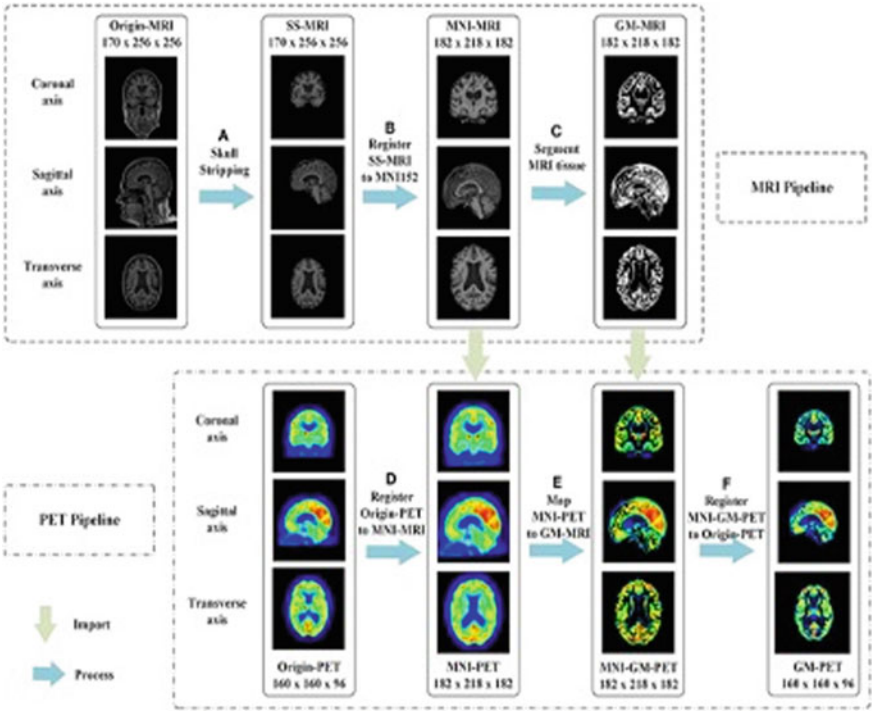

Fig. 2 The multimodal image fusion approach involves combining data from a variety of sources

the application of an affine transformation, an image that differs from the original PET scan is created. It is possible to achieve both goals if work is done on both at the same time. Switching to a resolution that uses less processing power and storage space on the device could be a good idea.

3.1 The Data Sources

The data used in this investigation were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, which may be viewed online at the following URL: https://adni.loni.usc.edu. The use of this dataset enabled the gathering of the information required for this investigation. A multinational collaboration of researchers known as the Alzheimer's Condition Neuroimaging Initiative is currently employing imaging technologies to understand more about Alzheimer's disease. This program was created with the primary purpose of doing in-depth research on Alzheimer's disease (ADNI). The primary purpose of this research is to identify clinical, radiological, genetic, and biochemical markers for Alzheimer's disease. The two major outcomes of this endeavor are the early discovery of the illness

Table 1 Regarding demography, the data are displayed using the mean and standard deviation

Subjects	Quantity	Gender ratio	Age	MMSE	CDR
NC	128	72/56	74	28.15	0.03
MCI	162	109/53	75	25.33	1.27
AD	97	55/42	74	17.84	2.75

and the monitoring of the illness's course. To reach this aim, we will perform this research. Because the bulk of ADNI participants came from a varied range of North American nations, data gathering, and synthesis required a wide range of sources. Data from the ADNI participants was obtained and analyzed for this purpose. This book covers several centuries following the Common Era. The relationship between the two imaging modalities was investigated using FDG-PET and T1-weighted MRI images of the same people. This is merely one of the numerous factors that influenced the individuals' willingness to participate in the study. MPRAGE scans are so named because it is widely accepted that MRI scans are the most accurate imaging technology. Table 1 displays the clinical data obtained from research participants.

For an MRI picture to be properly processed, the following steps must be completed in the correct order: This phenomenon is induced by a combination of slowing time, B1 anomalies, and the resonant N3. The brightness of the picture may be changed using either a Grad warp or a B1 calibration scan. In Adobe Photoshop, you may receive the required scans for each of them. If the gradient model has distorted your geometry, you may correct it by doing a Grad warp calibration scan or a B1 calibration scan. Grad warp may also be used to rectify any irregularities in the brightness of the image formed by the gradient model with a few clicks. Using a peak-sharpening approach on the N3 histogram, it is feasible to raise the total signal intensity and get the desired result. An Example Because various manufacturers build the RF coils, they use them in very different ways, the pictures will require substantial post-processing before they can be used for anything. Before incorporating the material into our investigation, we carefully prepared it.

Many steps must be completed before the FDG-PET images from the initial baseline can be appropriately analyzed. This is the point at which the analysis may begin. These technologies are used to generate PET data, which can then be efficiently communicated via a variety of channels. If all these processes are accomplished in the correct order, the intended outcome should be realized. Following the injection, the patient will undergo six FDG-PET scans, each lasting five minutes; the first scan will begin between 30 and 60 min later. The following frames will be co-registered with the initial recovered frame to create a time-varying co-registered image. This feature was designed with the purpose of providing a dynamic and current perspective of the patient in mind. To prepare for the procedure, the various frames are co-registered before the process that will merge the distinct frames into one. The objective is to minimize the influence of patient movements on the examination's findings. Using the data from the co-registration research, we do the computation described into determining the average of the six unique photos. The image is then transformed

into a grid of voxels with the following dimensions: 160 by 160 by 96, with each voxel having a 1.5 mm side length. This grid will eventually act as the framework for the finished piece of art. This has been done to guarantee that the move goes off without a hitch. The adjustments have had an impact on the structure's front and rear commissures. To assure the accuracy of our results, we closely adhere to the guidelines indicated below. The result is then overlaid using a mask designed specifically for the photo's subject to preserve uniform brightness throughout. If you adopt this method, the individual voxels that make up the mask will have an average value of 1, adding an extra layer of protection. The third stage of the technique, which is specifically designed for the scanner, comprises applying the image in its normalized and filtered form. At half the maximum, this approach generates a picture with an isotropic resolution of up to 8 mm full width. This is done to offer the reader a consistent visual experience from paragraph to paragraph.

CNN's current success may be attributed to the network's wide range of services in the field of medical image classification. Convolutional neural networks in two dimensions (2D) are utilized in techniques. However, in directions perpendicular to the plane in which they function, they neglect the anatomical environment. This happens as we analyze the 3D medical picture slice by slice. According to research, a 3D CNN that employs 3D data as a full input has the potential to outperform a 2D CNN. This is true even if it raises both the computational complexity and the memory requirements. This remains true despite the increasing complexity of computing and the demands placed on memory. Both designs are discussed in the chapter. In the sections that follow, we will go into further detail about how we employed each of these CNNs to effectively complete AD classification tasks. Both CNNs were constructed by our team using the TensorFlow framework. The goal of this study is to compare how well the GM-PET modality works to how well other CNNs work so that conclusions can be made about how to use it.

3.2 Simple 3D CNN

The advantages and disadvantages of each of these additional options will be discussed in greater depth later. Before proceeding, we will discuss these considerations in further detail in the phrases that follow. Only four of the 3D Simple CNN's 11 layers shown in Fig. 3 are used for convolutions. The diagram demonstrates how to tell the difference between the two. Because it has fewer parameters, the 3D Simple CNN is less prone to becoming overtrained than deeper networks.

The image below shows how the central node acts as the structural support for the Conv-main block (s). The three phases that must be performed to complete this section must be always followed. Continue reading to learn more about these shows. This approach also employs an s-dimensional convolution matrix (ReLU). To safeguard the "Feature Extraction" section of our system, we have four Conv-blocks that may be arranged in one of three ways: 3, 8, or 32. (3,64). This results in a two-fold increase in total channel count at each iteration, as well as a directly

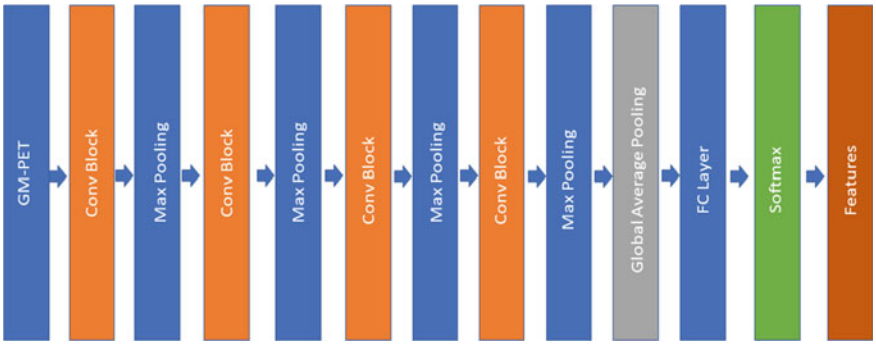

Fig. 3 A 3D basic CNN structure is used to categorize AD

proportional increase in the size of the convolution kernels (3, 3, 3). A layer called the max-pooling layer separates every pair of Conv-blocks in the third dimension. Numerous indicators indicate that this stratum will grow greatly in the future (2, 2, 2). This effect is achieved by combining the two layers. The total is larger than the sum of its parts due to the synergistic influence of these features functioning together. An FC layer and a softmax layer are then integrated into a single structure for use in AD classification. This ensures that the desired outcomes are obtained. You'll determine whether to proceed with this step based on how well the Feature Extraction phase went. It seems to reason that our approach of integrating several photos will outperform alternative methods in a head-to-head comparison. This is because to the ease with which a 3D Simple CNN may be created.

3.3 Utilizes Three-Dimensional Multi-Scale Convolutional Neural Networks

Many UNet-based networks have accomplished a variety of biological image recognition tasks effectively [36–38]. This is because a U-shaped network with skip links may be able to capture data that is both location-specific and contextually relevant more effectively. Figure 4 shows why we feel it is critical to try using a 3D Multi-Scale CNN to identify Alzheimer's disease patients. This realization was the catalyst for the initiative.

The Group Label Prediction module handles multi-scale data collection and integration, while the Feature Extraction module handles group predictions. Both aspects comprise the Multi-Scale Data Acquisition and Integration System. One of the many useful tools offered in the Feature Extraction module is the Feature Extraction subset. As shown in Fig. 4, convolutional layers in a common CNN design contain channel counts and kernel sizes of (3, 3). We were able to alleviate overfitting by making improvements such as reducing the number of channels in the convolutional layers.

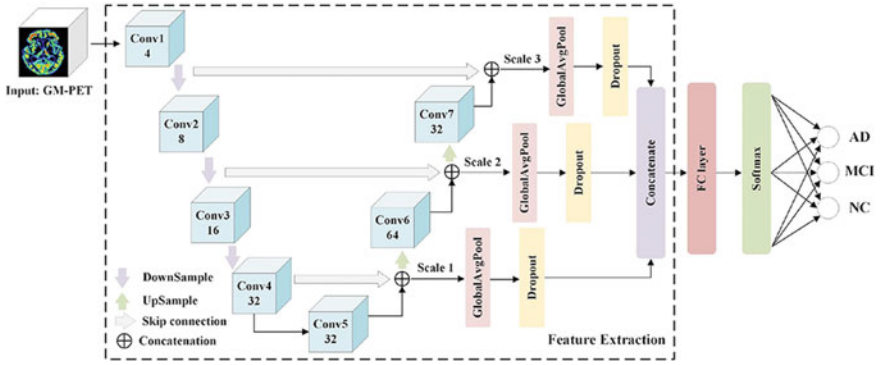

Fig. 4 The Alzheimer's disease classification using CNN

Deep layers are typically associated with pictures rich in semantic significance, whereas shallow layers are frequently associated with image characteristics rich in fine detail. The latter is generally characterized by extremely thin layers. Both types of data must be collected to make an accurate diagnosis of Alzheimer's disease, which can be accomplished through a variety of methods. There are various ways to accomplish this. After being down sampled, the outputs of the first and second convolutional layers are mixed with those of the seventh and sixth convolutional layers. This is done to guarantee that everyone understands each other. At this time, the outputs of layers 4 and 5 of the convolutional neural network are also intermingled. While processing 3D scans as inputs, this scenario employs three alternative scales to circumvent the GPU's memory access limits. The GAP layer and dropout layer results are mixed before being sent to the next classifier. The integrity of the multi-resolution components must be preserved.

Accuracy may improve because of this change. This guarantees that the multi-resolution properties of the original are retained. Finding a multi-scale feature with a high level of granularity could be very important for making a reliable test for Alzheimer's disease shown in Fig. 5.

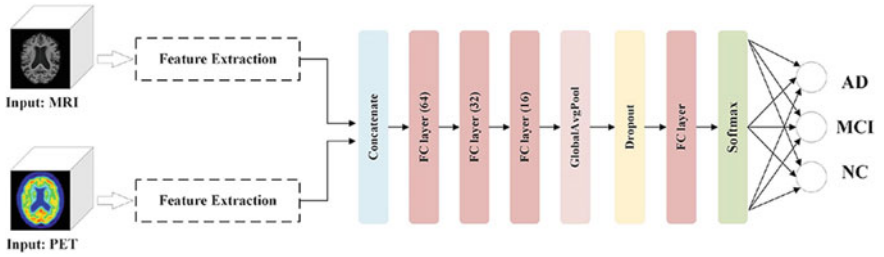

Fig. 5 Framework for Alzheimer's disease diagnosis: increased production and effectiveness

4 Results

If high-resolution 3D data were employed, the CNN training step would need more processing power than is currently accessible. To swiftly produce singleton data, it is important to first choose from the input data randomly after data purification. The Cutting Room should be your first stop before doing anything else. Figure 2 shows that, across all imaging modalities, there were significant portions of background space. We can reduce the amount of information required without negatively affecting any brain areas if we just eliminate background information that isn't beneficial in the right locations. The new MRI machine is much smaller than the previous one, measuring 176 inches by 208 inches by 176 inches as opposed to 182 inches by 218 inches by 182 inches. Both the PET and the GM-original PET's metric dimensions have been lowered from 192 by 192 by 96 to 112 by 128 by 96. To elaborate on the second point, the sampling procedure's components are as follows: Each time a slice is collected, a transverse axis built into the sample divides it in half. An MRI scan has 176 by 208 by 88 pixels, a PET scan has 112 by 128 by 48 pixels, and a GM-PET scan contains pixels that are the same size as PET pixels. These figures can be used to make estimates regarding image size. As a result, even if the resolution decreases, the sample size may increase. This adds to the network model's ongoing development and improvement.

All the networks assessed here were built with TensorFlow, a deep learning framework. These tests are intended to differentiate between normal ageing and various kinds of dementia, including Alzheimer's disease. Earlier studies separated the population into two groups due to the ease with which AD and NC could be recognized from one another. Studies must be conducted to learn more about the distinctions between the two types of information. Adam, who has a learning rate of 1e-4 at the start of the training phase, helps to keep exact weights when developing the network optimizer. Because we used tenfold cross-validation, we were able to perform extremely exact computations, making it much simpler to compare our results to those of other organizations. Comprehensive testing and analysis of a sample. Following the statistical analysis, the individuals in the sample are divided into ten distinct subgroups. After we exceed the 500-repeat barrier, we will alternate between two methods after each trial to fine-tune the learning rate. If we continue in this fashion, we will be able to accurately modify our learning rate. (1) If the rumor is confirmed, it will be a severe setback. Consider the following to be the worst-case scenario. (2) The learning rate is lowered if the validation set's accuracy does not improve after 20 repetitions of exposure to the training set. As a result, it has occurred even if the average pace of human learning has not doubled. We need to get everything organized as soon as feasible so that we can accomplish this assignment as soon as possible. If the validation loss doesn't go down after 50 training cycles, the operation will stop right away.

When assessing the overall performance of the system, the classification accuracy (ACC), sensitivity (SEN), and specificity (SP) metrics will be widely used. The standard deviation (SD) is a way, to sum up, the results of a tenfold test. The mean

standard deviation is a statistical measure of variation. Our primary goal is to assess the potential usefulness of our picture fusion approach in comparison to the current diagnostic paradigm for tasks involving AD classification. In addition to utilizing the results of previous unimodal scans such as MRI and PET as a baseline, our strategy for detecting Alzheimer's disease includes the feature fusion method. This is now a possibility because the module is compatible with both formats. This is one of the module's probable applications. The use of this data may aid in the discovery and treatment of health concerns. Overfitting can be reduced to some extent by using a GAP layer in conjunction with a dropout layer when building a model. After you achieve the correlation fusion level, it is strongly encouraged that you build three FC layers, each with a different number of nodes: 64, 32, and 16.

4.1 Identifying Differences by Comparing AD and NC

Table 2 summarizes occurrences based on whether they were categorized using a single modality, several modalities, or different network topologies, all of which contribute to their classification as AD or NC. While multi-modality systems are preferable because they can use data from both types of scans, single-modality techniques rely solely on MRI or PET scans (MRI and PET). Image fusion is one of the multi-modality strategies mentioned, although feature fusion is another option. When we compare our picture fusion strategy to the other two multimodal approaches already in use, the case for its superiority becomes stronger. Its sensitivity, at 93.33%, was only second to the gold standard. Despite having the lowest accuracy and specificity of the three approaches, the feature fusion methodology has the highest sensitivity (95.55%). When paired with a tried-and-true image fusion approach, the 3D Multi-Scale CNN achieved the greatest possible rate of classification accuracy (95.22%). Classification accuracy increased by at least 4.75 percentage points as compared to unimodal techniques, while sensitivity and specificity increased by 6.27 and 3.46% points, respectively. By combining many images into one, we beat both AD and NC in a classification task competition.

4.2 Identifying Differences Between MCI and NC Outcomes

The network topologies and classification accuracy of various MCI and NC approaches are shown in Table 3. The proposed image fusion solution beats other approaches by a substantial margin. With the help of the 3D Simple CNN, our image fusion strategy was able to obtain a best-case classification accuracy of 88.48.6.5%. This approach was the most successful overall since it was exceptionally sensitive (93.44%) and specific (82.18%). The proposed picture combining technique improved classification accuracy by 6.11%, sensitivity by 1.25%, and specificity by 11.62%, suggesting that it efficiently includes a wide range of information. When

Table 2 Outcomes of using AD and NC might change under different network installation and configuration scenarios

Network	Modalities	Accuracy	Sensitivity	Specificity
3D simple CNN	Unimodal MRI	90.90	87.42	92.08
	Unimodal PET	93.20	90.24	95.38
	Feature fusion	94.33	95.55	92.73
	Proposed method	95.22	93.33	96.15
3D multiscale CNN	Unimodal MRI	89.99	87.22	91.54
	Unimodal PET	90.47	88.17	91.92
	Feature fusion	94.77	94.44	94.61
	Proposed method	95.22	94.47	95.37

Table 3 Findings from MCI and NC study that looked at a range of different modalities and networks

Network	Modalities	Accuracy	Sensitivity	Specificity
3D simple CNN	Unimodal MRI	80.57	88.60	70.24
	Unimodal PET	73.10	73.92	71.68
	Feature fusion	99.59	93.20	70.85
	Proposed method	77.12	94.55	83.29
3D multiscale CNN	Unimodal MRI	77.12	78.61	75.38
	Unimodal PET	69.66	76.05	81.75
	Feature fusion	94.28	91.74	74.66
	Proposed method	86.11	85.72	86.71

combined with the 3D Multi-Scale CNN, our technique of fusing pictures still gave the highest rates of accuracy (85.09%), specificity (85.60%), and sensitivity (84.69%). Our technique outperformed the alternatives chosen by most experts by at least 11.33% points. On the MCI versus. NC test for classifying, the suggested method of "image fusion" was the best choice.

4.3 Variations in Observed Results Between AD and MCI

Table 4 is a summary of what was found when single and multimodal techniques, as well as supporting networks. It is designed to be used in a therapeutic environment using the information in Table 4. We were able to raise the accuracy of Alzheimer's disease diagnosis to 84.837% by combining our picture fusion approach with the usage of the 3D Simple CNN. As a result, we were able to achieve an 84% success rate. Ranked second thanks to a successful combination of high specificity (94.69%) and sensitivity (68.98%). When compared to unimodal approaches, the picture fusion

methodology improved classification accuracy by 6.53%, sensitivity by 10.83%, and specificity by 5.00%. We were able to obtain previously unattainable classification accuracy by including a 3D Multi-Scale CNN into our picture-fusing technique. Surprisingly, the overall score was 80.805.9%. This is a significant juncture in our journey. The feature fusion method was also the most precise. Based on what we found, our method was the best way to tell the difference between people with Alzheimer's and those with moderate cognitive impairment.

Classification assessments, including comparisons of AD, normal aging, and MCI in the context of normal aging, are significantly more difficult than the binary classification tasks (NC). When applied to a job requiring three classifications, the efficacy of both unimodal and feature fusion systems decreased significantly; nonetheless, our image fusion approach remained the most successful tactic across all assessment criteria. The classification accuracy of the 3D Simple CNN is 75.45%, the sensitivity is 59.518%, and the specificity is 100%. This percentage is high 85.41% to be precise.

Our photo fusion method outperformed the competition in terms of classification accuracy by at least 10.73% in terms of sensitivity and 6.2% in terms of specificity. We discovered that combining multiple photos with the 3D Multi-Scale CNN resulted in the highest possible classification accuracy of 71.52%. The specificity was 83.40%, and the sensitivity was 55.67%, according to the data. Furthermore, we observed that our image fusion approach beat its current counterparts in terms of sensitivity (4.03% points), specificity (2.37% points), and accurate classification rate (93.3%). Our strategy of employing fused pictures to address the problem involving several classes has been shown to be effective (Table 5).

Table 4 Results of multiple modalities using different networks for people with AD and MCI in the form of unit percentages

Network	Modalities	Accuracy	Sensitivity	Specificity
3D simple CNN	Unimodal MRI	83.58	57.60	88.61
	Unimodal PET	89.41	68.57	90.71
	Feature fusion	92.10	79.44	90.26
	Proposed method	95.94	79.30	95.71
3D multiscale CNN	Unimodal MRI	79.51	63.81	88.60
	Unimodal PET	84.18	72.02	80.40
	Feature fusion	91.58	64.52	96.05
	Proposed method	91.91	82.28	96.05

Table 5 The deployment of AD, MCI, or NC will have varied results depending on the approach and infrastructure employed

Network	Modalities	Accuracy	Sensitivity	Specificity
3D simple CNN	Unimodal MRI	75.11	58.21	89.19
	Unimodal PET	71.76	54.61	86.50
	Feature fusion	76.59	59.79	81.25
	Proposed method	85.65	61.42	96.52
3D multiscale CNN	Unimodal MRI	77.35	50.68	80.83
	Unimodal PET	60.48	53.94	85.09
	Feature fusion	79.26	62.75	92.14
	Proposed method	82.63	66.78	94.51

The specified ratio of one amount to another

4.4 Discussions and Evaluations of the Most Cutting-Edge Research Methodologies

The results of task-specific classification were examined using the given image fusion approach, and the findings were compared to those obtained utilizing cutting-edge multimodal methodologies (Table 6). Our method, which combines image fusion with a 3D basic CNN, surpassed every existing multimodal diagnostic tool on every test currently used to detect Alzheimer's disease. The results corroborated this. Although the preparation for our technique to fuse multimodal images is significant, the significant reduction in network parameters gained as a direct result more than compensates for the effort. In contrast to the original collection of pictures gathered in diverse ways, the classification network gets a single unified image. This photo collection has taken the place of the previous one. We can greatly cut the amount of time we need to spend using this strategy. When compared to other techniques developed for the same objective, the current method for picture fusion does not result in a considerable increase in the amount of processing complexity or memory required.

4.5 Conceptualization in Three and Four Dimensions

As shown in Fig. 6, we investigated the source images and related attributes over a wide range of modalities and subject groups to demonstrate the efficacy of our image fusion technique. This was done to compare our findings to those obtained from other studies that employed different approaches. The images to the left of each cell provide a new perspective on the subject by lighting it from various angles. When MRI and PET brain slices were examined, we discovered that the Alzheimer's patient had the lowest metabolic rate and the greatest loss of brain tissue. This was

Table 6 The following are some areas where our classifiers outperform those already in use: AD, MCI, and NC diagnoses

Method	AD versus NC	MCI versus NC	AD versus MCI	AD versus CI versus NC
Multi-modality classification	92.5	93.2	–	64.80
Robust deep model for improved classification	92.5	88.5	82.2	–
Multi-modal classification	92.9	80.6	–	71.3
Multimodal and multiscale deep neural networks	85.60	96.48	–	–
Multi-modality cascaded convolutional neural networks	94.37	85.45	–	–
Multi-modal AD classification	90.13	93.64	–	–
Hypergraph-based multi-task feature selection	93.62	91.1	–	–
Multimodal data analysis	82.10	93.64	–	–
Proposed method	95.22	90.59	–	–

evident when juxtaposing the two scenarios. Given the two options, this was an astute comment. The capacity of GM-PET to totally replace MRI and PET for measuring metabolic levels may be available soon. PET and MRI are the current gold standards for identifying brain atrophy. Because the final image only showed the GM area, GM-PET scans revealed no artefacts in the surrounding brain tissue, particularly near the skull. We believe our technique for image fusion is better than others since it takes advantage of the richness of information included in the photos.

Figure 6 depicts some of the imaging modalities available for the diagnosis of neurodegenerative diseases. These disorders include dementia, mild cognitive impairment, and other comparable difficulties. The photos on the right of each of the nine cells labeled with the letters "A" through "I" show the Grad-CAM findings for each of the nine separate slicing's across the subjects shown in the images of the cells. The contour regions of interest are shown in red in the 3D Grad-CAM output, while the metabolic characteristic zones are shown in yellow. Depending on their metabolic features, the areas of interest are indicated with a green circle on both the MRI and the gamma-metabolic positron emission tomography (GM-PET) images. The areas of interest are readily visible in both pictures. A green circle has been

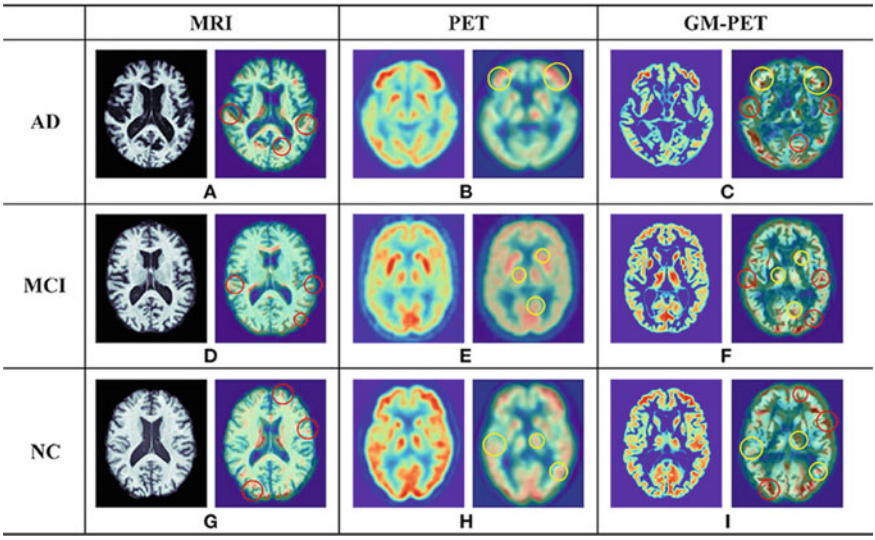

Fig. 6 Imaging modalities

drawn around these locations to draw attention to them. In theory, two circles might exist simultaneously in the same location and time.

One of the most significant and critical variables was determining whether the multimodal GM-PET data was sufficient for CNN's feature extraction module. Figure 6 shows how we were able to successfully incorporate 3D Grad-CAM technology into the 3D environment. The images in the cells on the far right depict the fundamental CNN's second convolutional layer. The highlighted image CAMs earn a higher relevance score from the convolutional layer. The red circles reflect several notable traits found in the MRI images. The shape of the item and the degree of surface roughness along its edges were the key concerns in the evaluation. According to the PET slice analysis results, there was a strong correlation between the areas of interest and those with greater metabolic rates. The issue areas were marked by yellow circles. The convolutional layer of the GM-PET model was expected to merge the contour and metabolic data to generate a single score. For example, the versatility of the GM-PET modality would allow for the use of a broader variety of Alzheimer's disease diagnostic criteria. This observation might be due to the adaptability of the medium in question.

This is done so that multimodal data can highlight more subtle illness implications. To create a fused GM-PET modality, the proposed fusion technique combines data from FDG-PET scans conducted in the same imaging region with data from brain MRI scans that identify GM tissue. This technique is carried out to make the modality accessible. Because the GM tissue region has been determined to be the most helpful indication of the existence of the illness in prior research, diagnostic techniques for Alzheimer's disease often focus on this location (10, 11, 45). (10, 11, 45). Figure 2

shows a GM-PET image demonstrating the success of this fusion process. As seen in Fig. 2, this picture combines structural information from the MRI with metabolic information from the subject's brain PET scan. View the graphic to learn more about how the combined images operate. To decide, compare the two images side by side and examine the differences. To put it another way, you will be able to independently verify these outcomes. We were able to observe that this was the case. The use of software enabled the identification of this significant advance. When this happens, it means that GM-PET may be able to provide more accurate modality information that may be used for categorizing. Furthermore, when it comes to addressing the challenge of aligning multiple properties seen in multimodal pictures, our image fusion technique may be more successful than approaches based on multimodal feature learning. This is since our method blends the two learning theories. This happens during the user's system enrolment and after registration is finished.

To complete each of these assignments (AD versus MCI versus NC), you must select if a certain item falls into the yes or no group (AD versus MCI versus NC). To avoid this difficulty, we suggested employing a three-dimensional multi-scale convolutional neural network (CNN) that considers the dimensions of both the size and placement of the features. During the development process, the following checks were made to ensure that none of these networks inappropriately fitted their training data. As an initial step, the total number of convolutional layers must be lowered. Following that, we will try a convolutional layer with fewer channels. Add GAP and dropout layers as a last step to eliminate any remaining signs of noise. A single-input network is also employed in the proposed Alzheimer's disease diagnosis paradigm. Feature fusion techniques, on the other hand, take advantage of multiple-input networks. To do this, our image fusion technology integrates data from many imaging techniques into a single, comprehensive picture. It is the precise circumstance because of the aforementioned factors. Furthermore, our image-fusing technique may be successful in drastically reducing the overall number of CNN parameters. It may be a direct result of it.

To assess the success of the approach we provided for merging images, we ran several tests and studies on it. This is since multimodal approaches use the proposed image fusion strategy for feature fusion. This is the root of the problem. This is because when the findings of different multimodal research approaches are combined, a plethora of data is created. When we were given a difficult task that included three distinct categories, our approach for integrating photographs performed considerably better than the other method for merging characteristics. This indicates not just the overall success of our picture fusion technique, but also how effectively it adapts to the many categorization networks that we subject it to. This is since independent investigations undertaken by CNN and HLN both yielded the same results. Furthermore, when compared to previous advances in the field of multimodal learning-based systems, our solution for image integration performed significantly better. However, there were times when it fell short of expectations in terms of sensitivity and specificity. Even though the proposed approach of photo fusion was frequently used to produce the best results, it did not work on a few occasions.

5 Conclusion

In this section, we'll investigate GM-PET imaging, a hybrid imaging technology that combines MRI and PET scans to diagnose Alzheimer's disease. Our strategy mainly relies on combining many photos. Aside from structural imaging, the GM-PET approach may one day be able to offer information on how the brain operates. Furthermore, the mode considerably reduces the amount of visual noise, making it much simpler for the viewer to focus on the important aspects of the image. Using cutting-edge 3D Grad-CAM technology, we were given a birds-eye perspective of the CNN broadcast area. It is hard to say whether this effort was successful. It was anticipated that by doing so, the study's findings would eventually be incorporated into routine therapy practices. According to the findings of our study, our technique of image fusion surpasses both the unimodal and feature fusion approaches, demonstrating that the recently found approach of picture fusion is superior to the other after comprehensive testing. As a result, our picture fusion technique is not only a very successful way of performing AD classification tasks, but it is also extremely easy.

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Machine Learning Models for Alzheimer's Disease Detection Using Medical Images

Yusera Farooq Khan, Baijnath Kaushik, and Deepika Koundal

Abstract Human brain is an exclusive, sophisticated, and intricate structure. Neurodegeneration is the death of neurons which is the ultimate cause of brain atrophy resulting in multiple neurodegenerative diseases. Neuro-imaging is the most critical method for the detection Alzheimer's and quantification of brain atrophy. Magnetic resonance imaging (MRI), computed tomography (CT), single-photo emission computes tomography (SPECT), and positron emission tomography (PET) are the widely used neuroimaging techniques to image/estimate altered brain tissue and to assess neurodegeneration associated with Alzheimer's. Traditionally, neuroradiologists incorporate clinically useful information and medical imaging data from various sources to interrelate the structural changes, reduction in brain volume, or changes in patterns of brain activity. In recent years, machine learning and artificial intelligence-based approaches continue to garner substantial interest in neurobiology domains and have emerged as powerful tools for the efficient prediction of neurological and psychiatric disorder-related outcomes. Traditional machine learning algorithms show limitations in terms of the data size and image feature extractions. To address such concerns, Deep Learning Algorithms relying on Deep Convolution Networks (DCN) and Recurrent Neural-inspired Networks (RNN) have advanced to more powerful paradigms to solve the complexity of multistate brain imaging data and to provide extensive solutions in the better understanding of mechanistic details of the progression of brain atrophy in Alzheimer's disease. The rationale of this study is to provide an in-sight to role of Machine learning for AD detection using neuroimaging data.

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1 Introduction

The introduction of artificial deep neural networks innovations into healthcare could expand access to healthcare by providing new insights into diseases and leading to the discovery of new astonishing findings. Conventional therapeutic diagnosis is often based on sequences visible from medical images. Over the past few years, there is an exponential increase in the development and adoption of the machine learning (ML) and deep learning (DL) based algorithms of artificial intelligence for analysing the dynamic neuroimaging data and aiding physicians to apply automatic neuropathology prediction and diagnosis strategies. Although, machine learning technique remains one of the most popular methods for the extraction of various features of brain images but deep learning methods are currently attracting tremendous attention in neuroimaging because of intelligent algorithmic selection, extraction, and classification of essential anomalous features of brain scans. In this chapter, we provide a comprehensive review of the use of computer-aided diagnosis system for early perdition of neurodegenerative disorders and volumetric analyses of brain lesions using machine learning and deep learning algorithms.

1.1 Neurodegeneration

Neurodegeneration is an umbrella term for the progressive loss of structural or functional integrity of nerve cells, which leads to brain- and nerve-related pathologies, creating disturbances in nervous system and causing neuronal diseases like AD, PD, HD and ALS [1, 2]. Of these disorders, dementia is the most significant cause of disease worldwide, with an estimated 50 million people worldwide suffering from AD and related disorders. Neuro-degenerative diseases are devastating and largely inoperable state strongly linked with age and brain dysfunction [3].

Neurodegenerative diseases are multifactorial disorders caused by a combination of genetic, environmental and lifestyle factors. Neurodegeneration is often associated with protein misfolding that leads to cytotoxicity and disruption of cellular protein homeostasis. Recent studies have shown that the accumulation of abnormal or misfolded proteins such as amyloid-beta (A-beta), tau, and alpha-synuclein (-synuclein), synaptic dysfunction, synaptic loss, neuroinflammation are common pathological processes in major neurodegenerative diseases [4]. It is believed that the combination of transcriptional errors, human gene mutations and environmental factors are involved in the pathogenesis of neurodegenerative diseases. To be precise, the presence of certain risk factor genes makes us more vulnerable and susceptible to neurodegenerative diseases. A study conducted by the University of Glasgow in collaboration with the MRC Protein Phosphorylation and Ubiquitination Unit at the University of Dundee has revealed the role played by a gene called UBQLN2 [3].

The study also mentioned that UBQLN2 removes toxic protein clumps from the body and protects the body from their harmful effects. The researchers found that the main role of UBQLN2 is to help the cells get rid of toxic protein clumps. The protein clumps, which arise as part of the natural aging process, are entangled and disposed off by UBQLN2. However, when this gene is mutated or misfolded, it cannot help the cells to dislodge this toxic protein clump, leading to neurodegenerative diseases [5]. These misfolded or mutated proteins are also called brain-killers.

1.2 Consequences

Ageing is the one of the major risk factors for most neurodegeneration-related abnormalities. Ten percent of people over the age of 60 years are affected by neurodegenerative diseases. In addition, with the aging of the population, the prevalence of neurological diseases continues to rise. The World Health Organization (WHO) estimates that 47.5 million people worldwide have dementia and 7.7 million new cases are diagnosed each year. In addition, it is estimated that more than 30 million people suffer from Alzheimer's disease and five times as many from Parkinson's disease. This number is expected to increase to about 100 million by 2050, which is an alarming increase. In addition, the cost of caring for Alzheimer's patients is expected to increase from $200 billion per year to $1.2 trillion by 2050 [6]. Treatment options for AD are limited, and there are consequently no substantial options to reverse the progression of the disease.

1.3 Medical Imaging

Indeed, medical imaging has changed the face of medical diagnosis. In 1895, Wilhelm Conrad Röntgen, a professor at the University of Würzburg in Germany, changed the world by taking X-rays of his wife Bertha's hand and was awarded the Nobel Prize for his work [7]. This was the first time it was possible to see inside the human body. In the modern era, medical imaging technology is one of the most rapidly developing medical data sources. Researchers and neuroscientists have begun to observe the inside of the brain in order to understand how it works and functions. Medical imaging has revealed abnormalities affecting specific parts of the brain, such as the frontal and temporal lobes and the limbic system, making diagnosis easier and allowing treatment to begin immediately. Sometimes a disease can be revealed before it is felt. For many diseases, including cancer, the earlier the disease is diagnosed, the better the chances of survival. Doctors can use neuroimaging techniques such as MRI, CT, and diffusion weighting (DW) to diagnose these debilitating conditions in the brain. MRI can identify stroke lesions in a matter of minutes, and MRI images produce higher quality images than regular X-rays or CT scans. The radiological images used in the routine examinations are generally stored and transferred in DICOM (Digital Imaging and Communications in medicine) and NIFTI (Neuro-imaging informatics technology initiative) formats [8].

1.4 Rise in the Use of Artificial Intelligence (AI) in Healthcare for Computer-Aided Diagnosis (CAD) Using ML and DL Based Neuroimaging

The world is changing, and one of the changes that will influence our future is Artificial Intelligence (AI), which is revolutionizing every aspect of human life. The previous machine revolution/machine age expanded the mechanical power of humans. In this new machine revolution, not only human mechanical power but also mental power of humans has been amplified. Computers are going to swap not only physical labor, but also mental labor. Machine learning algorithms enable computers to become smarter by learning skills from past experiences and data. Machine learning has become a key to filling computers with knowledge, and knowledge is what enables brainpower [9]. Deep learning is based on neural networks, an approach to machine learning inspired by the human brain, and began in 2012 with speech recognition for cell phones using neural networks. Since then, breakthroughs have occurred in the field of computer vision [10]. Computers are now able to perform the amazing task of recognizing patterns and contents of images. As a result, computers are playing an increasingly important role in medical diagnosis using medical images [11, 12]. If neurologists could predict neurodegeneration years in advance, what would change? How can artificial deep neural networks help scientists to achieve this goal? In recent years, medical image analysis has provided techniques for recognizing patterns in neuroimages and studying brain connections and their pathological changes for better diagnostic support systems.

The review article is outlined as follows: General background of Alzheimer's disease: causes and consequences are discussed in Sect. 2. Medical Images used in Diagnostic Approaches for Alzheimer's disease is discussed in Sect. 3. In Sect. 4, use of AI in computer aided diagnosis using ML and DL is discussed. Section 4 discusses use of various machine learning and deep learning approaches. Section 5 provides the conclusion the study.

2 Alzheimer's Disease: Causes and Effects

This is the most common cause of cognitive turn down. Alzheimer's disease can be sporadic or familial. The most important sporadic variant responsible for causing AD is aging [13]. The other important reason for developing AD other than age is due to the increased presence of an allele known as Apolipoprotein-E4 (ApoE4). Apolipoprotein-E4 (ApoE4) has been associated with an increased threat of AD. Another protein known as apolipoprotein E2 (ApoE2) is actually a protective variant in nature against AD and decreases the risk of AD [14]. Apolipoprotein-E4 (ApoE4) harbouring individuals display early onset of AD. In terms of familial factors, there is often a very strong association with what is called Down syndrome, or trisomy

21. Other genes that are associated with development of AD include the presenilin-1gene and presenilin-2 gene. The presenilin-1 gene locates on chromosome 14 and presenilin-2gene locates on chromosome 1. Out of all these factors, age happens to be the most important factor for the development of the AD in patients [15]. To understand the pathophysiology associated with the AD, it is necessary to understand the significance of changes in secretase activity of amyloid-β precursor protein (APP), an important cell surface receptor [16]. There are two possibilities for this difference in secretase activity. The first possibility is that the enzyme α-secretase acts first in the degradation of enzyme alpha-secretase, followed by the enzyme γ-secretase. The second possibility is that the enzyme β-secretase acts first, followed by the activation of the enzyme γ-secretase. In the first possibility, the amyloid-β precursor protein (APP) [17] degrades into a soluble peptide. In the second possibility, on the other hand, the amyloid-β precursor protein (APP) forms an insoluble peptide [18]. This insoluble peptide is called as amyloid-β peptide (Aβ or A-β). This amyloid-β peptide (Aβ) may be involved in the formation of oligomers that aggregate in the cell. Once aggregated within the cell, it may lead to the formation of amyloid-β plaques. These amyloid- β plaques are toxic to neurons. Another protein which is also responsible for AD is Tau protein. Tau protein is responsible for attaching itself to microtubules in order to stabilize the structure of nerve cell bodies. However, when this tau protein is phosphorylated, it begins to detach from the microtubules. The dislodged tau protein begins to aggregate in the cell. This highly phosphorylated tau protein becomes involved in the formation of neurofibrillary tangles. The amyloid beta precursor protein (APP) is believed to be influenced by a gene on chromosome 21. Normal individuals have two copies of chromosome 21; those with three copies of chromosome 21 are more likely to overproduce APP, increasing the likelihood of amyloid-β plaque formation. This condition of having three copies of chromosome 21 is known as Down syndrome. Therefore, many patients with AD often show clinical signs of Down syndrome after the age of 65. Most patients with Down syndrome develop this type of disease by the age of 40. In the disease process of AD, neurons and neuronal networks disintegrate, and many areas of the brain begin to shrink. The final stage of AD is called cerebral atrophy. In this process, the volume of the brain is significantly reduced. Table 1 lists causes and consequences of AD.

3 Neuro-Imaging Used in Diagnostic Approaches for Alzheimer's Disease

Researchers and neuroscientists aim to look inside the brain in order to understand its functioning, functionality, and pathological and physiological changes. There are several brain imaging techniques and diagnostic tests that can assist the physician create his/her assessment by looking inside the brain. The relevant medical imaging techniques are described below.

Table 1 Causes and conciquences related to Ad

Alzheimer's Disease	Age	Sporadic variant responsible for causing Alzheimer disease is age
	Family history	Close blood relative like mother, father, or sibling has AD; the chances are up to seven times greater that they may develop the disease
	Genetics (heredity)	Gene that matters most is Apolipo-protein-E (APOE)
	Head injury	Brain injury, most commonly caused by accident is serious
	Heart head connections	Damaged arteries, intrusive with blood flow, depriving brain cells of O_2 and vital nutrients like glucose
	e4	Raises AD risk
	Loneliness and depression	Loneliness levels, depression, and increased AD risk

For neuroimaging, there are various modalities that can provide a quantitative picture of the structural properties of the brain and complex pathologies. This allows physicians to better understand disease progression and the body's response to treatment. Over the past few years, the fast development of non-invasive neuro-imaging techniques has opened up new possibilities for the investigation of human brain complexities and specialized functionalities [19]. Several techniques including Magnetic Resonance Imaging, diffusion-weighted Magnetic Resonance imaging, Computed Tomography, Single-Photon Emission Computed Tomography, and Positron Emission Tomography play significant role in the scanning of the complex structures of the brain and assessment of neurodegenerative disease patterns [20].

3.1 Magnetic Resonance Imaging Technique (MRI)

It is an imaging technique that uses magnetic fields and radio waves generated by RF coils to image the internal organization of the tissues/organs in the body. A large magnet generates a uniform magnetic field around the body. A large magnet produces uniform magnetic field around the body. The system measures the radio waves emitted by atoms that are subjected to a magnetic field. The appearance of tissue in MR images depends on the chemistry of the specimen and the MR sequence employed. T2-weighted images are the most common MR images, and tissues with high water and fat content have a relatively high number of hydrogen atoms, making them appear brighter and sharper. Bone, on the other hand, appears darker on T2-weighted images [21]. T1-weighted gadolinium-enhanced images (T1-Gd), and Fluid

Attenuated Inversion Recovery (FLAIR) are sequences that are commonly used with T2-weighted scans in neuroimaging. A magnetic field has the property of polarizing atoms in the specimen placed in this field. A series of radio wave pulses passes through the region of interest, and stimulate protons to break out of the magnetic field sequence. The protons recalibrate by releasing energy in the form of radio signals, and the sensors catch that energy.

3.2 Computed Tomography (CT)

Computed tomography is a painless diagnostic test that uses 3600 X-rays and a computer to generate images/scans to capture successive images of brain tissue. CT images can be used by doctors to diagnose AD in particular and to pinpoint the exact location of brain damage and neurodegeneration in general. Longitudinal variations in brain volume are allied with longitudinal continuum of memory loss. Inside a CT machine, a gantry rotates around the brain while an X-ray beam is emitted, and a detector measures the amount of radiation absorbed by the body [22]. As the gantry rotates, many images are taken from different perspectives. The collected data is sent to a computer attached to the machine, which uses the information gathered by the detectors to generate images. The various images taken in this way help doctors to diagnose areas that are prone to neurodegeneration.

3.3 Single-Photo Emission Computes Tomography (SPECT)

Single-Photo Emission Computes Tomography technique in psychiatry is creating a revolution by helping out the psychiatrist to save generations. This imaging tool allows us to see the functional metabolism of synapses. The above tool uses gamma rays to visualize the inside of the body. SPECT essentially unravel three things: normal activity, hyper-activity or hypo-activity. As its name suggests, it is based on radioactive material that emits single photons. Technetium is a very important atom in this technology. A particular type of SPECT is DatScan, which uses Ioupane Iodide-123 as a drug to measure dopamine levels in the patient's brain [23].

3.4 Positron Emission Tomography (PET)

Positron Emission Tomography is an another form of medical imaging tool for measuring the metabolism [24]. By injecting a radioactive tracer into the body by interventional injection, PET can measure blood flow, oxygen consumption, and glucose metabolism to diagnose the stage of disease and reveal brain function in three dimensional formats. In a PET scan, a detector measures photons and uses the

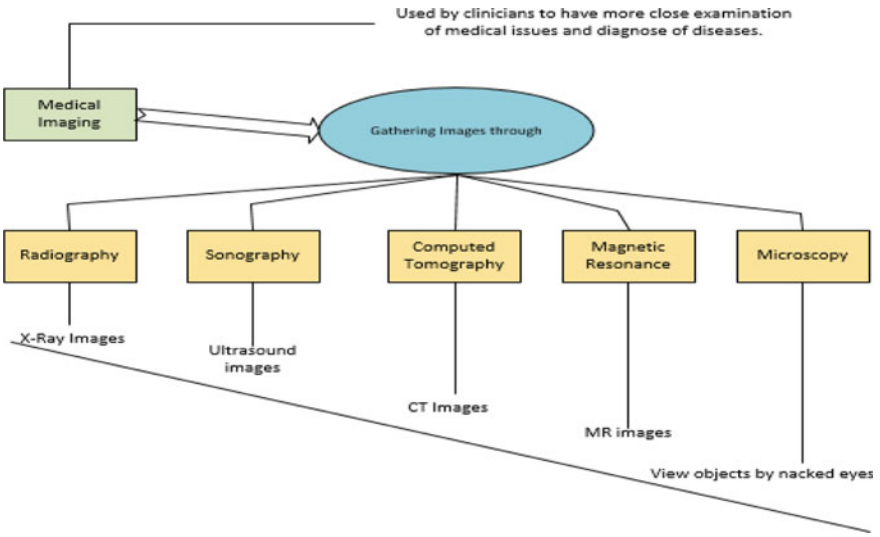

Fig. 1 Medical imaging techniques for diagnosis

information to produce an image that shows the dissemination of fluorodeoxyglucose (a radiopharmaceutical) in the body. Figure 1 representing the methods of gathering images.

4 Use of Artificial Intelligence in Computer Aided Diagnosis (CAD) Based on Machine Learning and Deep Learning Algorithms

The medical community is facing major challenges in the detection and diagnosis of several life threatening diseases. Every year, thousands of patients lose their lives due to various diseases. The best way to save these patients is through early detection and diagnosis of these diseases. However, diseases cannot be diagnosed until symptoms appear, which may be too late. Artificial intelligence is attempts to understand and build intelligent systems by accessing big data, advanced machine learning algorithms, and increasing computing power [25]. In the future, AI may be used to diagnose diseases before they occur and to stop them before they develop. Figure 2 depicts the hierarchy of support system for medical diagnosis, from image acquisition and reconstruction CAD.

The basic idea behind machine learning is to program a computer that can learn on its own through experience "The only source of knowledge is experience"—Albert Einstein. ML uses large data sets to create intelligent systems for decision making. The way ML works is that we feed it images and train it to distinguish

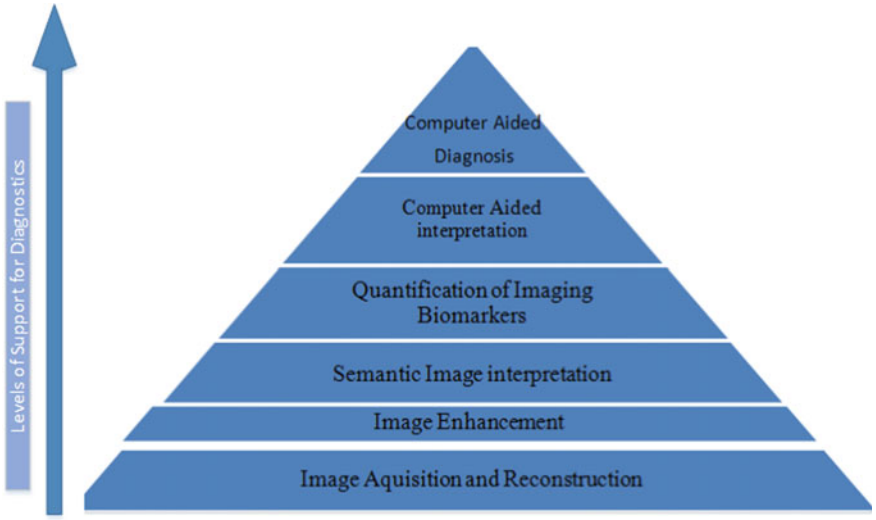

Fig. 2 Conceptual of image acquisition and reconstruction to CAD

between people with advanced disease from healthy people. Because these machines learn with experience, they get better and better as we feed more and more data to make certain these computers become smarter and more precise in diagnosis. The computers can recognize early signs of diseases that human eyes cannot see. Machine learning models are just as good as training data. In machine learning, a huge amount of data set is given to the classifier, which simply does some processing based on the data sets and tries to predict the outcomes. The technology of machine learning has solely enabled computers with new capabilities [26].

Feature engineering: is a process of using machine learning algorithms and knowledge of the data at hand by applying hard-coded transformation to the data before putting it into a model. Feature engineering is very important because machine learning algorithms are not smart enough to learn features on their own. The essence of feature engineering is to make a problem easier by representing it in a simpler way. Since many models have been created over the years by researchers and data scientists, the appropriate choice of model is important. Different models are suitable for different types of data, such as image data, patterns, numerical data, and text data. An excellent rule is considered for training-evaluation split in the following order: 80%-20% or 70–30%. The power of ML is that it can make predictions and differentiate between inputs by using the model in spite of using human opinion and manual-convention. Machine learning uses advanced algorithms to make decisions based on what they have learned and learn from the information provided to these algorithms. Deep learning uses a hierarchical set of algorithms to create a learnable ANN and thus makes intelligent decisions on its own.

Table 2 Shows classic machine learning and deep learning techniques for disease detection

	Anomaly	Classification	Detection	Segmentation
Classical machine learning	1. KNN 2. SVM 3. Clustring tech	1. Naive Bayes 2. SVM 3. Random forest 4. Neural network 5. Decsion tree	1. Feature based 2. Classifier based 3. Motion based	1. Clustring methods 2. Region growing 3. Model based segmentation
Deep learning	1. Auto encoder 2. RBM 3. Deep belief networks	1. CNN 2. RNN	1. CNN 2. RNN	1. CNN 2. Auto encoder 3. Deep belief NN 4. GAN 5. Variational auto encoder

Table 2 shows few classical machine learning and deep learning techniques for disease prediction. Both of these descend under the broad category of artificial intelligence. Deep learning algorithms are highly accurate that can assimilate features from unprocessed data with a high degree of accuracy, without the need to explicitly extract features from unprocessed data. Deep learning models are designed to analyze and make decisions in the same way that the human brain thinks and draws conclusions. Computers do not look at images the way humans, computers look at numbers.

4.1 Pre-Processing of MRI and CT Images for Machine Learning

The initial outline resampling, registration and bias field correction are decisive steps in the direction of MIA. Medical images are stored in a format called DICOM (digital imaging and communications in medicine), which can be accessed by an image processing toolbox. In brain imaging, only the brain is considered; tissues outside the brain (skull, fat, skin, etc.) are not necessarily included. Extraneous tissues often create hindrance with learning process and interfere with segmentation, regression, and classification tasks. By using the skull striping algorithm, a brain mask can be generated and the background can be reduced to zero.

i. Re-sampling: To solve the problem of standard resolution, image resampling is necessary. Magnetic resonance images and computed tomography images, like natural images, do not have a standard resolution. 3D-CNNs are trained on data acquired with a resolution of $1 \times 1 \times 3$, and inputting images with a resolution of $1 \times 1 \times 1$ is expected to yield suboptimal results. Therefore, the best quality can be obtained by resampling using B-splines to bring the image closer to the desired standard resolution.

ii. Medical image registration: Medical images are transformed from heterogeneous data sets into a single coordinate organization. Objects in a set of images are aligned by implementing geometric transformations and local displacements, and can be directly compared. This is due to the fact that the intensity of the tissue is not constant between different MR scanners. This needs to be removed and can be done by a process of bias field correction. This can have a very significant impact on the performance of the algorithm if not taken into account in preprocessing.
iii. Bias-field correction: This is a preprocessing that removes the consequence of bias filed. As the name implies, it corrects the low frequency intensity and non-uniform uniformity present in the MR image before classification is performed.

This uneven uniformity is because of the uninvited signals that temper the generated images. This correction filters out biased images that need to be corrected due to the non-uniform magnetic field of the MR system.
iv. Intensity-normalization: This method is useful for eliminating scanner variability. The Fuzzy C-Means (FCM) normalization technique, commonly used in neuroimaging, combines speed and quality and is capable of creating coarse tissue classifications between white matter (WM), gray matter, and cerebrospinal fluid from 3D brain images based on T1-weighted scans. A white matter segmentation mask is generally employed to estimate the average value of white matter with a user-defined constant module. This normalization strategy almost always seems to yield the desired prediction accuracy in brain imaging scans.
v. Image segmentation: One of the most important steps in medical image processing, where machine learning is currently being used, is image segmentation, which attempts to separate either pathological and anatomical structures by specific types of structures.

4.2 Algorithms Based on Machine Learning

Many studies have shown that the onset of neurodegenerative diseases begins 10–20 years before clinical symptoms appear. Although the molecular mechanisms of neurodegenerative diseases vary, many phenomena such as neurite retraction, synaptic dysfunction and destruction, and ultimately neuronal loss, are considered to be characteristic of neurodegenerative diseases. In the last few decades, our understanding of neurodegenerative diseases has been advanced by intense research on many fronts. Genetics and pathogenesis of selective loss of neurons of have contributed significantly, generated a wealth of knowledge which became the base for the development of new technologies and several therapies for neurodegenerative disorders.

However, many studies have used data sets from a small number of patients, or a small number of images or proprietary data sets. Clinically, diseases are recognized either from the patient's symptoms or from medical images such as MRI for AD or DatScan for PD. The most difficult challenge is to identify the disease in its

early stages, before symptoms appear. In the past, researchers mainly used their own datasets to study AD and followed computer vision techniques. At that time, classical machine learning tools required feature extraction to be done manually, so when done explicitly, support vector machines (SVMs) were preferred [27].

In 2008, the AD Neuro-imaging initiative (ADNI) released a dataset that included AD patients, mild dementia patients, and healthy older adults. ADNI compiled MRI, FDG-PET, and CSF biomarker testing outcomes for each individual, as well as multiple clinical features over a three-year period. The ADNI dataset is now available in several formats. Currently, the ADNI dataset consists of results from hundreds of subjects and serves as a benchmark for AD detection research. In previous studies, features were selectively extracted from the input images of the dataset, and the features were used to train a model using supervised machine learning classification methods. Even for PD, researchers revealed datasets with a small number of patients, few images or proprietary datasets for automated detection. Depending upon the features and parameters selected, different ML techniques have been implemented for this complicated task. As explained in the previous section, there are several well-known tests that are indicators of PD. The disease is diagnosed entirely by the clinically observed symptoms of the patient or by DatScan. When ML is used for computer-aided diagnosis of PD, it is common to use speech data sets, handwriting analysis, sensor data, image data, etc. Table 3 provides an overview of the contributions of artificial intelligence and machine learning to neurodegenerative disease detection and diagnosis over the past few years. Deep learning is considered as the best approach because it is more robust to noise and can perform implicit feature extraction with low error. Performance of DL becomes greater as the scale of data increases. DL train algorithm that is more accurate with enough data without feature engineering (without explicitly writing the rules). Deep Nets achieve accuracy beyond that of classical ML and scales effectively with more data.

Practical challenges for ML in medical Imaging.

Table 3 Shows related work done using various feature extraction and classification techniques

Study	Data-source	Feature extraction	Classifier
[28]	Proprietary	Surface based mesh modelling and feature selection	SVM
[29]	Proprietary	ROI extraction	SVM
[30]	Proprietary	Manual segmentation	AdaBoost SVM
[31]	ADNI	Regional volume segmentation and manual segmentation	OPLS
[32]	ADNI	Cortical thickness tensor based morphometry and manifold learning	LDA, SVM
[33]	ANDI	Extraction of ROI, Multi-task Feature Selection	SVM
[34]	ANDI	Auto-encoder and softmax regression	SVM
[35]	ANDI	SAE & Multi Modal data fusion	DNN with softmax
[36]	OASIS	Slice selection and PCA	SVM

Since most machine learning approaches are based on supervised techniques, training data is critical. Training data is expensive in terms of man-power, cost, time and expertise are required for this task. Training Data manually can be imperfect (wrongly labelled), and manually annotating new data for each test domain is not a practical solution. If data is not perfectly labelled, it will not validate effectively.

4.3 Rise of Deep Learning in CAD

Deep Learning (DL) origin and Growth: DL has been around for quite some time, starting with the McCulloch and Pitts model (Neural Net) in the 1950s, or around 1943 when neural networks were first introduced. From there, it went on to Hebb's Law in 1949, supervised learning by Rosenblatt in 1958, and associative memory in 1980. This concept of associative memory plays an important role in learning and understanding how neural networks associate certain patterns, which means that neural networks learn to understand what a particular class of images looks like. During the 1960s and 1980s, many neuroscientific, biological neuroscientific [22], and mathematical discoveries were made that allowed us to understand how multi-layer perceptron feed-forward occurs and how we can use it to perceive objects visually. To understand how we recognize objects, a new term emerged in the 1980s, neo-recognition, or max spooling, which meant reducing the complexity of the network. From this, another concept emerged: backpropagation. Backpropagation refers to how to back propagate errors, but since 2000, we have moved beyond the era of standard neural networks and entered an era called deep learning. Deep learning is a method that has evolved greatly because there are so many connections between networks, which mean that the number of multiplications and nonlinear operations is very large.

The advent of GPU's based CNN quickly influence and alter memory to accelerate the creation of images in a frame buffer projected for output to a display device. Deep learning neural networks, from neurons to RNNs, CNNs, autoencoders, and deep learning, have been proven to outperform other algorithms in accuracy and speed. Figure 3 shows the time line for deep learning.

4.3.1 Deep Learning in Medical Imaging

DL is being used as a tool to analyze MRIs in two major ways: classification and segmentation. Classification is the process of labelling an MRI image as normal or abnormal, while segmentation is the process of outlining various tissues. Before deep learning, it was actually the more classical ML techniques that helped us the most.

For example, Scikit learn is an open source and widely used Python library that is well developed to guide us when we have data science problems. It helps us to know which method to use, be it classification, regression, dimensionality reduction, etc. Now we can do all this with deep learning. In particular, Medical image analysis

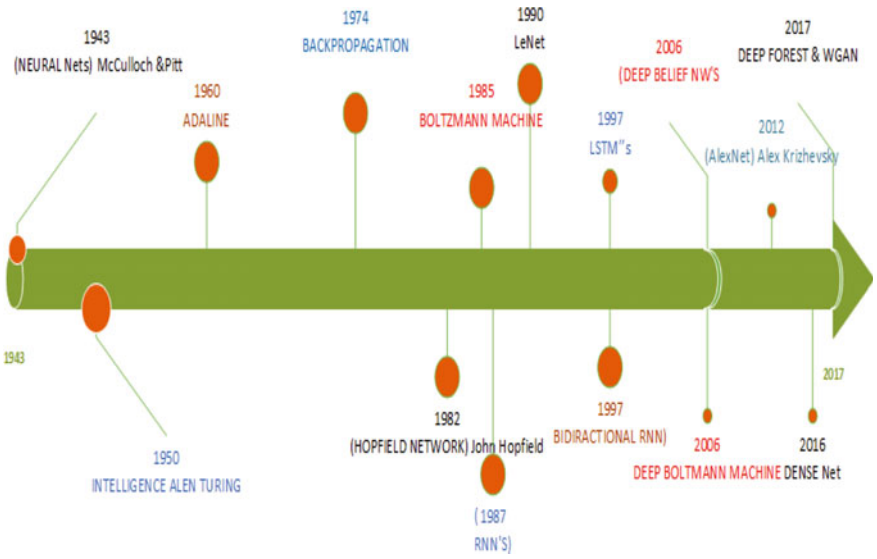

Fig. 3 Shows time line for deep learning

is a technique that we use quite a lot, and deep learning based on decision trees works very well. MRI which has a huge impact on deep learning and indeed image reconstruction, is a great modality because it is safe. MRI acquisition is inherently a slow process. Slow acquisition process is good for acquiring images of static objects like brain and bone but not good for moving objects like heart, foetus and liver because MR images are not that fast. There are two ways to acquire MR images: real-time MR images and gated MR images. There are options for acquiring MR images as real-time MR images and gated MR images. Real-time MR images are fast but two-dimensional (2D) and have relatively poor image quality.

Convolution neural network (CNN): is basically a collection of filters in a two-dimensional (2D) array (e.g., a 3 × 3 matrix). When it receives an input image, this 2D array/filter glides over the input image all the way until no other images are visible to browse. This process is called convolution and is referred as a convolutional network. In the convolution setting, the first filter is for identifying patterns such as straight lines and curves. The first layer is for retrieving and extracting patterns from the input image data. Deeper filters enhance CNN's ability to handle more complex pattern recognition related issues [37]. The degree of deepening determines the quality of the information obtained. There has been a clear shift from doctors doing everything manually to computational systems that support and assist them, and in the modern era, deep neural networks (NNs) and CNNs are helping doctors to diagnose problems. In the recent times, CNN algorithms and their variants have become very prominent and have made a significant impact with respect to medical imaging [38, 39]. Due to the variety and large number of images being generated,

Table 4 Deep learning applications for different disease diagnosis based on medical imaging

Deep learning method	Application area	Data source
Convolution Neural Network (CNN)	Alzheimer's disease	MRI, PET
Convolution Neural Network (CNN)	Cardiac CAC	CT
Convolution Neural Network (CNN)	Diabetic retinopathy	Fundus image
Convolution Neural Network (CNN)	Brain lesion segmentation	MRI
Convolution Neural Network (CNN)	Lung cancer	MRI
Deep Neural Network (DNN)	Lung Cancer	CT
Convolution Neural Network (CNN)	Blood analysis	Microscopic
Convolution Neural Network (CNN), Deep Neural Network (DNN)	Blood Vessel	Fundus

a sub-stream has been formed which results in a very important aspect of medical imaging diagnosis called computer aided diagnosis. Table 4 shows a brief list of various deep learning applications in medicine. This shift is mainly due to people's desire for better care, improvements, and more accurate outcomes. DL in medicine is an innovative step, ranging from screening for cancer, monitoring diseases to suggesting modified treatments.

4.3.2 Reasons for the Use of Machine Learning and Deep Learning in AD Detection

Before deep learning, there was a time when people started using random forests because they realized that a lot of decision trees can make a very powerful classifier. In 2012, unsupervised pre training, AlexNet, came into existence. AlexNet is the name of a convolutional neural network designed by Alex Krizhevsky. The optimal classification performance obtained using multimodal neuroimaging and fluid biomarkers were coupled using DL. DL algorithms continue to improve in performance and appear to offer promise for diagnostic assessment of AD utilizing multimodal neuroimaging data [40]. AD research that employs deep learning is continually expanding, improving performance by combining more hybrid data types, such as omics data, enhancing transparency with explainable methodologies that contribute knowledge of particular disease-related characteristics and processes. Since then, there has been a significant shift so that random forests are no longer the

first choice, and standard convolutional neural networks are the baseline. The deep learning models used these days are arranged in such a way that many hidden layers are stacked on top of each other. The way these hidden layers are stacked makes it possible to learn extremely complex associations between input and output data. This is where the power of deep learning comes in. DL has recently been able to replicate ANNs to achieve multilayer ANN computations. ANNs are compilations of trainable mathematical units that are composed of layers that work together to solve convoluted tasks.

5 Conclusions

It is estimated that each individual has some form of neuro-degenerative disease such as AD, PD, ALS or fronto-temporal dementia. Numerous neuro-degenerative diseases are sequelae of neuro-degeneration process. As a result, the treatment cost is predicted to rise dramatically. Over 30 million people around the world have AD and it is 5 times less as many have PD. The Number of people with AD will increase to about 100 million by 2050 which is quite a tremendous increase. Therefore, it is necessary to examine the challenges and problems from the perspectives of the early detection/diagnosis. In the recent years, machine learning and artificial intelligence have emerged as powerful tools, providing algorithms that can solve classification problems in neuro-imaging data. However, machine learning algorithms have limitations in size of data and feature extractions. Deep Learning algorithms based on deep convolution networks (DCN), long short term memory (LSTM) and recurrent neural networks (RNN) in the recent past have emerged as more powerful paradigms with deep feature extraction layers to solve the complexity of neuro-imaging data and provide a wide range of medical imaging solutions. Therefore, it is clear that algorithms based on deep neural networks (e.g., DCNN) have become a major tool that allows neurologists to have a great impact on patients care by developing software based systems for accurate detection and interpretation of diagnosis through classifications models. Such algorithms in medical imaging enables early as well as quick diagnostic with visualization, treatment planning and outcome evaluation. These algorithms have a great potential to improve the ability to accurately map a patient's tissue sample from the inside to a specific diagnosis. Hybrid models based on DL algorithms such as (RNN, LSTM and 3D-deep convolution neural networks (3D-DCNN)) as a classification model for the early detection and diagnosis of Alzheimer's are effective. The outcomes of the proposed model are compared with existing algorithms to confirm the effectiveness of the proposed model.

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Machine Learning Models for Diagnosing Alzheimer's Disorders

Kamini and Shalli Rani

Abstract Alzheimer's disease is a neurodegenerative disorder which affects millions of people around the world. Machine learning (ML) models have emerged as a promising tool in early diagnosis and prediction of Alzheimer. One popular approach is to use neuroimaging data to train ML models to classify individuals as either having Alzheimer's disease or being healthy. These models can also be used to predict the progression of the disease in individuals over time. Another approach is to use ML models to analyze data from cognitive tests to identify patterns that may indicate the onset of Alzheimer. ML models can also be used to develop personalized treatment plans for individuals based on their cognitive profile. While there is still much work to be done in this field, ML models show great potential for improving our understanding and management of Alzheimer's disease. These models have the potential to provide more accurate and timely diagnoses, identify at-risk individuals earlier, and improve treatment outcomes.

Keywords Machine learning · Alzheimer disorder · Health · Increasing life expectancy

1 Introduction

Millions of people throughout the world are afflicted by the progress of Alzheimer which is generally considered as a significant public health issue. According to World Health Organization, an estimated 50 million people currently have dementia, with Alzheimer's disease. By 2050, large number of people are supposed to experience such disorder to triple to 152 million. Thus, characterization of such disease is performed on the basis of progression of degeneration of neurons lying within brain, leading to cognitive decline and memory loss. While the exact causes of Alzheimer is not understood yet, collaboration of genetic and environmental factors are considered as a responsible factors behind its cause.

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The accumulation of beta-amyloid plaques and tau protein tangles in the brain is a hallmark of the disease and is thought to contribute to the disruption of neural communication.

Currently, Alzheimer is incurable, and available treatments can only temporarily alleviate symptoms. Early diagnosis as well as intervention are vital to improve outcomes, making development of tools as well as methods for early detection and prediction a critical area of research. Machine learning models have shown promise in aiding detection at an initial stage as well as prediction of Alzheimer. By analyzing patterns in neuroimaging data as well as cognitive test results, these models can identify individuals at risk of developing the disease and enable early interventions. In a recent review article, authors highlight the potential of machine learning approaches to improve the diagnosis, prediction, and treatment of Alzheimer's disease [1].

Machine learning (ML) models have shown great potential for aiding initial diagnosis as well as prediction of Alzheimer. By analyzing patterns in neuro-imaging data and cognitive test results, these models can identify individuals at risk of developing the disease and enable early interventions, ultimately improving outcomes. One approach of using ML for Alzheimer's disease is analyzing neuroimaging data to train models to classify [2] individuals as either having Alzheimer's disease or being healthy. These models can also be used to predict the progression of the disease in individuals over time. Another approach is to use ML models to analyze data from cognitive tests to identify patterns that may indicate the onset of Alzheimer.

Demonstration of various studies for significantly showing the potential of ML models in detecting early signs of Alzheimer's disease has been performed by various authors. Marquand et al. [3] found that ML models trained on neuroimaging data could accurately predict stage of Alzheimer's in individual patients up to three years before clinical symptoms appeared. Similarly, Jie et al. [4] utilized deep learning model which could accurately classify individuals with Alzheimer based on their neuroimaging data.

Development of ML models for Alzheimer's disease is an active area of research, with many promising approaches being explored. As the technology and understanding of the disease continue to advance, utilization of ML in diagnosing Alzheimer as well as prediction is expected to become even more effective.

2 ML Based Medical Examination Description for Diagnosing Alzheimer Disorder

Medical examination plays a crucial role while diagnosing Alzheimer, and machine learning (ML) models are increasingly being used to aid in this process. ML models can analyze data from a variety of medical examinations, including neuroimaging data and cognitive test results, to identify individuals at risk of developing the disease and enable early interventions.

One of the most common types of medical examination used in Alzheimer's disease diagnosis [5] is neuroimaging, such as magnetic resonance imaging (MRI) and positron emission tomography (PET). These imaging techniques can reveal the presence of amyloid beta plaques and tau protein tangles in the brain, which are key markers of Alzheimer's disease. ML models can analyze these images to accurately identify the presence and location of these markers, and use this information to predict the progression of the disease.

Cognitive tests, such as Mini-Mental State Examination (MMSE), are utilized frequently in Alzheimer diagnosis. These tests assess an individual's cognitive function, including memory, attention, and language abilities. ML models can analyze the results of these tests to identify patterns that may indicate the onset of Alzheimer's disease.

ML models can also be used to analyze data from other medical examinations, such as blood tests and genetic tests, to identify biomarkers associated with Alzheimer's disease. By combining data from multiple sources, ML models can provide a more comprehensive and accurate assessment of an individual's risk of experiencing such disorder.

Overall, utilization of ML models during medical examination for Alzheimer's disease has great significance in diagnosing and enabling earlier interventions, ultimately leading to better outcomes for those affected by this debilitating condition.

3 Alzheimer Datasets Description

There are various datasets available for Alzheimer's disease research, each with its unique features and applications. Here are some commonly used datasets in Alzheimer's disease research:

i. Alzheimer's Disease Neuroimaging Initiative (ADNI): This dataset includes imaging, clinical, and genetic data from over 1,500 individuals suffering from Alzheimer with healthy images. It also includes MRI, PET, and other imaging data, as well as cognitive test results and clinical data. ADNI has been widely used to develop and evaluate machine learning models for Alzheimer's disease diagnosis and prediction [6].
ii. Australian Imaging, Biomarkers and Lifestyle (AIBL) Study of Aging: This dataset includes imaging, clinical, and genetic data from over 1,000 individuals with Alzheimer and normal controls. The dataset includes MRI, PET, and other imaging data, as well as cognitive test results and clinical data. AIBL has been used to study the relationship between imaging biomarkers and cognitive decline in Alzheimer's disease [7].
iii. The Open Access Series of Imaging Studies (OASIS): This dataset includes imaging and clinical data from over 1,400 individuals, including those with Alzheimer's disease, mild cognitive impairment, and healthy controls. The dataset includes MRI data and clinical data, as well as cognitive test results.

OASIS has been used to develop and validate machine learning models for Alzheimer's disease diagnosis [8].

iv. Alzheimer's Disease Exome Sequencing (ADES) Project: This dataset includes genetic data from over 5,000 people suffering from Alzheimer and normal scans. The dataset includes exome sequencing data, as well as clinical data. ADES has been used to identify genetic variants associated with Alzheimer's disease [9].

These datasets, along with others, have been instrumental in advancing our understanding of Alzheimer's disease and developing new diagnostic and therapeutic tools. Researchers can access these datasets through various platforms, like Alzheimer's Disease Data Sharing Initiative (ADDSI) and Global Alzheimer's Association Interactive Network (GAAIN).

4 ML Models' Methodology for Diagnosing Alzheimer's Disorder

There are various machine learning models that have been proposed for the diagnosis of Alzheimer's disease using neuroimaging and clinical data. Here are some commonly used methodologies along with their authors and references:

i. Convolutional Neural Networks (CNN): CNNs have been used to classify Alzheimer and normal images based on MRI inputs. These models use multiple convolutional and pooling layers to learn complex features from the image data. Some studies have also incorporated transfer learning techniques to improve the performance of these models [10, 11].

ii. Support Vector Machines (SVM): SVMs have been used for classification of Alzheimer via features extracted from MRI, PET, and other neuroimaging modalities. These models use a linear or non-linear hyperplane to separate the two classes of data. SVMs gained high accuracy while diagnosing Alzheimer [12].

iii. Random Forest (RF): RF is a type of ensemble learning model that combines multiple decision trees to classify Alzheimer's disease. RF has been used for classification of Alzheimer via utilizing features extracted from MRI, PET, and other neuroimaging modalities. These models have shown high accuracy in diagnosing Alzheimer's disease [13].

iv. Deep Belief Networks (DBN): DBNs are a type of deep learning model that have been used to classify Alzheimer's disease using MRI and other neuroimaging modalities. These models use multiple layers of neurons to learn complex features from the input data. DBNs are included for achieving high accuracy while diagnosing Alzheimer [14].

These machine learning models, along with others, have shown promise in accurately diagnosing Alzheimer's disease. However, there is a requirement for further

research to test their effectiveness along with ensuring their practicality in clinical settings.

5 Architecture of ML Models in Diagnosing Alzheimer's Disorders

Here are some examples of the architecture of machine learning models that have been proposed for the diagnosis of Alzheimer's disease by various authors although basic methodology of diagnosing Alzheimer disorder has been shown in Fig. 1:

v. Multi-modal Deep Learning Architecture: This architecture combines different types of neuroimaging data, such as MRI and PET, to classify Alzheimer's disease via collaborating CNN and LSTM networks for learning complex features from input data [15].
vi. Graph Convolutional Networks: Graph convolutional networks (GCNs) have been used to classify Alzheimer's disease using brain network data. The model uses multiple graph convolutional layers to learn the spatial and structural features of the brain networks [16].
vii. Multi-task Learning: This architecture combines multiple tasks, such as diagnosis and disease progression prediction, to improve the performance of the model. The model uses a combination of CNNs and recurrent neural networks (RNNs) to learn features from neuroimaging and clinical data [17].

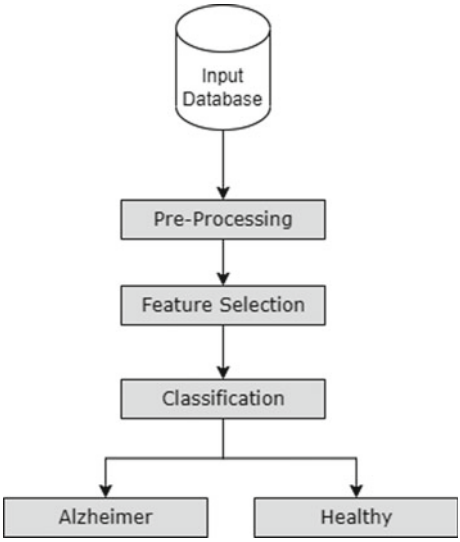

Fig. 1 Basic architecture of ML model for diagnosing Alzheimer disorder

viii. Capsule Networks: Capsule networks are proposed to classify Alzheimer using MRI data. The model uses capsules, which are groups of neurons that can learn different features of an image, to improve the accuracy of the model [18].

These are just a few examples of the different architectures which are proposed to detect Alzheimer using machine learning. Each architecture has its own strengths and weaknesses and may be more appropriate for certain types of data or diagnostic tasks. Further research is required to test models' effectiveness as well as determination of utilized clinical utility.

6 Comparison of ML Models in Diagnosing Alzheimer's Disorders

Several models of ML are proposed for the diagnosis of Alzheimer, and here are some of the comparisons among these models with references:

i. Convolutional Neural Network (CNN) vs. Support Vector Machine (SVM): In a study, Sarraf et al. [15] compared CNN and SVM performance on MRI input, CNN model outperformed the SVM model with an accuracy of 95.0% compared to 88.6%.
ii. Multi-modal vs. Single-modal Data: In a study by Sarraf et al. [15], they compared the use of single-modal (e.g., MRI) and multi-modal (e.g., MRI and PET) neuroimaging data found that the multi-modal data improved the accuracy of the model. The study used a combination of CNNs and LSTM networks.
iii. Deep Learning vs. Traditional Machine Learning: In another study, Li et al. [17] compared the performance of deep learning models, including CNNs and recurrent neural networks (RNNs), with traditional machine learning models, such as SVM and logistic regression. The deep learning models achieved higher accuracy and AUC values than the traditional models.
iv. Ensemble vs. Single Model: An ensemble model that combined multiple deep learning models was found to perform better than any single model alone according to study done by Li et al. [17]. The authors used a combination of CNNs and RNNs on MRI data.

Overall, these studies suggest that deep learning models, particularly CNNs, may outperform traditional machine learning models in the diagnosis of Alzheimer's disease. The use of multi-modal data and ensemble models may also improve the accuracy of the model. However, further research is required to test its findings and for determination of clinical utility of such models.

7 Contributions of ML Models in Diagnosing Alzheimer's Disorders

Machine learning models have made significant contributions to the diagnosis of Alzheimer's disease. Here are some of the key contributions with references as shown in Fig. 2:

i. Improved Diagnosis Accuracy: Machine learning models gained better accuracy while diagnosing Alzheimer using a various biomarker, including neuroimaging and genetic data [18].
ii. Early Detection: Machine learning models can aid in detection of Alzheimer initially, which is critical for effective treatment and management [19].
iii. Personalized Medicine: Machine learning models can enable personalized medicine approaches to treat as well as managing Alzheimer by identifying individual risk factors and predicting disease progression [20].
iv. Identification of Biomarkers: Machine learning models can aid in the identification of biomarkers for Alzheimer's disease, which can lead to the development of new diagnostic and therapeutic approaches [21].
v. Reduced Cost and Time: Machine learning models can help reduce the cost and time associated with Alzheimer's disease diagnosis by automating the process of image analysis and interpretation [22].

In summary, machine learning models have made significant contributions to the diagnosis of Alzheimer's disease by improving accuracy, enabling early detection and personalized medicine, identifying biomarkers, and reducing cost and time. These contributions have the potential to improve patient outcomes and advance our understanding of the disease.

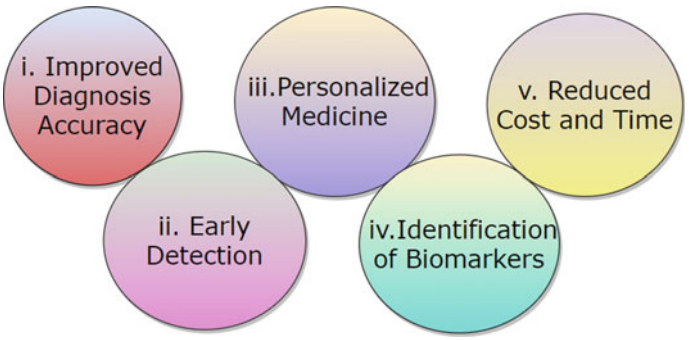

Fig. 2 Contributions of ML models in diagnosing Alzheimer

8 Challenges and Opportunities of ML Models in Diagnosing Alzheimer's Disorders

While machine learning models hold promise for improving diagnosis of Alzheimer, several challenges as well as opportunities relevant to it exist too which need to be addressed. Here are some of them with references.

8.1 Challenges

i. Interpretability: The lack of interpretability of the model can hinder its clinical application and adoption [20].
ii. Lack of Standardization: One challenge is the lack of standardization in imaging and data acquisition, which can lead to variability in the data and affect the performance of the model [21].
iii. Data Imbalance: The imbalance in the number of samples between the healthy and diseased groups can also affect the performance of the model and lead to bias [23].

8.2 Opportunities

i. Early Diagnosis: Machine learning models have the potential to aid in the early diagnosis of Alzheimer's disease, which can lead to better treatment and management of the disease [19].
ii. Personalized Medicine: The use of machine learning models can also enable personalized medicine approaches to treat and managing Alzheimer [20].
iii. Drug Development: Machine learning models can also aid in the development of new drugs to treat Alzheimer by identifying biomarkers and drug targets [21].

In summary, while there are several challenges associated while utilizing ML models for detection of Alzheimer, there are also opportunities for improving early diagnosis, enabling personalized medicine approaches, and aiding in drug development. Addressing the challenges and leveraging the opportunities can help improve the clinical utility of these models.

9 Results and Discussion of ML Models in Diagnosing Alzheimer's Disorders

Machine learning models have shown promising results in diagnosing Alzheimer's disease. Here are some of the key findings and discussions with references:

i. High Accuracy: Several studies have reported high accuracy rates of machine learning models in diagnosing Alzheimer's disease using various biomarkers such as neuroimaging, cerebrospinal fluid, and genetic data [24, 25].
ii. Early Detection: Machine learning models have demonstrated the ability of diagnosing Alzheimer initially, which is critical for effective treatment and management [19, 26].
iii. Identification of Biomarkers: Machine learning models have aided in the identification of potential biomarkers for Alzheimer's disease, which can lead to the development of new diagnostic and therapeutic approaches [27, 28].
iv. Interpretability and Explainability: One of the major challenges of machine learning models is their lack of interpretability and explainability. However, recent studies have proposed methods for interpreting and explaining the decisions made by these models, which can enhance their clinical utility [29, 30].

Comparison of existing ML Models has also been given below in Table 1 on the basis of diagnosis of Alzheimer's disorder which is further comprises of publication year, author details, references, tools, techniques, dataset, percentage of performance metrics.

In summary, machine learning models have shown promising results in diagnosing Alzheimer's disease by achieving high accuracy, enabling early detection, identifying potential biomarkers, and improving interpretability and explainability. These results suggest that machine learning models have the potential to significantly improve the diagnosis and management of Alzheimer's disease.

10 Conclusion

Machine learning models have shown great potential in diagnosing Alzheimer's disease by achieving high accuracy rates, enabling early detection, identifying potential biomarkers, and improving interpretability and explainability. These models have the potential to significantly improve the diagnosis and management of Alzheimer which can provide better patient outcomes as well as quality of life. However, there are still challenges that need to be addressed, such as the need for larger and more diverse datasets, standardization of data collection and analysis, and validation of the models in clinical settings. Despite these challenges, the progress made in the development and application of machine learning models in diagnosing Alzheimer's disease is encouraging and holds promise for the future. Further research and collaborations between clinicians, data scientists, and researchers will be critical to advancing this field and improving the lives of individuals affected by Alzheimer's disease.

Table 1 Comparison of existing ML models for diagnosing Alzheimer's disorder

Model	Publication year	Reference	Tools	Techniques	Objectives	Dataset	Performance metrics
SVM-RFE	2014	Eraslan et al. [31]	MATLAB	Support Vector Machine (SVM) with Recursive Feature Elimination (RFE)	To identify significant features for Alzheimer's disease classification	ADNI dataset	Accuracy: 91.5%
Random forest	2015	Liu et al. [32]	R	Random Forest (RF)	To predict Alzheimer's disease using neuropsychological tests	ADNI dataset	Sensitivity: 91%, Specificity: 91%, Accuracy: 91%
LASSO	2016	Lin et al. [33]	MATLAB	Least Absolute Shrinkage and Selection Operator (LASSO)	To identify potential biomarkers for Alzheimer's disease	ADNI dataset	Accuracy: 80.5%
3D CNN	2018	Suk et al. [34]	TensorFlow	3D Convolutional Neural Network (CNN)	To diagnose Alzheimer's disease using MRI images	ADNI dataset	Accuracy: 81.4%
Autoen-coder	2019	Guo et al. [35]	TensorFlow	Autoencoder	To identify biomarkers for Alzheimer on the basis of MRI inputs	ADNI dataset	Accuracy: 86.2%

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Alzheimer's Disease Diagnosis Using MRI Images

Mahmoud Ahmad Al-Khasawneh, Abdulrahman Alzahrani, and Alaa Alarood

Abstract As one gets older, the likelihood of this happening increases. Minor cognitive impairment may serve as an early warning sign of dementia, according to popular belief. Some of the claims stated here are not supported by sources. Alzheimer's disease and other kinds of neurodegeneration frequently manifest their first signs as dementia. People with poor intellect may struggle to discern between a sick and a healthy reference group. Our system can efficiently extract as much data from the scan as was feasible by using the entire three-dimensional magnetic resonance imaging images as input. The multichannel meta-discourse learning approach improves the system's and network's categorization abilities as well as their ability to make large generalizations. One option for achieving this goal is to broaden the number of available educational routes. The binarization loss and the unchaperoned contrastive loss are combined into a single loss to achieve this. Combining the binarization loss and the unchaperoned contrastive loss results is a realistic method that may help you achieve your aim. We ran many experiments using the acquired data to put our system through its paces and verify its value. These findings show that our method might be used to diagnose Alzheimer's disease, dementia, and mild cognitive impairment (MCI). Individual adaptation to their preferred mode of learning is one method that, if implemented, has the potential to significantly boost the value of educational experiences. By creating a fresh perspective on education, the network may be able to assist us in classifying data in a more accurate and appropriate manner in a wider range of scenarios.

Keywords Alzheimer's disease · Mild cognitive impairment · Magnetic resonance imaging · Regions of interest · Deep learning

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1 Introduction

Alzheimer's disease (AD) is becoming increasingly common, reviving interest in neuroscience as a subject for investigating how the brain works [1]. Alzheimer's disease is a public health priority in every country, according to the World Health Council, because it affects seniors more than younger people. This brain disorder is progressive in nature, meaning that it worsens with time. Because of the nature of the process, a person having brain surgery may initially be unaware of what is happening to their brain. It's not out of the question that this may happen. Memory loss and difficulty speaking are two symptoms that do not always appear immediately after the first brain abnormalities [2, 3]. Many symptoms may take some time to manifest before designing a treatment strategy, so it is critical to distinguish between Alzheimer's disease, mild cognitive impairment, and normal brain function. This should be accomplished before designing a treatment approach. In terms of cognitive capacity, the normal group most closely resembles the Alzheimer's disease group. The group that deviates the most from the others is considered abnormal. In order to accomplish this, a thorough assessment of the patient is required [4]. Figure 1 depicts the findings of three-dimensional brain scans on patients with varying degrees of disease. The scans were also performed on patients who looked to be in excellent physical condition. In theory, the progression of a disease might be tracked by evaluating how it alters the anatomical makeup of the brain. This is because each of these disorders is associated with natural aging.

According to these studies, the systems can spot abnormalities because they don't need human input during the feature creation stage, and deep learning works better than standard machine learning approaches. Deep learning makes it possible to automatically pull out characteristics from photos that can then be used to put things into groups. The term "deep learning" refers to this method. The four most important feature extraction approaches allowed by deep learning are as follows: To propose prospective remedies, several approaches, such as 2-D slices [4], 3-D global slices, and 2-D regions of interest (ROI), have been applied. In this case, feature extraction is regarded as complete after the criteria have been met. The initial stage in extracting features from three-dimensional pictures is to flatten them down to two dimensions. By selecting backdrops that will be most beneficial to you, you may lessen the influence of those that will not. However, if you followed this method, you would be discarding vital information that was saved in the spaces between the pie pieces. Using the 3-D patch-based approach, the initial 3-dimensional pictures are separated into specified 3-dimensional patches. The next phase makes use of these fixes. At that moment, the classifier is "trained" with these patches. Real 3D photos must be utilised to get the highest level of accuracy in the findings. If this strategy were used, the player would lose geographic information anytime they shifted between patches, even though it would reduce processing costs and the learning curve. By segmenting the original pictures into portions that reflect distinct anatomical components such as grey matter, white matter, or the hippocampus, the ROI-based technique allows the network to be trained using other anatomical properties [5]. This is accomplished

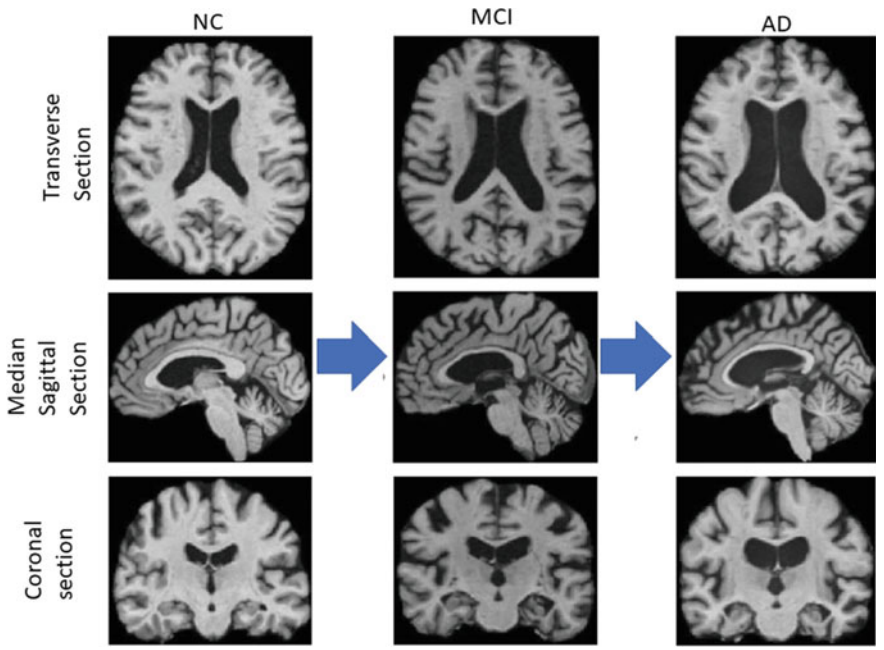

Fig. 1 Three-dimensional brain magnetic resonance imaging (MRI) images of people suffering from various degrees of illness severity

using indicators relating to the amount of return on investment. With this technique, the network's processing capacity will be directed towards the data that will have the most influence on the classification problem. In either instance, the morphological structure of the image will change, affecting the data stored inside and resulting in data loss. By employing a three-dimensional overall viewpoint, it may be possible to preserve as much of a picture's spatial information and finer details as is practically possible. When we compared the various strategies, we discovered that putting the complete image into the network held the most potential.

2 Related Work

In this study, we look at the possibility of creating a self-operating Alzheimer's disease diagnostic system based on multichannel contrastive learning and three-dimensional convolutional neural networks (3-D CNN). When compared to previous publications' self-supervised contrastive learning methodologies [6], the innovative methodology presented here stands out. Self-supervised description learning is one way to efficiently pre-train an unsupervised network. To achieve class invariance, a large amount of unlabeled data is first exposed to two separate transformations. This

produces class invariance, which may subsequently be used to get supervision data. The formation of class invariance is the outcome of these adjustments. When working with unlabeled data, this approach employs a two-stage data processing pipeline. The manager's data was incorporated into the network's first training program. In the subsequent steps, new jobs are done using the pre-trained network. For supervised classification problems, we recommend employing multichannel contrastive learning in combination with unsupervised network pretraining. This research will help develop approaches for automated Alzheimer's disease detection that uses multichannel contrastive learning and 3-D CNN. When compared to previous publications' self-supervised contrastive learning methodologies [7], the innovative methodology presented here stands out. Self-supervised description learning is one way to efficiently pre-train an unsupervised network. To achieve class invariance, a large amount of unlabeled data is first exposed to two separate transformations. This produces class invariance, which may subsequently be used to get supervision data. The formation of class invariance is the outcome of these adjustments. When working with unlabeled data, this approach employs a two-stage data processing pipeline. The manager's data was incorporated into the network's first training program. In the subsequent steps, new jobs are done using the pre-trained network. For supervised classification problems, we recommend employing multichannel contrastive learning in combination with unsupervised network pretraining. This immediately leads to increased accuracy. Furthermore, the two-channel system is preferred over the multichannel approach because it can send supervisory data more effectively [8]. This is done so that the multichannel approach can employ more than two channels at the same time.

The use of the wideband contrastive learning technique was the first step towards better classification tasks for dementia vs. age-related normal aging and Alzheimer's disease vs. age-related normal aging. Both projects require comparing two different stages of aging. The work of correcting the previous categorization errors has now begun. These two tests were developed to differentiate Alzheimer's disease from the usual effects of aging. This component directly contributed to the generalizability of the network and task. As a result of this change, those in control of the project now have direct access to extra data. Another area of investigation was how the addition of new channels may alter how well a network functions. This was done to make assembling geographic information and other facts about certain photographs easier. We provided a wide range of data manipulation tools, such as expanding the edges, normalizing the histogram, and introducing noise [9]. As an added benefit, research was conducted on data amplification techniques and the potential effects those techniques may have on network performance. To build an efficient learning strategy that bridges the gap between supervised and contrastive learning, a dynamic fractional factorial design was created. This is how the experiment was carried out. The availability of empirical evidence supporting our method's application in clinical practice has improved its ability to distinguish between moderate cognitive impairment and Alzheimer's disease. These early efforts used cutting-edge technology at the time they were implemented.

Deep learning is recommended above other standard machine learning approaches since it does not require the user to manually generate the attributes that are used

in the model. Therefore, deep learning is the most reasonable alternative. Numerous studies have shown that CNN is excellent at locating visual clues that can aid in AD diagnosis. Recent research has used the 3-D CNN model to analyse 3-D picture data and extract numerous aspects. This phase was included in a lot of the trials that were conducted. Researchers have recently finished all the necessary preparatory work for these studies [10, 11]. When it comes to identifying Alzheimer's illness, for example, networks surpass other, simpler classification networks. To reach the classifier's findings, this approach includes combining the outputs of multiple separate convolutional neural network layers. As a result, they were exempted from doing feature extraction. In terms of accuracy and resilience, three-dimensional, highly supervised adaptive CNN beats both traditional classifiers and previous CNN-based approaches. The network has just generated three-dimensional full-body MR pictures [12]. As a result, the feature extraction process is simplified. Instead of depending on human annotations, it was suggested that self-supervised learning might be used to learn visual qualities from a vast collection of unlabeled photos or videos. Instead of the typical strategy, this one would be adopted. People would have to intervene significantly less frequently if this were not the case. This bodes well for the collection's possible future growth [13]. To solve this difficulty, academics often employ contrastive learning. Using two separate data transformation strategies, both positive and negative examples are given for contrast learning. This has been done to maybe resolve the issue, and because of the urgency of the current situation, these precautionary actions are being immediately applied. In this context, "positive samples" are photos that were all created from the same beginning point, and "negative samples" are images that were all created from separate starting locations. The network was trained with SimCLR by lowering the sinusoidal spacing between positive specimens and prolonging it between negative specimens. Our decision to proceed in this manner was based on the findings of the previously mentioned study. When compared to a wide range of alternative self-supervised learning procedures, the SimCLR method was shown to be the most successful. Working with enormous data sets will be required, which will necessitate a significant amount of computational power [14]. To address this issue, a specialized library that can temporarily store network output vectors is needed. This has directly impacted on the network's reliance on extremely large batch sizes. Using MoCo, people can learn visualizeise on their own. They use a queue and a motion encoder to create a real-time dictionary with their method. If you keep this dictionary nearby while studying, you'll notice that your efforts are more focused on achieving the desired results. SimSiam networks with strong empirical evidence to back up their claims that the network could successfully find critical information. Unfortunately, due to network constraints, we are unable to provide all of the presentation types authorized here. Negative samples, massive batch sizes, and momentum encoders are just a few of the subjects being researched right now [15]. If you want to increase training outcomes, you must first lower the difference between your two positive training samples. Furthermore, as compared to other, more traditional techniques of comparative schooling, multimedia meta-discourses may produce higher-quality data, making them suitable for use in the context of supplementary supervision. When conducting in-depth research on certain events, such a

tool is quite useful and practical [16–18]. It was done to see if the approach might be useful. This goal was made possible thanks to the algorithm. In the setting of identifiable symptoms, this strategy may be used to obtain a solid diagnosis of Alzheimer's disease. The final diagnostic data was then analyzed using three different runs of the 2D DenseNet approach, with the findings aggregated [19–21]. Using demographic information from the participants and data from the MRI scans, this setup may be able to draw some intriguing inferences. This channel arrangement would make it much easier to conduct parallel investigations on several fronts. Then, using the newly identified landmarks, several image patches from the original shot were reconstructed. A data-driven technique was used to identify the specific areas of MRI images that had anatomical traits that were historically relevant for discriminating. This strategy was used to narrow down the search. Prior to applying the FC layer, the feature map is flattened, which means that whatever spatial information it may have had is disregarded. This step occurs just before the FC layer is implemented. a bidirectional deep neural unit (Bi-GRU) and a two-dimensional convolutional neural network to the study's structure. These two elements would serve as the cornerstone for their investigation [22–24]. They'd base their investigation on both. This was done as a precaution to help reduce the consequences of the crisis. CNNs may fully disregard the properties of the three-dimensional data they analyse because of how the input is turned into a sequence of two-dimensional slices. This simplifies the consumption of content for real-time news networks. There are other slicing strategies, each of which may be used to eliminate a specific set of features. Because of its one-dimensional input space constraint, CNN is often used after a flattening layer. This is due to the layer's limited ability to process data in a one-dimensional input space [25]. These strategies are based on approaches that use CNNs as their foundation. If a flattening layer is added to certain three-dimensional spatial data, all feature maps that were maintained inside the original data are destroyed. This occurs whenever anything is stacked to make it flatter. In the spirit of this study, we advocate feature map mining with FSBi-LSTM to extract relevant contextual and semantic data. This will allow you to properly comprehend the subject. The use of MRI and PET to accurately diagnose Alzheimer's disease seems promising.

3 The Proposed Method

The dataset and the preparation techniques used in this study are described here.

3.1 Dataset

The T1-weighted, three-dimensional brain MRI images we used were from the available ADNI datasets. This is the initiative's primary area of research interest. Volunteers for ADNI come from all throughout North America. Through the ADNI dataset,

Table 1 Subject Demographics from Analyzed Datasets

Dataset	Group type	Gender (male/female)	Age (mean ± Std.)	MMSE (mean ± Std.)	CDR (mean ± Std.)
ADNI	AD	424/399	97.35 ± 9.98	45.49 ± 4.25	2.97 ± 2.47
	pMCI	327/89	97.95 ± 9.27	48.79 ± 3.93	2.72 ± 2.22
	sMCI	I77/99	98.62 ± 9.96	49.49 ± 3.99	2.69 ± 2.26
	NC	424/399	95.97 ± 8.59	49.32 ± 3.23	2.22 ± 2.22
AIBL	AD	55/68	95.56 ± 9.99	42.64 ± 7.68	2.97 ± 2.73
	pMCl	299/245	97.49 ± 8.38	48.46 ± 4.26	2.69 ± 2.35
	sMCI	69/67	96.89 ± 9.43	49.45 ± 4.29	2.68 ± 2.34
	NC	356/395	95.34 ± 8.39	49.99 ± 3.47	2.24 ± 2.42

we were able to collect 3746 MRI scans from 928 patients. Out of the total 928 individuals, 330 have been diagnosed with non-cognitive (NC) symptoms, 299 with AD, and 299 with MCI. We segmented the private data by category and then split it into a training phase (60%), test dataset (20%), and test set (10%) (20%). Table 1 displays demographic information on the people who participated in our MRI studies, including their category, number, gender, average age, standard deviation, and a total number of MRI scans.

Since its inception, multimodal image fusion has been able to integrate complementary data from photographs collected using several modalities. Before contemporary technology, things were done differently. Figure 2 depicts how we utilize the MRI as a mask in our method of image fusion. This allows you to avoid the FDG-PET scan in the whole GM area. This industry is heavily reliant on Alzheimer's disease diagnosis. The MRI scan is used as a mask to achieve this effect. This article will lead you through each stage of the multi-stage picture compositing process.

3.2 Data Preprocessing

These are the five phases that make up our data preparation procedure. For starters, resampling is necessary since the resolution of MRI images varies depending on the distances between 2-D slices. Therefore, the resampling technique was utilised to ensure that there was a consistent 1-mm gap between 2-dimensional slices [26]. Skull stripping [27] was used to hide the model's skull while it was being trained, since Alzheimer's disease has no effect on the skull. MRI pictures suffer from a grey inconsistency due to an uneven magnetic field, but this is an issue we were able to fix by using the intensity correction approach. Background-only slices have been removed from the photos by clipping them. Pictures illustrating the preprocessing procedure (Fig. 2) are provided to aid the reader's intuitive grasp of the procedure.

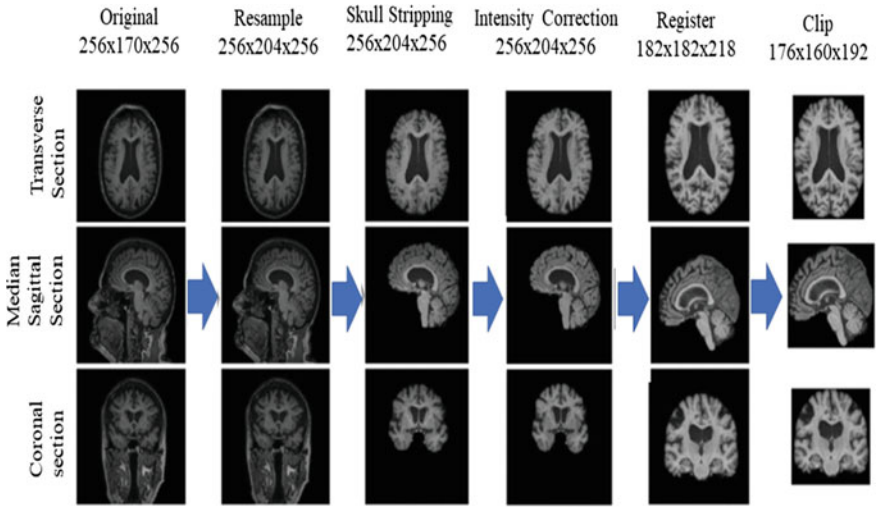

Fig. 2 The pre-processing parameters

Finally, we normalise the photos such that all the pixel values fall within the range of 0–1 using (1) [28]. Different data preparation techniques are shown in Fig. 2. A corona slice (row 3) is superimposed over a middle sagittal segment (row 1) and a transverse section (row 2). Each column represents a different phase of the operation (Row 3). Here, we provide a thorough introduction to the proposed multichannel dialogue learning method, which utilises a multi-U-Net network. As can be seen in Fig. 3, this system is constructed on a three-dimensional U-Net network architecture with multichannel descriptive learning and supervised learning. At first, we provide the framework with N-preprocessed, three-dimensional MRI images [29]. Moving forward, M-data transformation techniques are applied to the input photographs, yielding NM-modified images. Third, we use the NM images to build the output vectors for the NM network by feeding them into our 3-D U-Net one by one. Using i1, …, N, and j1, …, M as input pictures, we may write xi, j to represent the jth modified image. A unique hue is assigned to each of the channels. The notation trans j indicates the kind of data transformation applied to the jth channel's data. Three-dimensional U-Net takes as input the composited results of all the channels' transformations [30, 31]. The supervision loss is used to adjust three-dimensional U-Net and task head parameters. Network parameters are updated using the Adam optimization technique in a gradient fashion.

As shown in Fig. 4: Structural Breakdown of the proposed method, the network will cease worrying about the meta-discourse loss. Thus, a larger weight factor will make the network more sensitive to contrastive loss.

However, early in its training, the network does not have sufficient classification skills. A network will converge in an unexpected way if the contrastive loss is given too much weight. For starters, the right approach needs to make the network converge

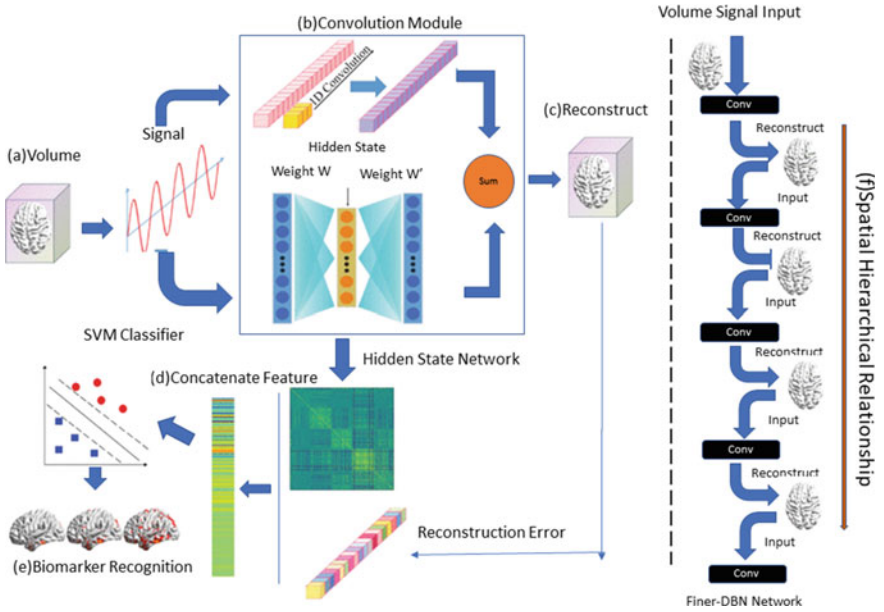

Fig. 3 The proposed method

on the required path. The network's capacity to make accurate classifications will rise as the number of training iterations grows. The network's convergence direction may then be fine-tuned by increasing the weight of discourse loss. This optimization issue was resolved with the help of the adaptive moment estimates (Adam) and their maximum returns. To get the most out of our testing, we've decided to replace the traditional projecting head setup with a hybrid of the 3-dimensional U-Net and Activity Head because CNN has plenty of competition from U-Net, we decided to base our framework on 3-D U-Net because it has been shown to be useful in the automated treatment of AD and MCI. Multiple convolutional neural networks (3-D ResNet, etc.) were tested, but 3-D U-Net gave the best results [32–34]. Figure 3 depicts the three-dimensional U-Net topology that we've developed. To cut down on the amount of math required, we convolutioned the input picture with a 2 by 2 by 2 kernel and a stride of 2. This reduces the size of the image to 1/8 of its original size. The decoder's architecture consists of a $2 \times 2 \times 2$ downsampling layer, a BN wrapping, a ReLU overlay, and a $3 \times 3 \times 3$ convolution network. It's possible that both deep and shallow features are used in the encoder and decoder layers that repeat and join data. Our decoding method utilises convolutional, Lb, and ReLU algorithms to provide 16-channel scale-independent results. After that, the worldwide average layer is used to convert the scale-variant outputs to 16-dimensional vectors. The ultimate output of this network is a 48-D vector formed by concatenating these 16-D vectors. We'll go through all the methods we've written to manipulate data. Figure 5 depicts the image's finalised form following the correction.

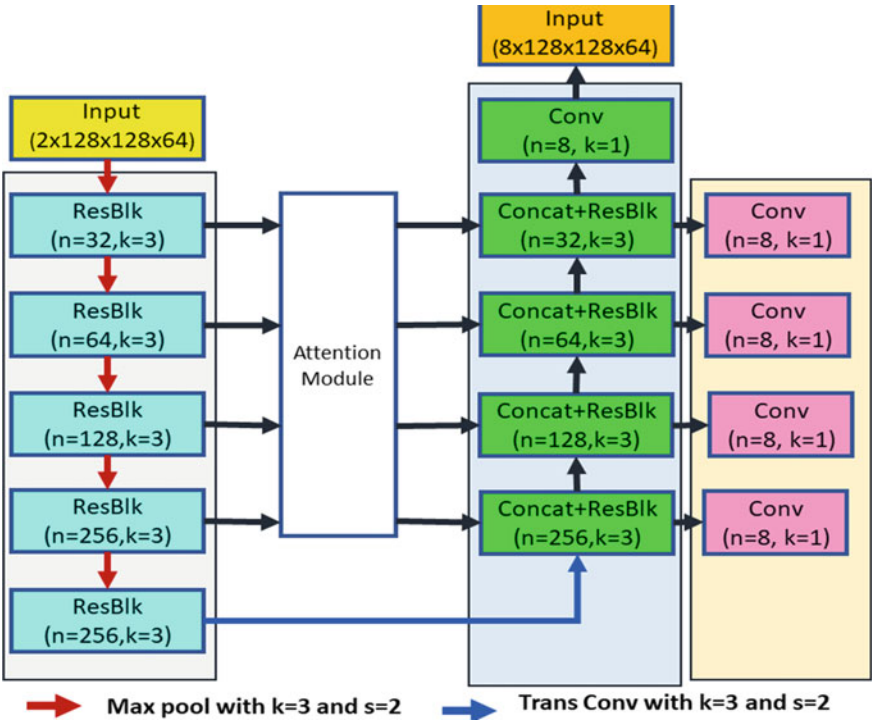

Fig. 4 The structural breakdown of the proposed method

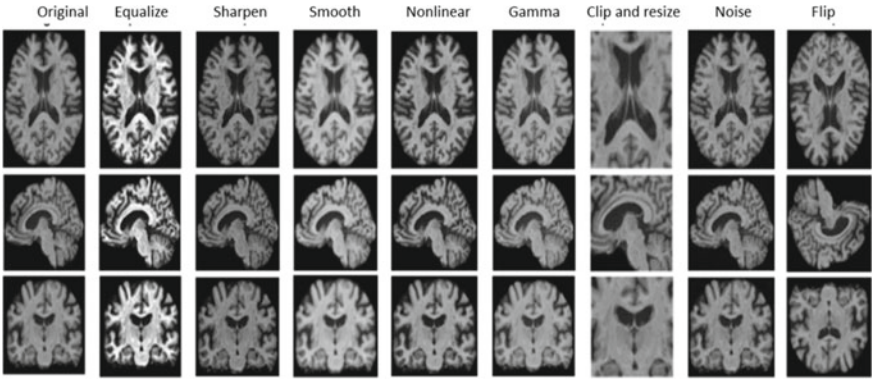

Fig. 5 Methods for transforming data diagrams there is a transverse portion (row 1), a middle sagittal section (row 2), and a coronal slice (row 3). Each column shows the picture after being subjected to a different data processing technique

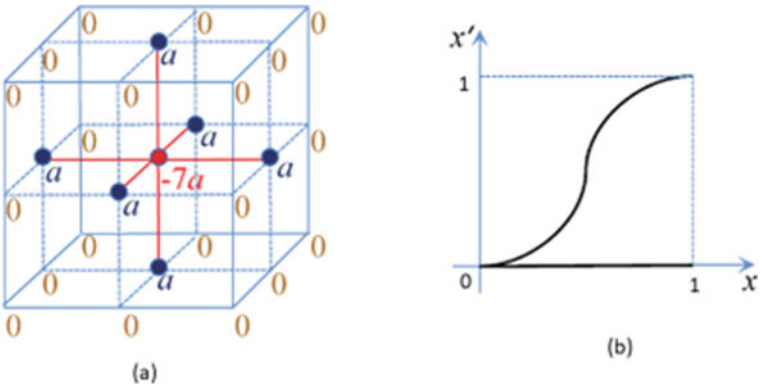

Fig. 6 The nonlinear transformation technique and the fixed convolution kernel in sharpening and smoothing **a** a convolution kernel **b** a change that is not linear

Histogram equalization, which improves visual contrast, is Method 1. Due to the enormous number of pixels occupied by the backdrop, which would have a negative effect on equalization, to do this, we multiply the image's pixel value by b before rounding it up to a number between 0 and b for each cell. Accordingly, we restrict our normalisation to pixels with values between [1, …, b]. We do it by making b equal to 255. In certain cases, sharpening may help bring out more detail in an image, while smoothening can reduce the overall effect of noise. To achieve the desired sharpening or smoothness, we convolve the original image with a fixed 333 convolution kernel. Figure 6 depicts the convolution kernel (a). In this case, we use a value of 0.25 for averaging and a value of 0.25 for sharpening (see Fig. 6a).

We found that a nonlinear modification we developed increased the contrast between grey and white matter within brain pictures. $x' = (2 \times 1)c\ 0.5 + 0.5$, $(2 \times 1)1c\ 0.5 + 0.5$, and $\times\ 0.5 \times 0.5$ is the nonlinear transformation. In the formula, x and x′ represent the before and after pixel values, while c controls the strength of the transformation. In this case, c is established at 0.75. Using this diagram (Fig. 6), we can see the transformation formula in action (b). Since most of the images are rather dim, we employ gamma correction to put them into acceptable ranges. The formula for the gamma transformation is $x' = x(11)$ View Source, where x and x′ are the original and transformed pixel values, respectively, and control the strength of the gamma transformation. A value of 0.75 is chosen here. Fifth, we resized the image to $88 \times 80 \times 96$ pixels by cropping off the irrelevant parts of the original picture. Following this, trilinear interpolation is used to bring the picture back to its original $176 \times 160 \times 192$ dimensions. Adding Gaussian noise to the picture with a median of 0 and a variation of 0.0008 may be used as a knowledge extraction approach. One further method of data transformation is to randomly flip the picture along each axis.

4 Results and Analysis

In this part, we test the main parts of our system, such as the projection-facing approach, the meta-discourse learning technique, the wideband strategy, and the data processing approach. We also looked at how changing the ratio of supervisory loss to contrastive loss affected the overall efficiency of the framework. In addition, the feature map that our model learned was shown using Grad-CAM. The training's convergence was then examined. Finally, we compare our techniques to the current gold standard. Both the AD and non-dementia (NC) diagnostic tests were successful in validating our strategy. As soon as 80 epochs had passed, training was complete. A starting proportional gain of 0.001 was provided. The rate of learning decreases as follows: 0.001 for some values of epoch between 0 and 79. The Grad-CAM visualisation attempt was likewise abandoned picked one of the findings from the threefold cross-validation for the Grad-CAM visualisation experiment after narrowing down our options using a random selection approach. During the trial run, there was only one channel available, and neither the data transformation techniques nor the Projection Helmet network was functional. After being preprocessed, the input photos did not undergo any more alterations in the testing phase. In the tests, four NVIDIA RTX 2080 Ti CPUs were used. We computed measures such as the F1 score, the radius under the ROC curve (AUC), the sensitivity, the specificity, the accuracy, and the ability to categorise data.

In this study, we looked at three different kinds of supervised learning: supervised learning alone (the "Baseline" condition), supervised acquisition using supervised multichannel discourse learning, data integration (Base + Trans), and ours. The stream count was fixed at 2 for both of our approaches and for Base + Trans. The first channel's input was the raw data without any processing, while the second channel's input photos were histogram equalised and randomly flipped. The baseline technique only required a single input channel, and it used the source pictures as its starting point. The baseline and base + trans techniques were unaffected by the projection head, to the detriment of everyone but the manager. We examined and discussed the results of Table 2 using Lsup as the loss function. In the table, red brackets indicate an increase from the baseline, while black ones denote a decrease. The sum of the six measures used for assessment is shown in the last column. This demonstrates that automated diagnoses of AD and MCI may benefit from the inclusion of supervisory information provided by the contrastive learning technique. This was the situation at the time due to the proliferation of various assessment systems.

Table 2 The projector's head's impact (in %)

Layers	Accuracy	Area under the curve	F1 score	Mean
0 Hidden layer	95.59	93.94	96.95	95.53
2 Hidden layer	94.84	93.69	96.32	94.95
3 Hidden layers	94.27	92.28	95.98	94.08

4.1 Effects of Multiple Channels

An analysis of how the model's channel count affects its classification accuracy was the focus of this investigation. The first channel's input was the raw, unaltered photos. Histogram equalization, brightening, adding chaos, and flipping were all used to alter the data in this study. The four adjustments were made to each original photo. The input of each of the M channels was chosen at random from among the four altered pictures (duplicate inputs were not permitted). As the variety of channels in a network grows, so does the volume of data used in the training process, which in turn significantly lengthens the time it takes to complete the training process. Since this is a setting for M, we'll use the value 5. If you look at Fig. 7, you can see how the model's categorization efficiency changes as the number of channels grows. In this case, the model's effectiveness was measured using the ACC, AUC, and F1 scores, three widely recognised measures. Figure 7 shows how the model performs better with additional channels when the AD and MCI classification techniques are used. The relationship between the two numbers provides strong evidence for this assumption. The ACC, AUC, and F1 are used in five different ways as part of the diagnostic process for Alzheimer's disease. The percentages for these three metrics increased by 4.12%, 6.2%, and 2.92% from their beginning points, respectively, to reach 95.06%, 93.98%, and 96.23%. These three factors contributed to a 4.52% point, a 7.77% point, and a 13.76% point rise in the accuracy of the MCI diagnosis from the baseline, for a total of 81.90%, 82.76%, and 82.70%, respectively. This suggests that the model's classifier may be improved by using the multichannel approach we proposed rather than the dual-channel technique. More channels have more of an effect, as seen in Fig. 7.

Two model channels were consistently used in this experiment. To begin with, the unaltered photos served as input to the first channel. Each of the eight data transformation techniques was applied to the second channel's input photos. The results of applying a variety of data processing approaches in the second channel are

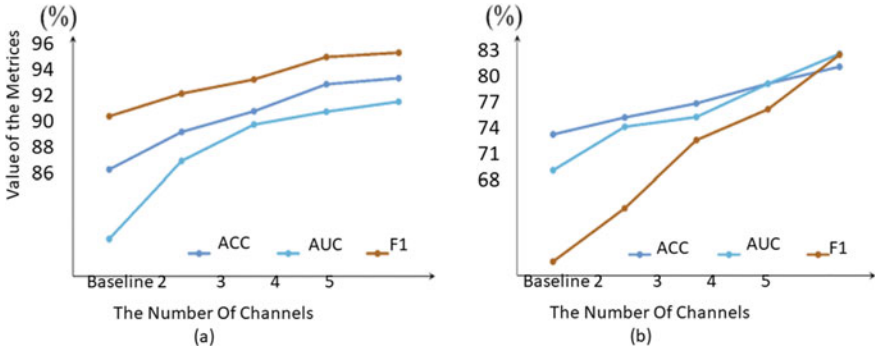

Fig. 7 The total number of channels **a** contrasting and comparing the facts of the AD and NC cases **b** NC versus MCI

compared and analyzed, along with the influence these techniques have on classification performance. As indicators of achievement within the context of this investigation, we decided to make use of the cross-validated average F1, the area under the curve (AUC), and the representative accuracy. The table demonstrates that technique is the preferred method of data transformation; sharpening and flipping may also significantly boost the efficiency of the program. Changes in the Gamma Radius, looking to add tones, multidimensional modification, and blending, can probably largely improve the star's ability to identify AD; however, the clipping but rather resizing methodology has a negative impact on that model's efficiency.

In this experiment that compared network performance using an AD classification task and an NC classification task, the weight variables between the controlled loss and the discourse loss had a big effect on how well the network worked. Four channels were selected. Images were flipped on the fourth channel, while histogram equalization, sharpening, and inversion were utilised on the first three. The network needs a modest boost at the beginning of training to converge on the correct solution space. For optimal network convergence, a sizable pool at the end of training is essential. Four channels were selected. Images were flipped on the fourth channel, while histogram equalization, sharpening, and inversion were utilised on the first three. We examined four scenarios: none with projection heads, one with one hidden layer, and two with two hidden layers. Table 2 displayed the results. This table shows that when there is no hidden layer in the projection head, the best results are achieved.

Figure 8 shows how we use Grad-CAM visualisation to show the parameters that were found using the baseline technique plus our method to show how useful our method is for gathering features. A different hue indicates important locations for categorization. Our approach may focus on learning more valuable traits and putting that knowledge to use in more situations, such as in the diagnosis of AD or MCI. This demonstrates that our approach may give more supervision input for extracting the features, hence enhancing the model's performance.

4.2 Convergence Analysis

All the parameters used in the experiment are like those used in studies of ablation. Figure 9 shows the simulation loss plots and the validation loss plots to show how well our actress did at fitting and converging during training. As shown in the figure, when we use our strategy and the Base + Trans strategy, the training time for both the AD and MCI diagnostics converges more quickly right before the 30th epoch. The results show that when we combined our method with the Base + Trans strategy, we were able to match the training data faster. Also, all three approaches eventually end up with a training loss of 0, which shows that they all fit the training data very well. After the 30th epoch, our method can lead to a lower value for the test dataset, which means it matches the validation data better. The validation loss often performs far worse than the training loss when it comes to convergence. Our future work will focus on finding a solution to this overarching issue.

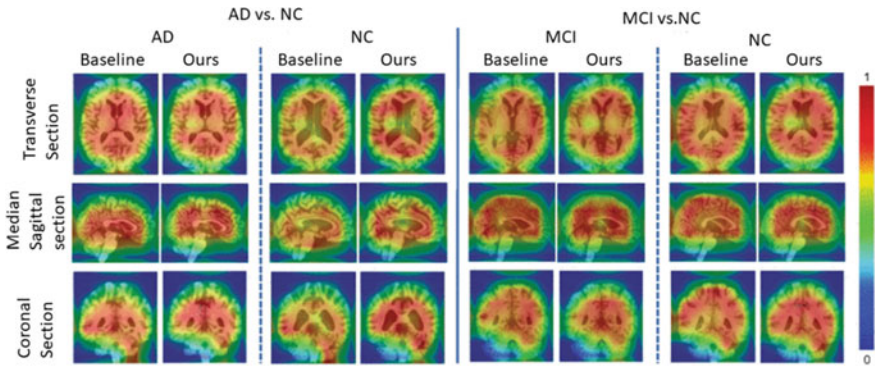

Fig. 8 The learned properties of our technique in grad-CAM compared to the baseline. Hypertension images from the AD versus NC classification test make up the first two columns, whereas NC photos from the same task may appear in the third and fourth, and MCI photos from the same set of classifiers might appear in the fifth and sixth. Sections could each contain a machine image from the AD versus NC classification problem

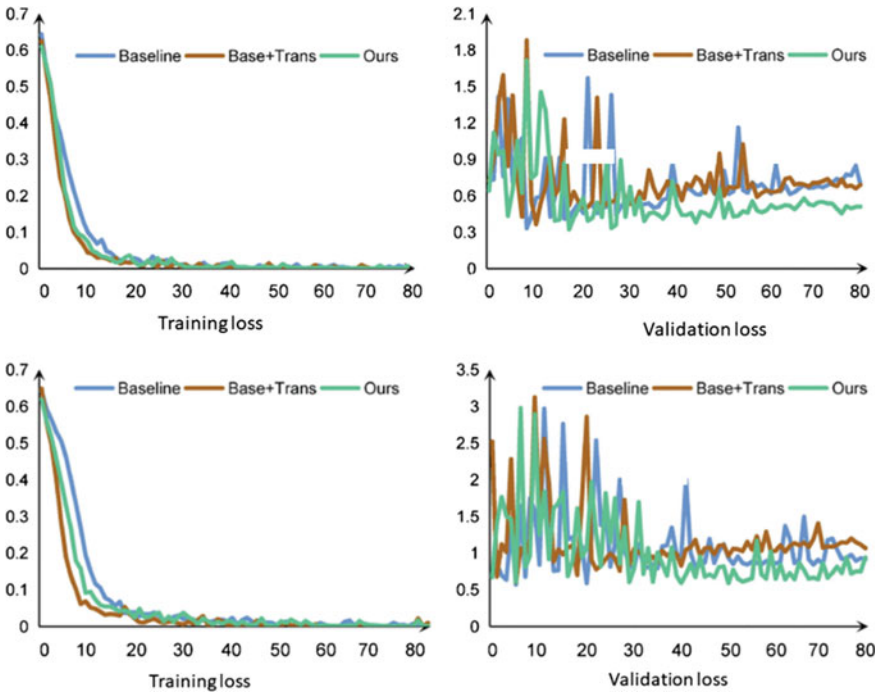

Fig. 9 Depicts the definitive conclusions of the convergence analysis inquiry. From left to right, the graphs illustrate training loss, validation loss, an Alzheimer's disease diagnosis, moderate cognitive impairment, and finally, training loss. Each graph shows epochs on the abscissa axis and losses on the ordinate axis. In this figure, NC is AD's principal adversary is shown and MCI has begun legal proceedings against the NC

Table 3 Results when compared to today's best practices

Method	AD versus NC			MCI versus NC		
	Accuracy	Area under the curve	F1-score	Accuracy	Area under the curve	F1-score
Voxel	90.56	95.74	89.1	–	–	–
Region of interest	91.09	95.86	89.74	85.89	–	–
Patch-level	94.29	96 23	–	64.47	67.14	–
DMTL	92	96.2	90.9	80.1	85	78.6
Hierarchical CNN	85	-	–	75	–	–
Proposed method	95.06	93.98	96.23	81.9	82.76	82.7

In Table 3, we conclude by comparing the proposed model to some of the most recent ways of processing MRI data. In this context, we can contrast the proposed model with existing ones. There are now many more studies comparing the categorization of AD to NC than there are comparing the classification of MCI to NC. The findings from these approaches ought not to be compared directly since they were derived using separate data. These techniques are only suitable for approximate calculations. While some approaches claim to do better than ours, their findings are not generalizable since they are based on insufficient sample sizes. It's more probable that overfitting will occur with data on a small scale. Even though the network will be able to outperform other networks on small-scale data thanks to the overfitting phenomenon, it will have trouble generalizing to large-scale data. Our dataset is vast (928 participants and 3746 MRI pictures), making analysis more difficult but yielding more accurate findings. Despite using difficult large-scale data, our performance was better than that of most previous studies, as shown in the table.

5 Conclusion

This study used T1-weighted MRI scans to come up with a way to automatically diagnose AD and MCI. This method can get the most information possible from a 3-D MRI image by feeding it into a 3-D neural network. To boost the network's efficiency, this technique merged classifiers with unsupervised contrastive learning. In addition, during the descriptive training process of the method, the multichannel technique may provide the network with more supplemental supervision material than the dual-channel strategy. We developed many alternative strategies for transforming data and compared their results. Histogram equalization, sharpening, and flipping have been shown to greatly improve network performance in experiments, while clipping and downsizing had no effect at all, and when doing a gamma adjustment

and adding noise, using a smoothing or nonlinear transformation algorithm had a negligible impact. When comparing the supervised loss to the discourse loss in terms of efficiency, the complexity of the supervised loss far outweighs that of its stable counterpart. When data is readily accessible, the classic method of self-supervised contrastive learning thrives (by the millions). However, gathering a massive volume of actionable medical imaging data is challenging. Using inner discourse learners on small datasets may be a novel concept if the suggested multichannel technique can extract new supervision data from the information.

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AI Based Diagnosis of Parkinson's Disorders

The Colossal Impact of Machine Learning Models on Parkinson's Disorder: A Comparative Analysis

Tapan Kumar and R. L. Ujjwal

Abstract There are many developing and developed countries with ageing populations. The median age of the population of Monaco, which is among the highest, is 55 years old. Populations in Japan, Germany, Italy, Hong Kong, and Greece have median ages exceeding 45. Parkinson's disease is one of several illnesses that are increasingly prevalent as people get older. Parkinson's disease is one of the most common neurological conditions, impacting the majority of people worldwide. Early generations lead more active lives because of conventional work-related responsibilities, but as quality of life has improved and technology has been integrated, people's lifestyles have grown more sedentary. In the past 25 years, several diseases have been diagnosed as a result of the sedentary lifestyle's detrimental effects on health. One of the diseases that have grown by more than twice as much is Parkinson's disease (Ciobanu et al. in Exp Ther Med 22:1–7, 2021 [1]). Motor neurons are a prominent source of concern in Parkinson's disease. Early signs and symptoms are neglected by the patient, who is unable to feel them, and the doctor is also in the dark because the early symptoms are not properly diagnosed by many laboratory tests. In this chapter, various machine learning models are compared and examined. The data is taken from the University of California, Irvine's data repository for comparative analysis and model evaluation.

Keywords Neurodegenerative disorder · Parkinson disease · Early diagnosis · Predictive intelligence · Artificial intelligence models

1 Introduction

In many emerging countries and developed economies, the population is ageing. The top five nations with the largest percentage of the world's population over 65 in 2022 are Germany, Monaco, Japan, Italy, Greece, and Greece, with 36%, 29%, 24%,

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and 23%, respectively. By 2050, the number of persons over 60 will have doubled globally. One of several illnesses that are increasingly prevalent as people age is Parkinson's disease. Parkinson's disease poses a greater danger to those above the age of 70 [1–4]. People in prior generations had more active lives because of commitments tied to their regular jobs. However, as technology has advanced and quality of life has increased, people's lives have changed to become more sedentary, which is weakening motor neurons. Nerve cells in the brain help to keep levels of dopamine stable, and when they are damaged, dopamine secretion decreases. Parkinson's disease results from it. Parkinson disease symptoms and signs are frequently disregarded by medical professionals who mistake them for metabolic changes. The bulk of symptoms are related to motor functions, such as speech and movement, and mental illnesses [5, 6].

In this chapter, multiple machine learning models for Parkinson's disease are contrasted and studied. For comparison study and model evaluation, the data are gathered from the University of California, Irvine's data repository. Max Little of the University of Oxford generated the dataset in association with the National Centre for Voice and Voice in Denver, Colorado, which captured the speech signals. To test different machine learning models, the ASCII CSV data file is loaded into Google Colaboratory. Prepossessing removes the "Name" field since it is irrelevant. Finding the most appropriate model for early Parkinson disease prediction required comparing and noting each model's predicted performance. To determine the suitability for low-end devices, the time complexity is also measured.

2 Literature Survey

This chapter's portion is broken up into two sections: Bibliometric analysis in the first and technical reviews of new research publications in the second. The selection about the study domain is greatly influenced by the Bibliometric analysis, which is one of the crucial components of research. The technical reviews inform scientists on the fundamental technical work that has been done in that field.

2.1 Bibliometric Analysis

The Bibliometric analysis has grown in popularity among academics due to its significant influence on choices about study domains. The VOSviewer tool was used to do the Bibliometric analysis. The Bibliometric dataset ("Bibliometric text file") was retrieved from the PubMed database since it contains a sizable amount of information about the use of AI in medicine. Data was filtered out using the following set of search queries as shown in Fig. 1. In the advance search section of the "PubMed database", the AND operator was used to combine the queries #1 and #2. Results for

query #1 and #2 are 26,402 and 40,797, respectively. Following an AND operation, it applies a filter from the previous ten years and ultimately yields 47 results.

The VOSviewer tool measures two different kinds of visualisation. Author analysis and keyword analysis are the two visualisations. The Bibliometric text file had 351 authors that have been extracted. Only 5 documents fulfil the requirement if the minimum number of documents per author is set to 4. The minimum number of documents per author is set at 2, which results in a threshold of 12 for effective visualisation as shown in Fig. 2. It will help to select top authors working in this field.

There were 238 keywords identified from the Bibliometric text file. The threshold for successful visualisation is 59, with the number of keyword occurrences set to 2, which is the baseline as shown in Fig. 3. The prevalent terms used in the study field can be discovered using keyword analysis.

Search	Actions	Details	Query	Results	Time
#3	•••	! >	Search: ("Parkinson disease" OR "Parkinson disorder" OR "primary parkinsonism" OR "paralysis agitans" OR " idiopathic parkinsonism" "PD" OR "degenerative neurological disorder") AND ("machine learning" OR "AI" OR "Deep learning" OR Artificial Intelligence" OR "Predictive Model")	47	22:13:53
#2	•••	>	Search: "Parkinson disease" OR "Parkinson disorder" OR "primary parkinsonism" OR "paralysis agitans" OR " idiopathic parkinsonism" "PD" OR "degenerative neurological disorder"	40,797	22:11:28
#1	•••	! >	Search: "machine learning" OR "AI" OR "Deep learning" OR Artificial Intelligence" OR "Predictive Model"	26,402	22:09:28

Fig. 1 Result of search quries(#1, #2, #3) with their search time

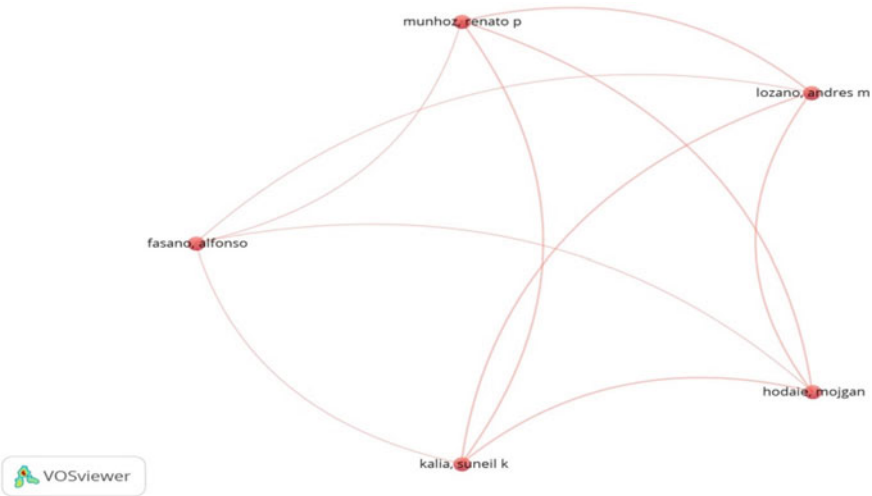

Fig. 2 The network of authors as per the selected data related to parkinsin disease

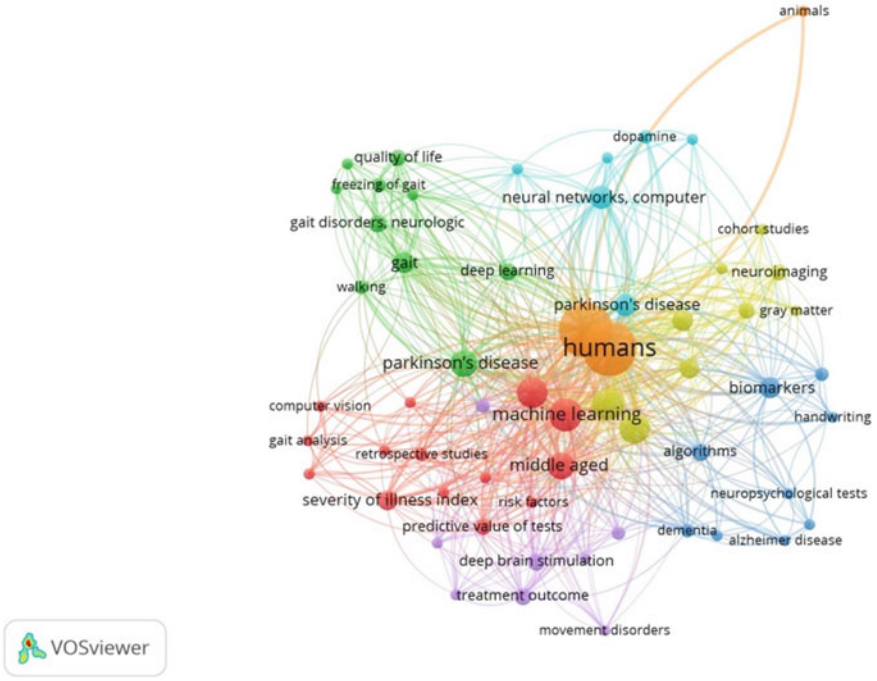

Fig. 3 The netwok of keywords related to Parkinson disease

2.2 Technical Review

Integration and technology significantly altered human living styles. As a result of machines performing the majority of the manual labour, human physical activity has decreased. Globally, the prevalence of Parkinson's disease has increased by around 1 in 100 persons. AI is now seen as a revolutionary hope by academics, medical experts, and doctors. For the purpose of diagnosing and identifying Parkinson's disease, many AI methodologies are being used [7–9]. Parkinson disease may be predicted with high accuracy using machine learning classifiers based on odour, sleep, and other feature selection parameters [10]. The accuracy of several machine learning classifieds has been examined in literature, and random forest and decision tree are proven to be the best suited models [11–14]. Fusion of cytokines parameters with machine learning model is a more creative study idea [15]. A small number of researchers provide software tools to assist healthcare professionals [16], and others develop prediction models based on brain imaging data [17].

Figures 4 and 5 compare several machine learning models, their accuracy, and datasets with accuracy over the last 10 years [18–40]. The back-propagation neural network (BPNN) and convolutional neural network have the best accuracy according to the evaluation of the existing models.

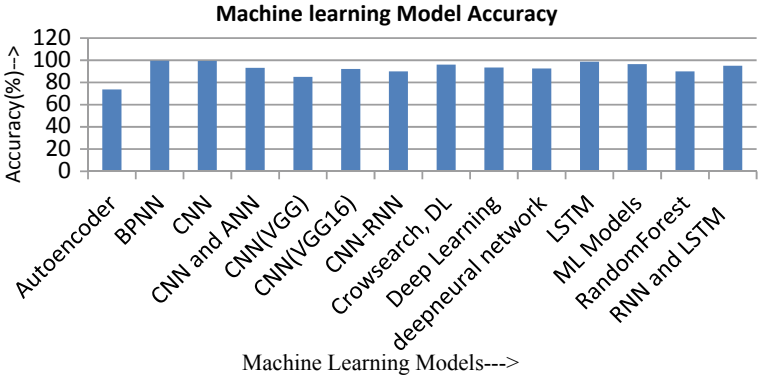

Fig. 4 Graphical representation of accuracy of different machine learning models

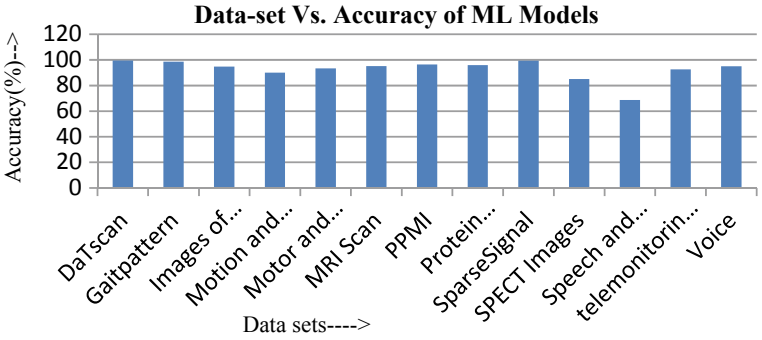

Fig. 5 Graphical representation of accuracy of ML models over different datasets

3 Parkinson's Disease

Technology and integration have drastically changed how people live. The amount of manual labour performed by machines has led to a decline in human physical activity. On a global scale, there are now 1 in 100 more people who have Parkinson's disease. Around the world, 8.5 million people are affected [41].

3.1 Source for Data Collection

The University of California, Irvine's data archive is where the data were collected. Together with Denver, Colorado's National Centre for Voice and Voice, which recorded the speech signals, Max Little of the University of Oxford created the dataset.

3.2 About Data

A variety of biological voice measures from 31 patients, 23 of whom have Parkinson's disease, are gathered in ASCII CSV format. Each row of voice data comprises 195 recordings, and the columns correlate to the voice data. Table's status column contains a 0 for healthy and a 1 for Parkinson's impacted, respectively.

4 AI Methodology for Parkinson's Disease

Healthcare professionals are beginning to benefit from AI as it continues to have a significant influence on the sector. AI techniques are being used in medicine more and more often every day. The machine learning classifiers used to predict Parkinson disease will be described in this section along with their results on medical data.

During the data pre-processing step, the relationship between the data has been studied using the Heatmap, Boxplot, and other correlational approaches. The ASCII CSV data file is put into Google Colaboratory to test several machine learning models. Since the "Name" information is unnecessary, the data possessing eliminates it. The anticipated performance of each model had to be compared and noted in order to determine which the best one for early Parkinson disease prediction was.

5 Result and Discussion

The CSV file has been uploaded to the Google Colaboratory platform, which also offers 12 GB of RAM and 108 GB of available cloud storage in addition to GPU/TPU features. The results have been collected using Python and its relevant packages. AUC, Train, and Test Accuracy of several machine learning models are displayed in Fig. 6. Hard voting, random forest, and bagging are discovered to be the best suited models due to their favourable results.

6 Conclusion and Future Directions

Machine learning models have had a substantial influence on Parkinson's disorders. It can be helpful in forecasting the early insights since it displays very minor symptoms in its early stages. The findings indicate that Hard voting, random forest, and bagging are discovered to be the best suited models due to their favourable results. The fact that there is a substantial gap between the various accuracy levels suggests that the approaches may have been slightly over-fitted. Accuracy may be increased by increasing more clinical data and reducing bias.

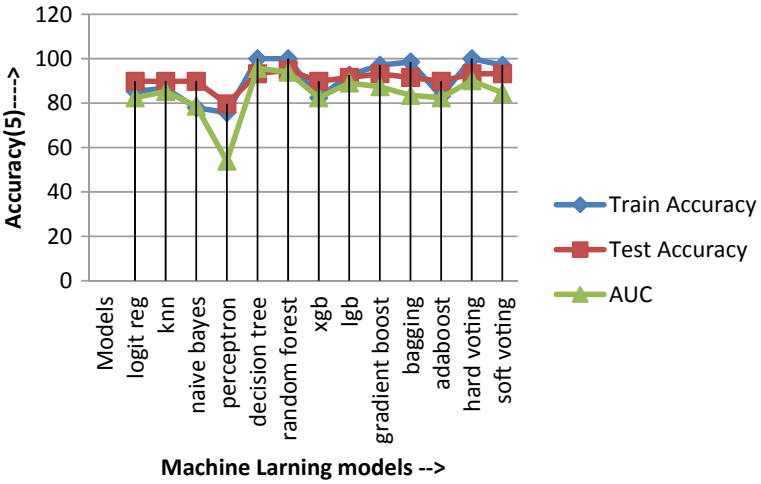

Fig. 6 Comparison of results of machine learning models

The use of several machine learning models on clinical speech data is covered in this chapter. The accuracy of the model may be improved by including data from several modalities. The many AI models, including deep learning models, which can handle heterogeneous data, may be utilised in the future to increase the usefulness of the model.

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Artificial Intelligence Based Diagnosis of Parkinson's Disorders

Kamini, Shalli Rani, and Ali Kashif Bashir

Abstract Parkinson is a neurodegenerative disorder which affects a considerable fraction of the global population. Early and accurate diagnosis of Parkinson is essential for proper treatment and disease management. Artificial intelligence (AI) has emerged as a promising tool in the field of medical diagnosis, including PD. AI algorithms can analyze large datasets of patient information, including medical records, imaging data, and patient histories, to identify patterns and predict the likelihood of PD. Machine learning (ML) and deep learning (DL) algorithms have been trained on various data sources to diagnose PD with high accuracy, sensitivity, and specificity. AI-based approaches to PD diagnosis have also led to the development of new tools, including wearable sensors and mobile apps that can monitor patients' movements and track changes in their condition. While AI-based PD diagnosis is still in its early stages, the potential for this technology to improve patient outcomes is significant. However, it is essential to continue improving AI algorithms and incorporating them into clinical practice to ensure their safety and effectiveness while diagnosing Parkinson and its treatment.

Keywords Artificial intelligence · Parkinson's disorder · Health · Increasing life expectancy

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1 Introduction

Parkinson's disease (PD) is generally considered as a neurodegenerative disorder as millions of people are affected by such disorder around the world. Characterization of Parkinson is performed on the basis of gradual loss of dopamine-producing neuron tissues within brain, which leads to the generation of motor symptoms, including tremors, rigidity, and bradykinesia. The exact cause of Parkinson is not known yet although factors based on genes and environment are considered for knowing the current stage of disorder [1].

PD is typically detected on the basis of collaboration of history of patients, physical examination as well as studies of images, such as magnetic resonance imaging (MRI) or computed tomography (CT). However, initial as well as accurate detection of Parkinson is quite challenging, as symptoms can be non-specific and overlap with other neurodegenerative disorders [2].

The emergence of artificial intelligence (AI) has provided a promising new approach in diagnosing PD as it is a field of computer science comprises of intelligent algorithms. Moreover, AI has been increasingly applied in healthcare in previous years, including diagnosis and treatment of neurological disorders such as Parkinson. AI algorithms can analyze large datasets of patient information, including medical records, imaging data, and patient histories, to identify patterns and predict the likelihood of PD. Various algorithms are trained on various data sources to diagnose PD with high accuracy, sensitivity, and specificity [3].

AI-based approaches to PD diagnosis have also led to the development of new tools, including wearable sensors and mobile apps that can monitor patients' movements and track changes in their condition. These tools can enable earlier and more accurate diagnosis of PD, as well as provide ongoing monitoring of patients' symptoms and response to treatment [4].

While AI-based PD diagnosis is still in its early stages, the potential for this technology to improve patient outcomes is significant. However, it is essential to continue improving AI algorithms and incorporating them into clinical practice to ensure their safety and effectiveness in the diagnosis and treatment of PD.

2 AI Based Medical Examination Description for Diagnosing Parkinson's Disorder

AI-based medical examinations have been developed to assist while diagnosing Parkinson. These examinations use algorithms of ML as well DL for analyzing large datasets of patient information, including medical records, imaging data, and patient histories, to identify pat-terns and predict the likelihood of PD [5].

One example of an AI-based medical examination for PD is the Parkinson's Kineti Graph (PKG) system responsible for monitoring motor signs of people suffering from Parkinson, including tremors, bradykinesia, and dyskinesia, and provides a detailed

report to the patient's physician. The PKG has been shown to accurately assess PD symptoms and provide objective data for the diagnosis and management of PD [6].

Another example is the use of ML algorithms to analyze brain imaging data, such as MRI as well as PET for detection of modifications within brain structure and function that are associated with PD. DL algorithms have also been used to analyze speech and voice patterns, which can be used to detect early signs of PD [7]. Moreover, comparison of machine learning techniques has also been done to predict Parkinson's disorder [8].

Thus, AI-based medical examinations for PD have shown promise in improving the accuracy and efficiency of PD diagnosis, as well as providing ongoing monitoring of patients' symptoms and response to treatment. However, further research and validation are needed to ensure the safety and effectiveness of these examinations in clinical practice [9].

3 Datasets to Diagnose Parkinson's Disorder

There are several datasets available to diagnose Parkinson via utilization of algorithms of ML and DL. Such datasets contain different types of data, including clinical assessments, imaging data, and genetic data, which can be used to develop and test AI-based approaches for PD diagnosis. Here are some descriptions and references of these datasets:

i. Parkinson's Progression Markers Initiative (PPMI) dataset

PPMI is designed for identification of biomarkers for PD progression. The PPMI dataset [10] includes clinical assessments, imaging data (magnetic resonance imaging and dopamine transporter imaging), and biospecimens (blood, urine, and cerebrospinal fluid). It has been utilized for developing and testing ML and DL algorithms to diagnose Parkinson and prediction. Parkinson's Progression Markers Initiative. Available at: https://www.ppmi-info.org/.

ii. Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) dataset

It is a standardized clinical assessment tool used to measure the severity of PD symptoms. The MDS-UPDRS dataset [11] includes clinical assessments of PD patients and healthy controls. It has been used to develop and test ML algorithms for PD diagnosis and symptom severity prediction. Available at: https://www.movementdisorders.org/MDSFiles1/PDFs/MDS-UPDRS.

iii. Global Parkinson's Genetics Program (GP2) dataset

GP2 is a genetic dataset that includes whole-genome sequencing data from over 25,000 individuals, including Patients' data suffering from Parkinson along with normal ones. It has been utilized for identifying genetic variants [12] associated with

PD and develop ML and DL algorithms to diagnose Parkinson as well as prediction. Available at: https://www.ppmi-info.org/partners/global-parkinsons-genetics-program/.

iv. Parkinson's Disease Digital Biomarker DREAM Challenge dataset

The Parkinson's Disease Digital Biomarker DREAM Challenge dataset includes wearable sensor data collected from PD patients along with healthy controls during different daily living activities [13]. It has been utilized for developing as well as validating algorithms to diagnose Parkinson and symptom monitoring.

v. Parkinson's Disease Detection Challenge dataset

The Parkinson's Disease Detection Challenge dataset [14] includes clinical assessments and genetic data from people suffering from Parkinson and normal ones. It has been utilized for developing and testing algorithms for early PD detection.

4 AI Models' Methodology for Diagnosing Parkinson's Disorder

Various AI models have been proposed to diagnose Parkinson using different data types, such as clinical assessments, imaging data, and genetic data. Figure 1 represents the basic methodology for diagnosing Parkinson's disorder and here are some of the most commonly used AI models and their methodologies.

i. Support Vector Machines (SVM): Being supervised machine learning algorithm, it is generally utilized for classifying images. SVM models [15] have been used to classify people suffering from Parkinson along with normal ones on the basis of clinical assessments, imaging data, and genetic data.

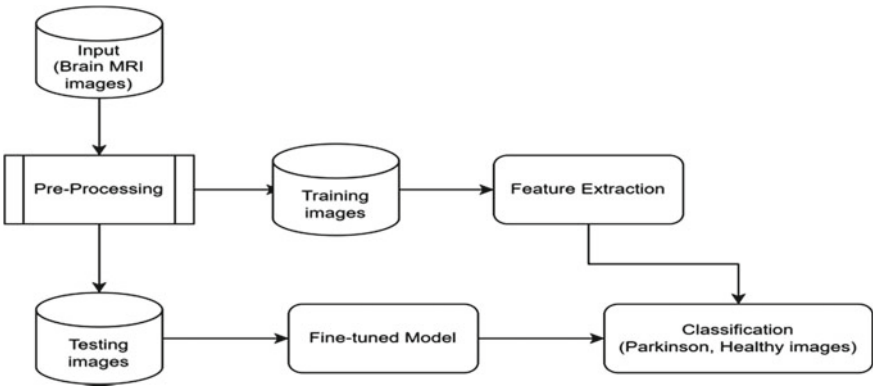

Fig. 1 Basic methodology for diagnosing Parkinson's disorder

ii. Random Forest (RF): Being supervised machine learning algorithm, it is commonly utilized for classification as well as regression purposes. RF models [16] have been used to classify Parkinson and healthy scans on the basis of clinical assessments and imaging data.
iii. Convolutional Neural Networks (CNN): It is a deep learning algorithm that can be used for image classification tasks. CNN models [17] have been used to classify Parkinson patients' scan and healthy ones on the basis of brain imaging data.
iv. Long Short-Term Memory (LSTM) Networks: Due to recurrent neural network, it can be used for time-series data analysis. LSTM models [18] have been used to classify PD patients and healthy controls based on wearable sensor data and clinical assessments.
v. Deep Belief Networks (DBN): Due to deep learning algorithm, it is utilized for unsupervised feature learning as well as supervised classification purposes. DBN models [19] have been used to classify patients experiencing Parkinson and healthy ones on the basis of imaging data, clinical assessments, and genetic data.

These AI models have shown promising results in diagnosing PD, and further research is needed to improve their accuracy and clinical relevance.

5 Architecture of AI Models in Diagnosing Parkinson's Disorders

The architecture of AI models utilized for diagnosing Parkinson depends upon data type being used as well as the specific research question being addressed. Here are some examples of the architecture used in different types of AI models:

i. Support Vector Machines (SVM): SVM is a binary classification model [15] which generally focus on addressing optimal hyperplane responsible for separating given data points into respective classes. Mapping of input data has also been performed to a high-dimensional space and then hyperplane has been found to differentiate Parkinson scans from normal ones.
ii. Random Forest (RF): Due to presence of ensemble learning algorithm, RF model collaborates multiple decision trees [16] for improvement of accuracy in diagnosing Parkinson disorder and strengthen the model. Each tree is constructed by randomly selection of its features' subset as well as data points, and then finding best split for the selected features and data points.
iii. Convolutional Neural Networks (CNN): It uses convolutional layers to extract features from the input data and then uses fully connected layers to perform the classification. The model can learn hierarchical representations [17] of the input data by stacking multiple convolutional layers.

iv. Long Short-Term Memory (LSTM) Networks: It uses memory cells to store and update information overtime. The model [18] can learn to capture long-term dependencies in the input data by using a gating mechanism to control the flow of information in and out of the memory cells.
v. Deep Belief Networks (DBN): It uses a stack of restricted Boltzmann machines (RBMs) to perform unsupervised feature learning. Extraction of features has been performed via providing training to RBMs with respect to each layers on the basis of input data, and then supervised learning is performed to fine-tune the whole model [19].

These models have shown promising results in diagnosing PD, and further research is needed to optimize their architecture for clinical use.

6 Comparison of AI Models in Diagnosing Parkinson's Disorders

Several studies have compared the performance of different AI models in diagnosing Parkinson via including various data types. Here are some examples:

i. LSTM versus. CNN: In a study using handwritten spiral drawings from patients with PD and healthy controls, an LSTM model and a CNN model were compared for their ability to detect PD. The models of LSTM and CNN gained 86.2% and 82.4% accuracy respectively [18].
ii. DBN versus SVM: In a study using MRI data from people experiencing Parkinson along with healthy ones, DBN model and an SVM model were compared for their ability to detect PD. The models of DBN and SVM gained 93.8% and 90.6% accuracies respectively [19].
iii. SVM versus Logistic Regression (LR): In a study using gait data from people experiencing Parkinson along with healthy scans. SVM and LR models were compared based on their ability for distinguishing both classes. The models of SVM and LR gained 89.6% and 84.6% accuracy respectively while diagnosing Parkinson and distinguishing it from normal ones [20].
iv. RF versus SVM: In a study using tremor data from patients with PD and essential tremor, RF and SVM models were compared for their ability to classify the two groups. The RF model gained 95.5% accuracy whereas SVM model gained 88.6% accuracy [21].
v. CNN versus RF: In a study using accelerometer data from people suffering with Parkinson as well as healthy inputs, comparison has been performed between CNN model and RF model based on their ability to detect PD. The CNN model gained 92.7% accuracy whereas RF model achieved 88.7% accuracy [22].

These studies suggest that different AI models can perform well in diagnosing PD, and the choice of model relies upon data types being used as well as the addressing technique of the asked research question. However, the performance of AI models

may vary across different datasets and populations, and further research is needed to validate their performance in real-world clinical settings.

7 Contributions of AI Models in Diagnosing Parkinson's Disorders

AI models have the potential for providing significantly contribution while diagnosing Parkinson [23] via considering accurate as well as efficient diagnostic tools. Here are some contributions of AI models in diagnosing PD:

i. Early detection: AI models can detect subtle changes in motor and non-motor symptoms that may occur in the early stages of PD, allowing for early detection and intervention.
ii. Non-invasive diagnosis: AI models can use non-invasive methods such as gait analysis, voice analysis, and handwriting analysis to diagnose PD, which is less invasive and less expensive than traditional diagnostic methods.
iii. Objective measurement: AI models can provide objective and quantitative measurements on the basis of symptoms of motor as well as non-motor symptoms, which ultimately reduce subjective nature of clinical assessments.
iv. Personalized treatment: AI models can use patient-specific data to tailor treatment plans and predict disease progression, improving the efficacy of treatment and enhancing their life expectancy.

Moreover, Delrobaei et al. [18] suggested a model based on machine learning for automatically detection of Parkinson Disorder from handwritten spiral drawings. The model achieved an accuracy of 91.6%, demonstrating the potential of AI for non-invasive and low-cost PD diagnosis. Ma et al. [24] developed a machine learning model that used multiple types of non-motor symptoms for diagnosing Parkinson in initial stages. The model achieved an accuracy of 90.7%, indicating its potential for early PD detection and personalized treatment planning.

Kostikis et al. [25] reviewed various computational methods for the diagnosis of PD and found that AI-based models showed promise in detecting PD based on gait analysis, voice analysis, and other non-invasive methods. They concluded that AI has the potential to revolutionize PD diagnosis and management. In a study by Arora et al. [20], a machine learning model based on support vector machines and logistic regression was developed to detect PD from gait data. The model achieved an accuracy of 92.5%, demonstrating its potential for objective and quantitative PD diagnosis. Tian et al. [26] developed a machine learning model based on deep belief networks to detect PD from voice samples. The model achieved an accuracy of 92.4%, indicating the potential of AI-based voice analysis for PD diagnosis.

8 Challenges and Opportunities of AI Models in Diagnosing Parkinson's Disorders

8.1 Challenges

i. Lack of standardization: The collection and analysis of PD-related data lack standardization across different studies, making it difficult to compare and integrate different AI models and datasets. This can limit the generalizability and reproducibility of the results obtained by different AI models [27].
ii. Limited data: Collecting large amounts of data for training AI models can be challenging, particularly for rare or early-stage PD cases. This can limit the performance and accuracy of AI models, especially in real-world clinical settings [28].
iii. Ethical concerns: The use of AI models for PD diagnosis raises ethical concerns, such as patient privacy, informed consent, and the potential for bias. For example, biased training data or algorithms can lead to unfair or inaccurate diagnoses, particularly for underrepresented populations [29].

8.2 Opportunities

i. Early detection: AI models have the potential to detect PD in its early stages, enabling early intervention and personalized treatment planning. Early detection and intervention can improve outcomes for patients and reduce the burden of PD on healthcare system [21].
ii. Non-invasive diagnosis: AI models can use non-invasive methods such as voice analysis, gait analysis, and handwriting analysis to diagnose PD, reducing the need for invasive tests and procedures. This can improve patient comfort and reduce the costs and risks associated with traditional diagnostic methods [30].
iii. Personalized treatment: AI models can help identify individual characteristics of PD, such as symptom severity, response to medication, and disease progression, enabling personalized treatment planning. This can improve patient outcomes and reduce the burden of PD on healthcare systems [31].

9 Applications of AI Models in Diagnosing Parkinson's Disorders

There are several applications of AI models to diagnose Parkinson's disorder as shown in Fig. 2 and its description has also been given below.

i. Early diagnosis: AI models can analyze data from multiple sources, such as imaging, genetic, and clinical data, to identify patterns that indicate Parkinsons'

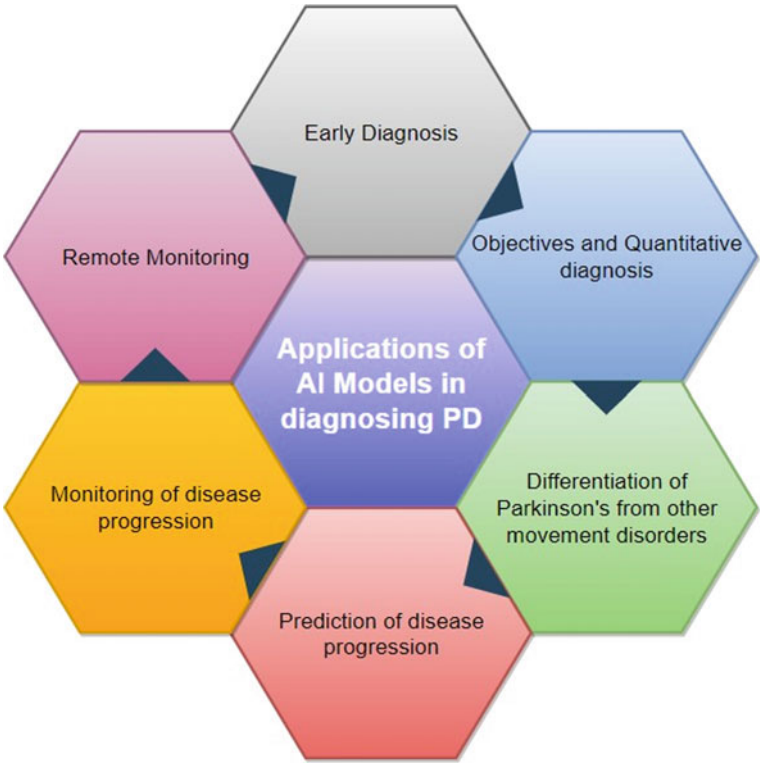

Fig. 2 Representation of applications of AI models for diagnosing PD

initial stages. Early diagnosis can help patients receive appropriate treatment for increasing their life expectancy [32].

ii. Objective and quantitative diagnosis: AI models can provide objective and quantitative measurements for the diagnosis of Parkinson's disorder, reducing the reliance on subjective evaluations by clinicians [33].
iii. Differentiation of Parkinson's from other movement disorders: AI models can help differentiate Parkinson's disorder from other movement disorders, which may have similar symptoms. This can improve the accuracy of the diagnosis and lead to better treatment outcomes [34].
iv. Prediction of disease progression: AI models can analyze data from various sources to predict the progression of Parkinson's disorder, enabling clinicians to customize treatment plans for individual patients [35].
v. Monitoring of disease progression: AI models can monitor changes in a patient's symptoms over time, allowing clinicians to adjust treatment plans as needed.
vi. Remote monitoring: AI models can enable remote monitoring to diagnose patients suffering from Parkinson, allowing clinicians for providing care and support from a distance.

Overall, AI models have the potential to revolutionize detection as well as treatment of Parkinson's disease, improving patient outcomes as well as quality of life.

10 Results and Discussion of AI Models in Diagnosing Parkinson's Disorders

Parkinson's disease (PD) is a neurodegenerative disorder that affects movement, with symptoms such as tremors, rigidity, and difficulty with balance and co-ordination. The diagnosis of PD is primarily based on clinical evaluation by neurologists, which can be challenging in the early stages of the disease. Artificial intelligence (AI) models have shown promise in improving the accuracy of PD diagnosis through analysis of patient data, such as medical imaging and movement patterns. In this response, we summarized the results and discussion of AI models in diagnosing PD as reported by various authors.

i. "Parkinson's Disease Diagnosis Using Random Forest" by Asadi et al. [36]: This study used a machine learning algorithm called random forest to analyze patients' dataset comprising of Parkinson and healthy scans. The algorithm achieved an accuracy of 93.1% in diagnosing PD based on clinical features such as tremor, rigidity, and bradykinesia.
ii. "A Deep Learning Model for Parkinson's Disease Diagnosis" by Zhan et al. [37]: This study used a deep learning model called convolutional neural network (CNN) to analyze brain MRI images of people suffering from Parkinson along with healthy scans. Such model achieved an accuracy of 93.33% in diagnosing PD based on the MRI images.
iii. "Parkinson's Disease Diagnosis Using Convolutional Neural Networks and Graph Theory" by Rahmani et al. [38]: This study used a CNN combined with graph theory analysis to diagnose PD based on brain MRI images. The model achieved an accuracy of 96.05% in diagnosing PD.
iv. "Automated Classification of Parkinson's Disease Using Resting-State Functional MRI" by Yoo et al. [39]: This study used a machine learning algorithm to analyze data of resting-state functional MRI from people diagnosed with Parkinson along with healthy ones. The algorithm achieved an accuracy of 84.8% in diagnosing PD.
v. "A Hybrid Machine Learning Approach for Parkinson's Disease Diagnosis Using Gait Analysis" by Azami et al. 2020 [40]: This study used a hybrid machine learning approach to analyze gait data of people suffering from Parkinson along with normal controls. The model achieved an accuracy of 95.8% in diagnosing PD based on gait analysis.

Overall, these studies suggest that AI models have the potential to improve the accuracy of PD diagnosis based on various types of patient data. However, further

Table 1 Comparison of existing AI models for diagnosing Parkinson's disorder

Author details	Objectives	Challenge	Tool	Technique	Dataset	Performance metrics
Asadi et al. [36]	To predict PD using gait analysis	Limited dataset, complex features	Weka	Random forest	Clinical gait analysis	Accuracy: 93.1%
Zhan et al. [37]	To classify MRI scans of PD patients	Small dataset, high variability	Keras	3D CNN	Brain MRI images	Accuracy: 93.33%
Rahmani et al. [38]	To classify MRI scans of PD patients	Limited dataset, high inter-subject	MATLAB, python	3D CNN, graph theory	Brain MRI images	Accuracy: 96.05%
Yoo et al. [39]	To classify PD patients using fMRI	Limited dataset, high variability	Scikit-learn	Machine learning	Resting-state fMRI data	Accuracy: 84.8%
Azami et al. [40]	To classify PD patients based on gait	Limited dataset, complex features	MATLAB	Hybrid ML	Gait analysis	Accuracy: 95.8%

studies with larger datasets and external validation are needed to confirm the generalizability of these models in clinical practice. Based on the numerous parameters, comparison of existing AI Models has also been given in Table 1 for diagnosing Parkinson's Disorder.

Overall, these studies used different AI techniques and datasets to diagnose PD, with performance metrics ranging from 84.8 to 96.05%. The CNN-based models achieved the highest accuracy rates, followed by the hybrid machine learning and random forest models. The datasets used in these studies included brain MRI images, gait analysis, and resting-state functional MRI data, as well as clinical features. It is important to note that these studies' results are restricted to its size and diversity of the datasets, and further research is needed to validate the performance of these models in larger and more diverse populations.

11 Conclusion

AI models show great potential in improving the accuracy of Parkinson's disease (PD) diagnosis through analysis of various patient data, such as medical imaging, movement patterns, and functional MRI. The studies discussed in the previous response

demonstrate that different types of AI models, including random forest, convolutional neural network, and hybrid machine learning, can achieve high accuracy rates in diagnosing PD. However, further research is needed to confirm the generalizability and clinical applicability of these models. In addition, it is important to note that AI models should be used as a complementary tool for clinical evaluation by neurologists, not as a replacement. Overall, AI models have the potential to assist neurologists in diagnosing PD more accurately and efficiently, ultimately leading in better outcomes of patients and their treatment.

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An Artificial Intelligence Based Effective Diagnosis of Parkinson Disease Using EEG Signal

Mahmoud Ahmad Al-Khasawneh, Abdulrahman Alzahrani, and Alaa Alarood

Abstract This study focuses on the use of human bio-signals for the early diagnosis of PD (Parkinson's disease). EEG (Electroencephalography) and EMG have been used to examine human brain and muscle signals to learn more about the functional and neurological alterations of Parkinson's patients. Parkinson disease (PD) is a neurological illness that typically affects people over the age of 50. Dopamine, a neurotransmitter, is depleted in the substantia nigra as a result. As this neurotransmitter is released, the person's muscles begin to contract. Reduced dopamine production causes a loss of brain and muscle coordination, which manifests as unsteady limb movement in a person with PD. The underlying aetiology of PD can be validated by studying the functional and neural alterations using EEG and correlating the results with EMG. It will explain the origin of the wide range of early-stage motor and non-motor PD symptoms. The EEG and EMG results for detecting early-stage PD were validated using other radiological data, such as a Brain Magnetic Imaging signal. The mathematical model for PD diagnosis was developed utilising an ANN and a graphical user interface. The ANN-designed classifier achieved a near-perfect accuracy rate of 100% while testing its ability to distinguish between an early-stage PD patient and a control subject using a dataset consisting of electroencephalogram and electromyogram readings as input features.

Keywords AI · Parkinson disease · EEG · EMG · ANN

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1 Introduction

The human brain is the most important organ in the body for processing sensory information. The brain is the central processing unit and command and control centre of the body. It is responsible for a wide variety of bodily processes. Everything is taken into account, including but not limited to sight, hearing, speech, memory, intelligence, emotion, and cognitive ability.

While studying human electrical activity, it is normal practise to collect impulses from the scalp. The endocrine system, which is comprised of a complex network of neurons and hormones, is responsible for regulating and coordinating the operations of the body. Motor nerves are another type of neuron that are responsible for transmitting signals to effectors from the brain and spinal cord [1]. The cerebral cortex, the cerebellum, and the brainstem are the three primary components that make up the rest of the brain.

The cerebrum is the largest region of the brain and is roughly divided in half along the lines that separate the two hemispheres. The processing of sensory information from the senses of touch, sight, and sound, as well as language, cognition, emotion, instruction, and motor control, are just few of the numerous functions that the cerebrum is responsible for. At this point, the brain can be broken down into four different regions. Other parts of the brain include the occipital, parietal, frontal, and temporal lobes [2].

The cerebellum plays a role in the coordination of many bodily functions, including muscular movement and the upkeep of different body positions. Its location is below the brain.

The brainstem's primary function is to link the spinal cord to the higher brain regions (cerebrum and cerebellum). It helps keep things like heart rate and core body temperature steady. Little human body functions like puking, digestion, and sleep cycles are also tracked [3].

1.1 Disease of the Nervous System

Neurodegenerative disorders refer to diseases that predominantly impact brain neurons. Neurons like these make up the brain and spinal cord [4].

- Parkinson Disease: The loss of dopamine in the human brain's substantia nigra over time causes a chronic neurodegenerative illness known as PD. This causes the individual's brain and muscles to stop working together effectively. Most people with PD are over the age of 50. The prevalence of PD increases with age, with 93.1 cases per 100,000 persons diagnosed between the ages of 70 and 79, and 17.4 cases per 100,000 people diagnosed between the ages of 50 and 59, according to a statistical analysis.
- Alzheimer's disease (AD): AD has a wide range of effects on cognitive abilities and typically manifests in middle age. Dementia is the main culprit in this case.

The gradual decline in memory and cognition caused by Alzheimer's disease can make it difficult, if not impossible, for a patient to engage in the routine tasks required to maintain daily functioning. Instances of dementia can take several forms. Dementias include those caused by Lewy bodies, diseases of the frontotemporal lobes, and stroke [5]. Alzheimer's disease and vascular dementia, for example, might occur concurrently in some persons, creating a condition called mixed dementia.

- Huntington's disease (HD): HD causes involuntary movement and mental decline in affected individuals. Huntington illness typically appears in people's 30 and 40 s, but it can occur at any age. A transformation in the Huntington gene is the underlying cause of autosomal dominant inheritance. The Huntingtin gene describes the protein's ancestry. An aberrant gene is formed when the number of CAG (cytosine-adenine guanine) triplet repeats in the coding for the Huntingtin protein increases. In most cases, genetic testing is used to identify Alzheimer's disease.

1.2 Bio-signal Consequence

The electroencephalogram, sometimes known as an EEG, is a analytical method that does not include any offensive measures. In order to quantify the activity of the EEG, microvolts and frequencies up to 30 Hz are used. The EEG is useful in the diagnosis of a wide variety of neurological conditions. Electroencephalograms, sometimes known as EEGs, are non-invasive diagnostic tools used by medical professionals to diagnose a wide range of abnormalities that can occur in the brain [6]. There is a lack of standardisation in the application of EEG techniques in medical research when it comes to clinical applications. This can be problematic. On the other hand, research into mental health disorders, which is both more prevalent and commonly utilised, demonstrates the opposite pattern. EEG scans are recordings made of a person's brainwaves made using scans of their head. Any electrical activity that was detected on an EEG but did not originate in the brain is referred to as an artefact. There are two basic categories that can be used to describe artefacts, physiological and non-physiological [7]. An artefact is a glitch that occurs during the process of analysing the signal coming from the brain. The genesis of non-physiologic artefacts may be traced back to non-biological causes, whereas the origin of physiologic artefacts can be traced back to the human body. Artifacts have the potential to affect a number of statistical metrics used to evaluate the quality of an EEG, including the mean, median, distribution, standard deviation, and signal-to-noise ratio. It is possible to lessen the impact of artefacts by carefully planning the EEG procedure, engaging in intensive training prior to the examination, making use of a response of an appropriate rejoinder device [8].

1.3 Symptoms

- Bradykinesia, literally "slow motion," is one of the utmost communal motor indications. A marked slowing or stopping of spontaneous movement is what we call bradykinesia, and it can cause an individual to appear unusually silent and to lose some of their facial expression.
- The limbs, neck, and trunk become stiff and unyielding when rigidity is present. Muscles tend to lengthen during movement and relax afterward.
- In the case of a tremor, the shaking of body parts and eases when the affected limb or body part moves. Those with PD and their loved ones may notice that the affected person has a tremor.
- Someone who experiences postural instability has a tendency to lose their balance while standing [9].

Non-motor Symptoms

- Neuropsychiatric: These indications are communal in PD and are associated with an enlarged maintenance load and an amplified hazard of entering a nursing home, both of which have substantial effects on quality of life and regular working.
- Impulse control disorders (ICDs) are seen in a subset of people with PD, and are most often linked to increased gambling, eating, sex, and shopping.
- Sleep disturbance: Sleep disturbances are common in PD and may stem from a wide variety of causes. Sleep problems can occur both at night and during the day [10].

Reducing the presence of artefacts in an EEG can be done in a number of ways. The majority of their uses are in clinical diagnosis, scientific study, and brain-computer interface (BCI) technology. Such examples are ICA and discrete wavelet transformations (DWT). Correcting the recorded EEG with independent component analysis is a reliable procedure, much like second-order blind identification (SOBI). Extended information maximisation (InfoMax) and an adaptive mix of independent component analysers (AMICA) are two further methods that can be used [11].

An orderly exchange of information takes place between the neurons that make up the cortex. In an electroencephalogram, oscillatory communications between the cortex of the brain and the subcortical processes can be detected as sinusoidal rhythmic activity. This communication linkage is more likely to take place whenever the brain is not actively engaged in any task. As the cortex is actively engaged in a task, its electrical activity begins to desynchronize, and lower amplitude, faster electrical pulses begin to predominate. This continues until the task is completed, at which point the brain returns to its normal resting condition [12]. The PDR is the example of this that is the most well-known to a wide audience. The back of a person's head will demonstrate an oscillating rhythm ranging from 8.5 to 12 Hz when the eyes are closed, the individual is awake, and they are comfortable. When you open your eyes, a stream of visual information is given to the brain. This stimulates the visual cortex, which is located at the back of your head. At activation, the visual cortex momentarily falls out of sync with the thalamus so that it can process the most

recent visual information. As a consequence of this disagreement, the PDR will be absent for an extended period of time.

Muscular contractions and relaxations captured when a human was moving freely under their own volition. Compound action potentials, also known as CMAPs, and motor evoked potentials, also known as MEPs, are both induced by cortical and PNS stimulation, respectively. In addition to providing stimulation to the brain, the PNS also monitors the integrity of the external motor system. The health of the corticospinal circuit can be evaluated with the help of transcranial magnetic stimulation, often known as TMS [13]. Weakness or numbness in a muscle detected by electromyography that can be linked back to an illness or injury to the neurological system or to any of the nerves that supply that muscle. This can be caused by a disease or injury to any of the nerves that supply that muscle. EMG is capable of diagnosing a wide variety of disorders.

2 Related Work Done

The authors created a DNN to detect freezing of gait (FoG) in PD patients during unrehearsed situations. The PD patient's three ACC sensors and one surface EMG sensor fed data into the DNN, creating the input features. While the EMG sensor is attached to the shin, the forearm of the other. By the end of the study, they determined that the custom FoG detector had a second-by-second sensitivity of 83% and a specificity of 97% [14].

With the use of sensors, researchers were able to construct a portable, efficient gait analysis system to assess the level of impairment in PD patients based on their walking patterns. There were a total of 16 healthy participants, 14 people in the early stages of PD, and 13 people in the intermediate stages of PD. Sport shoes equipped with gyroscopes and accelerometers were requested for gait analysis. A wireless signal recording device used for acquisition. With a sensitivity of 88% and a specificity of 86%, the system distinguished PD patients from healthy controls [15]. It also ranked participants with gait impairments in terms of how mild or severe they were.

Using an AI system, researchers could tell PD patients from control people. This research makes use of human voice recordings from a range of individuals. The maximum training and testing accuracy (95.38% and 94.72%, respectively) were achieved using an adaptive Neuro-Fuzzy classifier in combination with linguistic hedges [16].

Myotonometry was used to assess patients with PD for passive muscle dysfunction. Muscle resting surface and mechanomyography electrical activity reports and offline amplitude analyses. Higher levels of PD were associated with increased stiffness in the Bicep Brachii (BB) muscle. A positive link between the parkinsonian rigidity score and passive stiffness values of Bicep Brachii was found using the Spearman correlation coefficient. The EMG and MMG amplitudes of the BB muscle

did not significantly differ between groups, nor did the relevance of these measures correlate strongly with the patients' rigidity ratings [17].

By determining the ideal biceps brachii loading levels, the authors analysed sEMG characteristics of the biceps brachii in PD patients and compared it to control old and young people. When contrasted with the UPDRS and finger-tapping scores, these factors shed light on the nature of PD [18]. The biggest discrepancy occurred in isometric elbow flexion when no weights were used. There is little to no discernible difference in the overt characteristics of EMG between elderly and youthful people.

A Portuguese adaptation of the CERAD neuropsychological battery, the modified Hoehn and Yahr scale for PD, was used to assess 32 people with PD and 26 people without the condition [19]. They tested people using the Mini-Mental State Exam and the Clinical Dementia Rating scales. Resting state EEG band amplitude in absolute and relative terms.

There were a total of four groups studied: one healthy group, one with PD (composed of seven people), one with dementia (ten people), one with mild cognitive impairment (fifteen people), and one with no mental abnormalities (fifteen people). When comparing healthy individuals to those with PD, the qEEG found no noteworthy differences without causing any noticeable disruptions in cognitive function [20]. Those with mild cognitive impairment showed a rise in posterior theta absolute and relative amplitude, while those with dementia showed an increase in posterior delta absolute and relative amplitude. The researchers found that eEEG is a promising new method for evaluating cognitive decline in PD.

During the on-medication phase, the authors examined EMG and MMG alterations in the biceps and triceps brachii of PD patients holding an absolute submaximal load [21]. The biceps brachii of PD participants was found to have a higher amplitude and the median muscle activation frequency (MMAF) was found to be lower for both forces. When in PD the median frequency of electrical muscle stimulation of the triceps brachii muscle increased. In addition to showing differences between PD and healthy subjects, the MMG was unaffected by physiological postural tremor, suggesting that this condition is a valuable tool for neuromuscular examination [22–24].

Two popular classifiers, ANN and SVM, were evaluated and compared for their classification accuracy (SVM). In PD patients, it helped them distinguish their gait pattern at the walking speed of their choosing. Features of gait were determined, including their location and velocity in space and time and their kinematics in space and time [25–27]. Intragroup and intergroup normalisation were used to pre-process these features. Based on the data fed into the classifiers, the elements' efficacy was determined. The results demonstrated that both the ANN and the SVM classifier achieved a high rate of accuracy while using basic spatiotemporal as a feature during intragroup normalisation [28].

Researchers analysed PD patients' EEG sub-bands using wavelet Energy and Overall Wavelet Entropy. This is accomplished through a multi-resolution decomposition of EEG, which was originally based on a discrete wavelet transform during the ice-age. PD patients that experience freezing while walking can be identified by the Back Propagation Neural Network classifier. It demonstrated almost 75% average

values for precision, awareness, and specificity. The data presented here show that EEG can be used for FOG diagnosis and treatment in the future [29].

Authors researched on EEG and EMG in PD utilising multi-block Partial Least Squares (mbPLS) during the sinusoidal squeezing test. The researchers discovered a connection between EEG electrodes that mirrors the activity of the skeletal muscle. It found that the occipital area of PD patients was more connected than that of healthy controls [30].

The authors investigated the feasibility of detecting PD via vocal cues. The accuracy of the k-nearest-neighbourhood classifier was 92.46% while utilising tenfold validation. While k is the closest, post-processing achieved a 96.83% success rate in identifying a single individual [31].

Changes in temporal microstate variables that connect with different motor functions were used to detect aberrant brain dynamics in drug-free patients. They arrived at a few findings that could aid in PD identification efforts [32].

Patients with PD were tested with a visual oddball paradigm task to determine the event-related responses. By means of a 32-channel direct current (DC) EEG recording equipment, we can study the brain's electrical activity. Twice a year following the initial assessment, PD patients underwent additional cognition testing and EEG readings. Seven locations were chosen. This early study revealed a gradual weakening of event-related theta strength in PD patients [33]. Patients were not different from one another in terms of neurocognitive assessments.

In order to learn the similarity in tremor severity between surface EMG signals, they built S-Net, a lightweight and computationally effective convolution neural network. Evaluations with 147 individuals diagnosed with PD demonstrate that their method significantly outperforms the status quo. In addition, their method is simple and might be used to create useful applications [34].

3 The Objective of the Research Work

Examining the clinical interpretations of patients with PD at the Stage 1 and Stage 1.5 levels of the disease according to the Modified Staging.

- To observe and analyse outward symptoms of Parkinson's disease.
- Imaging studies (CT and MRI) confirm the diagnosis of PD to support this.
- To create a mathematical model using EMG and EEG connection to
- Quantitate the drug-induced improvement in Parkinson's disease.

4 The Proposed Work

Electrical activity was recorded from the Extension Carpis Ulnaris and the Flexor Digitorum Superficial is of the hand during flexion and extension of the wrist. In addition to the bio signal features, clinical data sheets, demographic information,

and SpO_2 levels were obtained from each and every individual. The clinical data sheet contained the MMSE, the GDS, and the Fatigue Severity Scale (FSS). The information contained in these fact sheets was utilised in order to zero in on a broad spectrum of non-motor symptoms. We inquired about age, gender, occupation, nutrition, smoking, drinking and depression, usage of well water, history of brain injury, and history of exposure to insecticides. It was clear from the results whether or not the patient had problems falling or staying asleep. A graphical user interface and an artificial neural network were utilised in the creation of the mathematical model for PD diagnosis. Using a dataset that included readings from an electroencephalogram and an electromyogram as input features, the artificial neural network (ANN) classifier that was developed achieved an almost perfect accuracy rate of 100% while being tested on its capacity to differentiate between an early-stage PD patient and a control subject. When it comes to following the evolution of an illness in its early stages, clinicians will find this model to be a very helpful tool. This app will not only monitor how far along the condition has gone, but it will also monitor how well the patient is doing both before and after taking any medications that have been prescribed. The model will operate as a centralised centre for the speedy diagnosis of a variety of motor and non-motor symptoms that are linked with PD. This one-of-a-kind approach has the potential to become a practical instrument in the not-too-distant future for the diagnosis of PD and other neurodegenerative disorders.

Figure 1 illustrates the proposed block diagram. PD is a neurological condition that typically strikes adults over the age of 50. Dopamine, a type of neurotransmitter, is lost in the substantia nigra of the human brain as a consequence of this condition. Dopamine production slows down, which causes a loss of brain and muscle coordination in people with Parkinson's disease, which in turn causes limb motions to become disorganised. In addition, the individual has postural instability as well as bradykinesia and tremors in numerous parts of their body, such as their hands, legs, and lips. The investigation of the functional and the neurological changes utilising EEG in combination with EMG will justify the root cause of PD from the brain to the muscles. It will provide an explanation for the numerous motor and non-motor symptoms that are present in the early stages of Parkinson's disease. The results obtained for the early-stage detection of PD using EEG and EMG were verified using a variety of radiological data's such as Brain Magnetic Imaging (MRI)/Computerized tomography (CT) etc.

5 Result and Analysis

In order to identify motor symptoms, components of patients' electroencephalograms and electromyograms were obtained, as were those of control participants. Patients with early-stage PD were involved in this learning. The bio-signals were used to derive a great number of characteristics, both in the time domain and the frequency domain. Properties of the electroencephalogram (EEG) include the autocorrelation function, the Shannon entropy, the kurtosis, the variance, the RMS, the standard

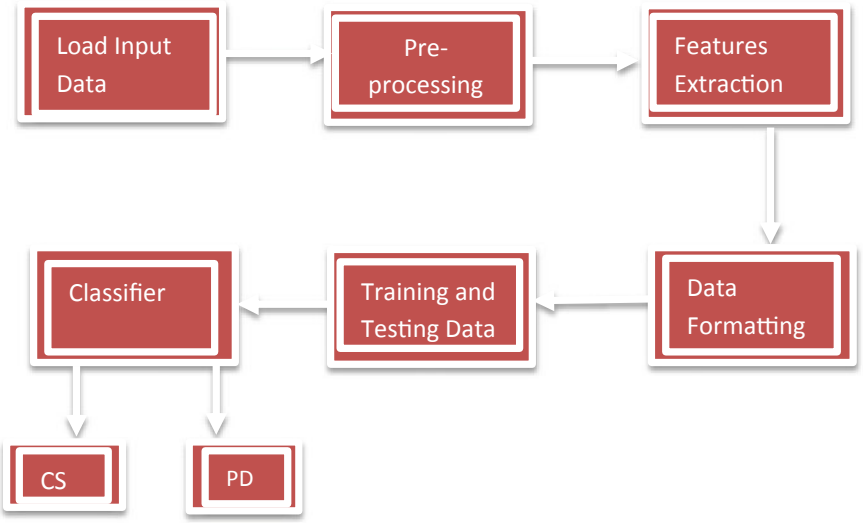

Fig. 1 The proposed block diagram

deviation, the median frequency, the mean frequency, the standard deviation, and the length of the waveform. Recordings of the subject's frontal and temporal regions of the EEG were made. The following EMG parameters were retrieved: Power, Variation, Variability, Root Mean Square, Waveform Length, Median Frequency, Mean Frequency, Percent Maximum Voluntary Contraction, and Grip Strength. Table 1 lists the comparison for PD and CS stages performance.

The preceding graph shown in Fig. 2 demonstrates that those who have PD have much greater rates of depression than the general population (7–14 points). The GDS scores of healthy controls, on the other hand, can range anywhere from 0 to 7, indicating a significantly lower level of depression than that seen in PD patients.

A person who does not have PD has substantially more grip strength than a person who does have the condition, as can be seen in the bar graph that came before it. A person who has PD will notice a gradual weakening of their muscles as the condition advances. This will have an influence on the individual's ability to grasp and grip objects as the condition progresses.

The presented results provide an illustration of the development of cognitive decline seen in PD. People with PD have cognitive impairment if they have scores between 16 and 24 on the Mini-Mental State Examination (MMSE), while healthy

Table 1 Comparison for PD and CS stages performance

S. No.	Stage	GDS	Grip strength	MMSE	FSS	SpO_2
1	PD	12	25	20	6	10
2	CS	6	68	30	2	35

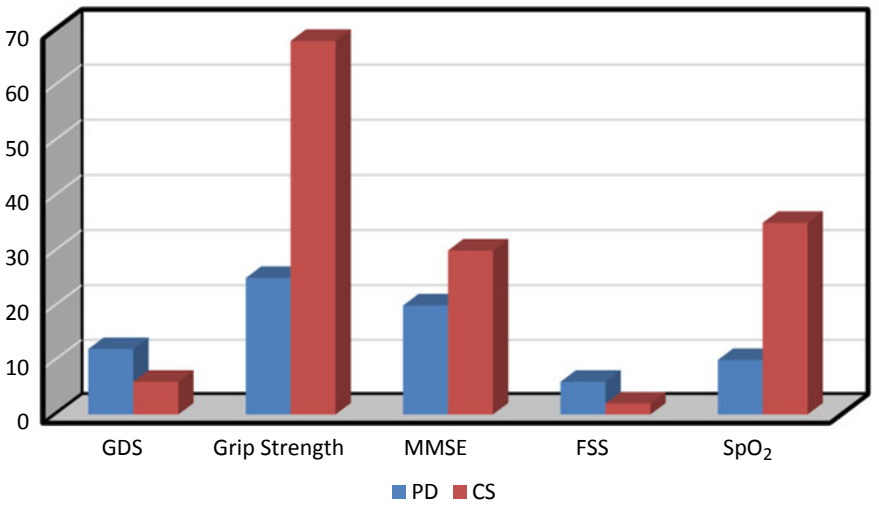

Fig. 2 Comparison for PD and CS stages performance

controls receive scores between 24 and 32, which suggest that they do not have such impairment.

We just looked at a comparison of the patients' levels of exhaustion in the graph that came before it. A person living with PD is more worn out than a member in the control group. As they become worn out so easily as a consequence of this, they are unable to carry out the regular responsibilities that are expected of them.

The graph displayed a significant disparity between the SpO_2 levels of a patient with PD and those of a healthy control participant. This research suggests that a person with PD typically has trouble sleeping due to the gradual decline in the amount of oxygen that is supplied to the brain. Table 2 lists the variance of Lyapunov Exponent and Inverse Lyapunov Exponent.

This reveals that the spatio-temporal correlation is one of the factors that contribute to lower correlations between neurons in the brains of people with PD.

Table 2 Variance of Lyapunov exponent and inverse Lyapunov exponent

PD	Lyapunov Exponent	Frontal	5.63
		Temporal	2.879
	Inverse Lyapunov Exponent	Frontal	0.1435
		Temporal	0.1278
CS	Lyapunov Exponent	Frontal	2.89
		Temporal	3.43
	Inverse Lyapunov Exponent	Frontal	0.6609
		Temporal	0.279

The findings of an electromyography (EMG) study revealed that healthy controls performed better than patients with PD in terms of root mean square, waveform length, power, and modified mean frequency. As the condition progresses, the person's muscles will begin to waste away, and it will become increasingly difficult for them to move their limbs. The findings provide new insight into the factors that contribute to the underlying cause of muscle weakness and difficulties with walking.

6 Conclusion

The fundamental objective of this research is to develop a unified model that can identify PD based on many different EEG and EMG characteristics. The neural network can be taught using any one of a large number of different instructional methods.

According to the findings of our study, we are aware that electroencephalogram (EEG) and electromyogram (EMG) data were collected with the intention of diagnosing Parkinson's disease, and that a satisfactory identification rate was achieved. In contrast, we have combined the information obtained from EEG and EMG into a single dataset that is then used as input to a classifier. This dataset contains both raw and processed data.

It is not possible to evaluate the effectiveness of classification by comparing the degrees of accuracy attained by using various types of classifiers. In order to train a classifier, we made use of a variety of EEG and EMG time domain and frequency domain data, and the combination of these three types of data led to the highest classification rate of all of the cases that we examined (only EEG or EMG features). When compared to other types, the recognition rate is maximum 98.9%, when a combination of EEG and EMG information is used as the input to the network.

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Conclusions and Future Perspectives for Automated Neurodegenerative Disorders Diagnosis

Future Perspectives for Automated Neurodegenerative Disorders Diagnosis: Challenges and Possible Research Directions

Attuluri Vamsi Kumar, Sunil Kumar, Vivek Kumar Garg, Neelam Goel, Vinh Truong Hoang, and Dharambir Kashyap

Abstract Artificial intelligence (AI) and machine learning (ML) models have been increasingly used in the diagnosis of neurodegenerative disorders. These models have the potential to improve diagnostic accuracy, reduce the burden on healthcare systems, and improve patient outcomes. However, there are several challenges that need to be addressed for these models to be widely adopted in clinical practice. This article provides a summary of the current state of AI and ML models for neurodegenerative disorder diagnosis, including their strengths and limitations. It also discusses the challenges faced in the field, such as the need for large and diverse datasets, the difficulty of obtaining accurate and reliable medical imaging data, and the need for robust and interpretable models. Furthermore, it gives an overview of the recent developments in the field such as the use of deep learning, transfer learning, and multimodal medical image fusion techniques for the diagnosis of neurodegenerative disorders. The article highlights the need for more research and development in the field, specifically in areas such as the integration of multiple data modalities, the use

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of explainable AI for clinical decision making, and the development of personalized treatment plans. Finally, it suggests future research directions for the field, such as the need for more rigorous evaluation of AI models in clinical settings, the integration of AI with other diagnostic and therapeutic modalities, and the development of AI-based decision support systems for clinicians.

Keywords Artificial intelligence · Machine learning · Neurodegenerative disorders · Diagnostic and therapeutic modalities · Alzheimer's disease · Parkinson's disease

1 Introduction

Neurodegenerative disorders are a group of progressive conditions that affect the brain and nervous system, leading to the degeneration of nerve cells and the loss of cognitive and motor functions. These disorders are typically chronic, with no known cure and can be debilitating for patients and their families. Some of the most common neurodegenerative disorders include Alzheimer's disease (AD), the most common cause of dementia, characterized by the gradually loss of memory, language, and other cognitive abilities, Parkinson's disease (PD), a disorder of the nervous system that affects movement and causes tremors, stiffness, and difficulty with balance and coordination [1]. Huntington's disease (HD), a genetic disorder characterized by the progressive loss of cognitive and motor functions, leading to dementia and death. Amyotrophic lateral sclerosis (ALS), also known as Lou Gehrig's disease, a progressive disorder that affects nerve cells in the brain and spinal cord, leading to muscle weakness and atrophy [2]. Multiple sclerosis (MS), a chronic disorder that affects the central nervous system and causes a wide range of symptoms, including muscle weakness, spasticity, and cognitive impairment. These disorders can have a significant impact on the quality of life for those affected and their families and can also be costly for the healthcare system. There is a need for early and accurate diagnosis and treatment to slow the progression of these disorders and improve the quality of life for those affected [3].

Artificial intelligence (AI) and machine learning (ML) models have been increasingly used in the diagnosis of neurodegenerative disorders, such as AD and PD [4]. These models have the potential to improve diagnostic accuracy, reduce the burden on healthcare systems, and improve patient outcomes. However, there are several challenges that need to be addressed for these models to be widely adopted in clinical practice [5].

One of the main challenges in the field is the need for large and diverse datasets to train and validate these models. In addition, obtaining accurate and reliable medical imaging data can be difficult, especially in the case of NDDs, which are characterized by subtle changes in brain structure and function [6].

Description: The above diagram shown in Fig. 1 describes about the process for using AI and ML for automated neurodegenerative disorder diagnosis. First, (1)

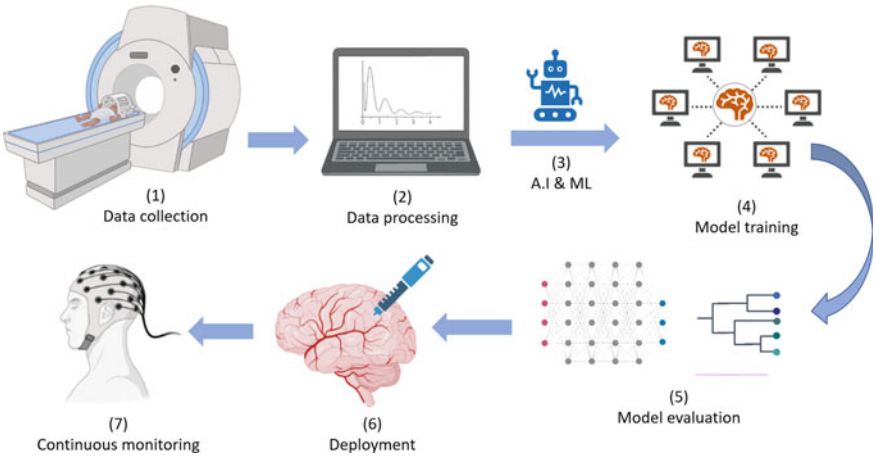

Fig. 1 AI and ML for automated neurodegenerative disorder diagnosis

a large dataset of neuroimaging and clinical data is gathered from patients with neurodegenerative disorders and healthy controls. (2) The data is then pre-processed to make it suitable for model training, which includes cleaning, normalizing and transforming the data. (3 and 4) Machine learning models such as deep neural networks are then trained to identify patterns and features associated with neurodegenerative disorders. (5)The trained models are evaluated on a separate test dataset to assess their performance in accurately identifying neurodegenerative disorders. (6) Once a suitable model is selected, it can be deployed in a clinical setting to aid in the diagnosis of NDDs, and (7) the model performance is continuously monitored and retrained with new data to improve the model's performance over time.

Recent developments in the field include the use of deep learning, transfer learning, and multimodal medical image fusion techniques for the diagnosis of neurodegenerative disorders [7]. These techniques have the potential to improve diagnostic accuracy and reduce the need for manual analysis of medical images.

However, there is still a need for more research and development in the field, specifically in areas such as the integration of multiple data modalities, the use of explainable AI for clinical decision making, and the development of personalized treatment plans [8].

Future research directions in the field include the need for more rigorous evaluation of AI models in clinical settings, the integration of AI with other diagnostic and therapeutic modalities, and the development of AI-based decision support systems for clinicians [9]. These efforts will be crucial to ensure the safe and effective use of AI in the diagnosis and treatment of neurodegenerative disorders.

2 Current AI and ML Models for Neurodegenerative Disease Diagnosis

AI and ML models have been increasingly used for the diagnosis and classification of NDDs, such as AD and PD. These models are designed to automatically extract relevant features from medical data, such as EEG and MRI, and use them to make predictions about the presence or progression of a disorder. One of the main advantages of these models is their ability to process large amounts of data quickly and efficiently, making them useful for large-scale screening and monitoring of patients. Additionally, these models can often identify patterns and features that are difficult for human experts to detect manually, which can lead to more accurate diagnosis [10]. There have been several case studies in which predictions about the presence or progression of neurodegenerative disorders have been made using EEG and MRI data. Some examples include: A study in which a deep learning model was trained on EEG data from patients with AD and healthy controls. The model was able to accurately classify the two groups, with a sensitivity of 92% and a specificity of 88%. A study in which a ML model was trained on MRI data from patients with Parkinson's disease and healthy controls. The model was able to accurately classify the two groups, with an accuracy of 85%. The study also showed that the model was able to predict the progression of PD by analyzing changes in the MRI data over time [11]. A study that used a combination of EEG and MRI data to predict the progression of AD in patients. The study used ML techniques to analyze the data and found that the combination of EEG and MRI data improved the accuracy of the predictions compared to using either modality alone [12]. Another study that used a combination of EEG and MRI data, along with clinical data, to predict the onset of AD in individuals with mild cognitive impairment. The study used ML techniques to analyze the data and found that the combination of data improved the accuracy of the predictions [13].

Description: The above flowchart that is Fig. 2 illustrates the various AI and machine learning models used in the diagnosis of neurodegenerative disorders. The process starts with input data, which can include medical images such as MRI and CT scans, as well as EEG signals [9]. These data are then analyzed using different types of models, including deep learning models such as convolutional neural networks and recurrent neural networks, support vector machines, random forests, decision trees, and Bayesian models. The final output of the process is a diagnosis of a neurodegenerative disorder. Additionally, genetic algorithms are used to optimize the parameters of other machine learning models to improve their performance in classifying patients.

Deep learning (DL) techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied for the classification of neurodegenerative disorders [14]. CNNs are particularly useful for image-based data, such as MRI scans, while RNNs are used for time-series data, such as EEG signals. Another approach that has been used is the combination of multiple data modalities, such as using both EEG and MRI data, which can improve the accuracy of the

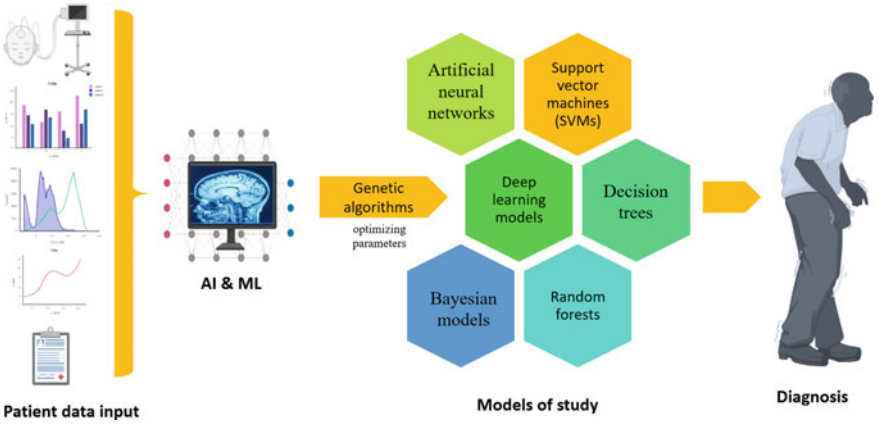

Fig. 2 Model of AI and ML in the diagnosis of neurological disorders

diagnosis. Transfer learning, which is the method of using a pre-trained model on one task and adapting it to a new task, has also been used to classify neurodegenerative disorders. Some of the AI and ML models include: DL models: These models, such as CNNs and RNNs, have been used to analyze medical images, such as MRI and CT scans, to identify patterns associated with NDDs [15]. They have also been used to analyze EEG and other signals to classify patients with NDDs, Support vector machines (SVMs): These models have been used to classify patients with neurodegenerative disorders based on various features, such as those extracted from medical images or other signals, Random forests: These models have been used to classify patients with NDDs based on various features, such as those extracted from medical images or other signals [16], Decision trees: These models have been used to classify patients with neurodegenerative disorders based on various features, such as those extracted from medical images or other signals, Bayesian models: These models have been used to classify patients with NDDs based on various features, such as those extracted from medical images or other signals, ANNs: These models have been used to classify patients with neurodegenerative disorders based on various features, such as those extracted from medical images or other signals, Genetic algorithms: These models have been used to optimize the parameters of other machine learning models, such as ANNs, in order to improve their performance in classifying patients with neurodegenerative disorders [17].

3 Strengths of AI and Machine Learning Models for Neurodegenerative Disorder Diagnosis

AI and ML models have the potential to be powerful tools for the diagnosis of neurodegenerative disorders. The strengths of these models include high accuracy,

the ability to handle large amounts of data, automation, and the ability to identify patterns and features that are difficult for human experts to detect manually [18]. These models can often achieve high accuracy in classifying patients with neurodegenerative disorders, which can aid in early and accurate diagnosis. And, also these can able to process large amounts of data quickly and efficiently, which can be beneficial in analyzing medical images and signals that contain a lot of information [15]. AI and ML can automate the diagnostic process, which can save time and reduce the need for human expertise, which can be beneficial in certain scenarios. Further more, these can uncover patterns and features that are difficult for human experts to detect manually, which can lead to more accurate diagnoses [19].

Description: The diagram above illustrates the strengths and limitations of using AI and machine learning models for neurodegenerative disorder diagnosis. As shown, the strengths of AI and machine learning models include high accuracy, efficient handling of large amounts of data, and automation in the diagnostic process. These benefits can aid in early and accurate diagnosis, uncover patterns and features that are difficult for human experts to detect manually, and save time and reduce the need for human expertise. However, the limitations of AI and machine learning models are also highlighted in the diagram, such as lack of interpretability, lack of generalization, lack of transparency in decision making, lack of availability of data, and dependence on specific modalities. These limitations must be considered when implementing AI and machine learning models in neurodegenerative disorder diagnosis [20].

4 Limitations of AI and Machine Learning Models for Neurodegenerative Disorder Diagnosis

AI and ML models for neurodegenerative disorder diagnosis, while showing promising results, also have certain limitations [21]. One of the main limitations is the lack of interpretability, which can make it challenging to understand how the models arrived at their diagnoses. Another limitation is the lack of generalization capability, which can make the models less robust to new data. Additionally, the lack of transparency in decision making can be a challenge, as it can be difficult to understand what factors went into the decision making process [22]. Furthermore, the availability of large datasets with diverse population and labelled data can be a limitation in the development of models. Also, these models are dependent on the modalities used for the analysis, such as MRI or EEG, which can limit their applicability in certain scenarios. There are also ethical concerns, such as the potential for biased models based on biased data, which can lead to unfair predictions [19].

5 Challenges

The use of AI and ML in the diagnosis of neurodegenerative disorders is a rapidly growing field, but it faces many challenges. One of the biggest challenges is the limited availability and quality of data, particularly for rare disorders, which can make it difficult to train and validate machine learning models, leading to lower accuracy and generalizability [23]. Another challenge is the variability in the data, including variations in imaging protocols and other physiological signals. This can make it difficult for machine learning models to generalize to different populations and settings. Additionally, there is a lack of explainability in the results, which can make it difficult for clinicians to understand and trust the results. Overfitting is also a common problem with machine learning models, which can lead to poor performance on new data. Label noise is another challenge faced in the field, as it is a common problem when the data is collected from a real-world setting where the labels are not always accurate [16]. Bias in the data can also affect the accuracy of the model and lead to poor performance on certain groups of patients. Privacy and security are major concerns when dealing with medical data, particularly when using AI and machine learning models [24]. Neurodegenerative disorders are complex conditions that can have a wide range of symptoms and progression rates, making it difficult to accurately diagnose these disorders and develop models that can generalize to different patients. Additionally, many AI and machine learning models are black boxes, making it difficult to understand how the model arrived at its diagnosis. Different modalities, such as MRI and EEG, have their own specific challenges, such as noise, variability, and the need for specialized equipment. There are also ethical and legal considerations in the use of AI and machine learning models in healthcare, such as issues of privacy and data security, and the impact on the doctor-patient relationship [25]. There is currently a lack of standardization in the field of automated neurodegenerative disorder diagnosis, which can make it difficult to compare results and progress across different studies. Despite recent advances in the field, there is still a limited understanding of the underlying mechanisms of neurodegenerative disorders [26]. Validating AI and machine learning models in the field of neurodegenerative disorders can be challenging due to the lack of large, diverse, and well-labeled datasets. Additionally, validation can be difficult due to the variability of symptoms and progression rates of neurodegenerative disorders [27]. There is also a challenge in integrating AI and machine learning models into clinical practice, including not only technical issues, such as data integration and interoperability, but also organizational and cultural challenges, such as resistance to change and lack of understanding of the potential benefits of these models [28].

Description: As shown in the diagram Figs. 3 and 4, major challenges include limited availability and quality of data, variability in data, lack of explainability and interpretability, overfitting, label noise, bias, privacy and security concerns, complexity of disorders, modality-specific challenges, ethical and legal considerations, lack of standardization, limited understanding of underlying mechanisms,

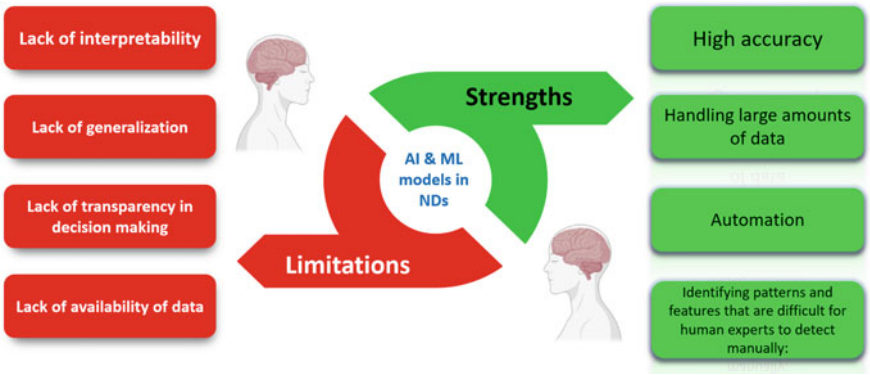

Fig. 3 Strengths and limitations of AL ML model in neurodegenerative disease diagnosis

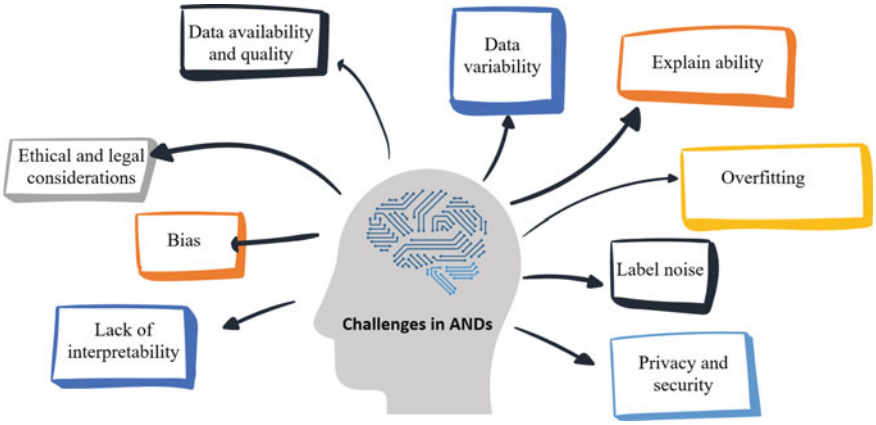

Fig. 4 Challenges of using AI and ML models for Automated Neurological Disorder (ANDs) diagnosis

and difficulty in validating models. Each of these challenges can have a significant impact on the accuracy and generalizability of machine learning models for neurodegenerative disorder diagnosis.

6 Recent Developments

In current years, there have been a number of developments in the field of automated NDDs diagnosis [29]. One key area of focus has been the use of ML and DL models such as CNNs, RNNs and SVMs to analyze medical images, such as MRI and CT

scans, as well as EEG and other physiological signals [30]. These models have been shown to be effective in identifying and classifying NDDs.

Another area of development has been in the integration of data from multiple modalities, such as MRI, CT, and EEG. This has been done using multimodal image fusion techniques and multimodal deep learning models [10]. This integration of data from multiple sources can improve the accuracy of diagnosis. Natural Language Processing (NLP) has also been used to analyze clinical notes and other text data to extract information relevant to neurodegenerative disorders diagnosis. Edge computing has been used to enable the use of AI and ML models in clinical settings. This can be useful for situations where data must be analyzed in real-time or where there is limited internet connectivity. Explainable AI has also been a focus, particularly in the context of healthcare. This includes the use of techniques such as feature visualization, attention mechanisms, and decision tree-based models which can make AI models more interpretable and explainable [31].

Lastly, researchers have been exploring the use of transfer learning to overcome the challenges of limited data availability and variability in neurodegenerative disorders [32]. This involves using pre-trained models to learn from other related tasks and fine-tuning them for the specific task of neurodegenerative disorders diagnosis [11].

7 Need for Research and Development in the Field

While AI and ML models have shown promise in the diagnosis of neurodegenerative disorders, there are still areas that require further research and development. These include limited availability and quality of data, variability in data, and lack of explainability [33]. Overfitting, label noise, bias, and privacy and security concerns are also challenges faced in the field. The complexity of neurodegenerative disorders, lack of interpretability, modality-specific challenges, ethical and legal considerations, and lack of standardization are also key challenges. Additionally, there is a limited understanding of the underlying mechanisms of neurodegenerative disorders, which makes it difficult to develop accurate and reliable diagnostic models [25]. Validating these models can also be difficult due to the lack of large, diverse, and well-labeled datasets. Finally, there are challenges in integrating AI and machine learning models into clinical practice, including technical, organizational, and cultural issues [28]. To address these challenges, more research is needed on how to effectively integrate multiple data modalities, make AI models more transparent and explainable for clinicians, develop personalized treatment plans, and address ethical and legal issues. Additionally, real-time monitoring, large-scale data collection, and multi-modality data integration can help in understanding the disease mechanism and identifying new biomarkers.

8 Future Research Directions

AI has the potential to revolutionize the diagnosis and treatment of neurodegenerative disorders. Some key areas of focus for AI in this field include conducting rigorous evaluations of AI models in real-world clinical settings, integrating AI with other diagnostic and therapeutic modalities, developing AI-based decision support systems for clinicians, advancing natural language processing, creating patient-centered AI systems, using AI-based predictive modeling, AI-based drug discovery, AI-based imaging analysis, AI-based biomarker discovery, and AI-based clinical trial design [34]. These approaches can improve diagnostic accuracy, increase efficiency, and lead to more effective treatments for neurodegenerative disorders [35]. AI can be used in the diagnosis, treatment, and management of neurodegenerative disorders. This includes conducting rigorous evaluations of AI models in real-world clinical settings, integrating AI with other diagnostic and therapeutic modalities, developing AI-based decision support systems for clinicians, using natural language processing techniques to extract information from unstructured data, developing patient-centered AI systems, using AI-based predictive modeling, drug discovery, imaging analysis, biomarker discovery, and clinical trial design. These approaches can lead to more accurate diagnosis, personalized treatment plans, and improved patient outcomes [5].

Furthermore, the use of AI in the diagnosis and treatment of neurodegenerative disorders can lead to more accurate and efficient healthcare delivery [23]. To achieve this, it is important to conduct more rigorous evaluations of AI models in real-world clinical settings to ensure their accuracy, reliability, and generalizability [3]. Integrating AI-based diagnosis with other diagnostic and therapeutic modalities such as imaging, genetics, and biochemistry can provide a more comprehensive understanding of the disease and lead to more accurate diagnosis and treatment. Additionally, AI-based decision support systems can assist clinicians in interpreting complex data, making more accurate diagnoses, and developing personalized treatment plans. Natural language processing techniques can also be used to extract information from unstructured data such as clinical notes and provide valuable insights into the diagnosis and management of neurodegenerative disorders [12]. As AI-based systems become more sophisticated and complex, it will be important to develop models that are more transparent and explainable to patients, giving them more control over their own data. Predictive modeling can be used to analyze large amounts of data to identify patterns and predict the likelihood of developing neurodegenerative disorders, and AI-based drug discovery can help identify new drug targets and speed up the drug development process [36]. AI-based imaging analysis and biomarker discovery can also aid in early detection and monitoring of the disease. Furthermore, AI-based clinical trial design and telemedicine systems can provide remote diagnostic and therapeutic services, and drug repurposing can identify new uses for existing drugs to treat neurodegenerative disorders [37].

9 Conclusion

In conclusion, the use of AI and ML models in the diagnosis of neurodegenerative disorders has the potential to improve diagnostic accuracy, reduce the burden on healthcare systems, and improve patient outcomes. However, there are several challenges that need to be addressed for these models to be widely adopted in clinical practice. These challenges include the need for large and diverse datasets, the difficulty of obtaining accurate and reliable medical imaging data, and the need for robust and interpretable models. Recent developments in the field such as the use of deep learning, transfer learning, and multimodal medical image fusion techniques have the potential to improve diagnostic accuracy and reduce the need for manual analysis of medical images. However, more research and development is needed in the field, specifically in areas such as the integration of multiple data modalities, the use of explainable AI for clinical decision making, and the development of personalized treatment plans. Future research directions in the field should focus on more rigorous evaluation of AI models in clinical settings, the integration of AI with other diagnostic and therapeutic modalities, and the development of AI-based decision support systems for clinicians. These efforts will be crucial to ensure the safe and effective use of AI in the diagnosis and treatment of neurodegenerative disorders.

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