

Early Detection of Neurodegenerative Diseases using Deep Learning Techniques: Issues & Challenges

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Abstract— Our body's control center is the brain. Newer and newer brain disorders are being identified as time goes on. The cumulative loss of immunological and neuronal function is what leads to neurodegenerative diseases including Alzheimer's, Parkinson's, Hunting ton's, and many others. According to recent trends, there will be 152 million peoples with various neurodegenerative diseases in 2050. In recent years, the use of artificial intelligence (AI), specifically deep learning (DL) has transformed the area of neurology. This paper introduces and discusses various deep learning algorithms, including Deep belief networks (DBN), Convolutional neural networks (CNN), Recurrent neural networks (RNN) and Autoencoders along with their theory and applications in neurological diseases prediction. This paper summarizes and highlights the most promising deep learning models for Alzheimer's disease (AD) diagnosis and risk factors by training on neuroimaging datasets combining PET and MRI images gathered using diverse modalities. This study also reviews the entire MRI processing chain—from acquisition to image retrieval, from segmentation to disease prediction which has been optimized for deep learning. Deep learning models are not meant to replace healthcare professionals, but rather to aid in recognizing illnesses and better decision-making. The ultimate goal is to help healthcare providers make more accurate diagnoses and intervene more quickly.

Index Terms— Neurodegenerative Diseases, Deep Learning, CNN, RNN, MRI, PET.

I. INTRODUCTION

Neurodegenerative disease is an irreversible and incapacitating ailment in which nerve cells stop working or die gradually. The elderly is the most significant risk factor for the occurrence of this type of disease. Most neurodegenerative conditions are deadly and usually get worse as people age. Alzheimer's disease (AD), Huntington's disease, and diffuse Lewy body disease (DLBD) are the most common ND diseases associated with dementia. Alzheimer's disease is the most frequent cause of dementia, accounting for 60% to 80% of cases [4]. Dementia patients experience memory loss, difficulty focusing, paying attention, or solving issues. Motor dysfunction (tremors and muscle stiffness), behavioral and psychological abnormalities, speech and language difficulties, and sleep disruptions are prominent signs of ND illnesses primarily affecting the elderly. Patients may struggle to complete everyday chores, names or maps. Age, heredity, education level, and the existence of other medical disorders are all risk factors for various brain ailments.

The condition is most frequently seen in those over 65, with a 5% occurrence rate between 65 and 74 years old and a 50% increased risk beyond 85 years old. However, early Alzheimer's disease diagnosis has been discovered in people aged 40 to 50 years [28]. According to current projections, there will be 152 million people suffering from various neurodegenerative disorders by 2050. Neuroimaging techniques like Computed Tomography (CT), Dopamine Transporter Scan (DatScan), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) that study the structure and function of the brain are the most powerful and well-known tool for precise and early prediction of numerous ND diseases. Khan et al [24], reviewed the most popular Machine learning (ML) classifiers support vector machine (SVM), random forest (RF), logistic regression (LR), random forest (RF), k-nearest neighbor (KNN), naive bayes (NB) and Deep learning models like recurrent neural networks (RNN), convolutional Neural network (CNN), Boltzmann machines, autoencoders, deep belief networks (DBN) and generative adversarial networks (GAN) to identify early-stage brain diseases. It significantly increases precision and enables earlier interventions to make better diseases identification. The CNN model performed better than existing models and might be utilized as an intelligent decision-support tool for the diagnosis of Alzheimer's disease, the most prevalent neurological ailment. The ability of CNNs to automatically learn features from data allows them to reduce the number of parameters without affecting model quality. CNN technology benefits from the high dimensionality of images, where each pixel is considered a feature. Combining SVM with other methods of machine learning algorithms can help detect patterns and relationships in data that may be difficult to detect, potentially enabling earlier and more accurate diagnoses of Alzheimer's and other neurological diseases. With the aid of cutting-edge ML algorithms and high-performance computing tools, these cutting-edge MRI pictures have made it possible to discover neurological disorders in a way that has never been conceivable before with an emphasis on neurodegenerative diseases.

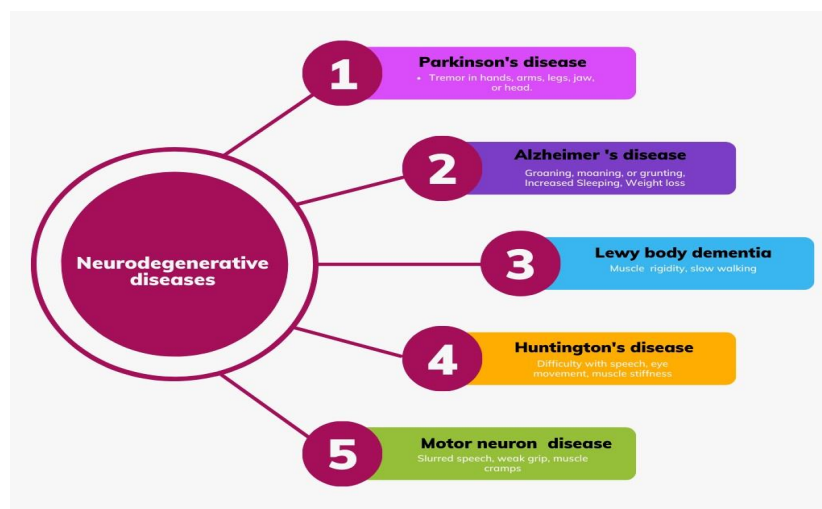


Fig. 1. Significant types and symptoms of neurodegenerative diseases

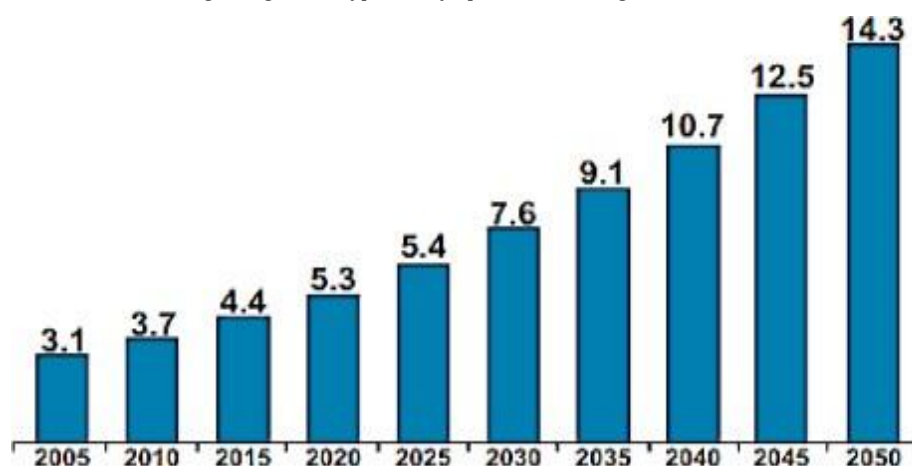


Fig. 2. Individuals affected with ND (in Millions) [24]

II. DEEP LEARNING TECHNIQUES IN NEUROLOGICAL DISEASE PREDICTION

A. Convolutional Neural Network

CNN, a type of Deep Neural Network, categorize features in images. They consist of convolution, pooling, fully connected layers, and an output layer [36]. With local receptive fields, shared weights, and down sampling, CNNs excel at learning pictures features, including edges and corners. Weight distribution across regions reduces parameters, making CNNs efficient at local features extraction while minimizing parameter count.

Pros: By training CNNs on enormous datasets of labeled brain images, we may detect patterns and features that are symptomatic of certain brain illnesses.

Cons: It is vital to emphasize that the CNN's performance and accuracy in analyzing new brain images are dependent on the quality and diversity of the training data, as well as the complexity and unpredictability of the neurodegenerative illnesses being targeted [14].

B. Recurrent Neural Network

RNN structures capture sequential data patterns, aiding in predicting neurological disease progression, diagnosis, and treatment outcomes using medical records and imaging. Architectures like LSTM or GRU enhance RNNs for long term dependencies. Leveraging RNN tech, healthcare can enhance early detection, prognosis, and personalized therapy for neurodegenerative disorders, advancing patient care through sequence modeling feature learning, and backpropagation based parameter optimization.

Pros: RNNs accurately model disease dynamics and changes in neurodegenerative diseases. They handle variable-length sequences, enabling accurate disease forecasting from patients' data of different durations, particularly valuable for longitudinal data and varied medical records.

Cons: Handling long sequences, restricted interpretability, data availability and quality, model complexity, and training time are all challenges in RNN models for neurodegenerative disease prediction.

C. Deep Belief Network

Deep belief network, a combined layer of a graphical model holding both directed and undirected edges makes up the DBN mode of a deep neural network (NN). It is made up of many layers of hidden units, each of which is connected to every other layer aside from the input units. Applications of DBN are to recognize images and speech, create photos, video clips, and motion-capture data.

Pros: When DBN is trained on a big dataset, the learned representations can be used for a new job, such as brain disease prediction. DBNs can be simply extended and modified to integrate additional layers, to handle specific properties of brain pictures, as convolutional layers [5].

Cons: DBNs' performance in MRI image recognition and disease prediction is dependent on the availability of vast and diverse datasets, as well as appropriate preprocessing and feature extraction techniques.

D. Autoencoder

Autoencoders (AEs) are made up of an encoder and a decoder. The encoder converts input to a code, while the decoder decodes the code to rebuild the original input. The most common versions are sparse AE, denoising AE, and contractive AE [13].

Pros: Autoencoders learn to capture distinguishing patterns and characteristics by training on a dataset that includes both healthy and diagnosed individuals, to produce a compact representation of patient data, such as medical imaging, genetic information, or clinical records, which aids in the discovery of probable disease signs.

Cons: It is crucial to highlight that autoencoders may not provide direct insights into the individual biomarker or disease pathways resulting in the prediction. Additional interpretation and analysis approaches are frequently necessary to obtain valuable insights from learned representations

III GENERAL DEEP LEARNING (DL) IMAGE RECOGNITION MODEL

A. Image Acquisition

Data gathering in deep learning brain illness prediction entails acquiring relevant and diverse data such as brain imaging scans (MRI, PET, CT), clinical records, genetic information, and cognitive tests.

B. Image Preprocessing

Using noise reduction, image scaling, and segmentation [25], this stage describes regulating visual contrast diversity and reducing some noise. Each image in the dataset was given a label so that various stages of the severity of the brain disease could be efficiently analyzed [35].

C. Feature Extraction and Classification

Model performs feature classification by pre-trained deep learning models like DenseNet169 and ResNet50. The input layer defines the image size and the convolutional layer uses padding to match the input and output layer sizes, the activation function (ReLU), the max-pooling layer minimizes the size of the feature map and eliminates redundancy, the fully connected layer and the SoftMax layer normalizes classifications.

D. Disease Prediction

For each test image, the CNN predicts the presence or absence of neurodegenerative illnesses, and the findings are compared to the ground truth labels to evaluate the model's accuracy and diagnostic performance.

E. Model Evaluation Metrics

Regression measures variance, root mean squared error (RMSE), R square coefficient, and validation curves like the AUC-ROC curve. Common measures like classification metrics, precision, recall, etc. are used to assess the model's performance and generalization capabilities.

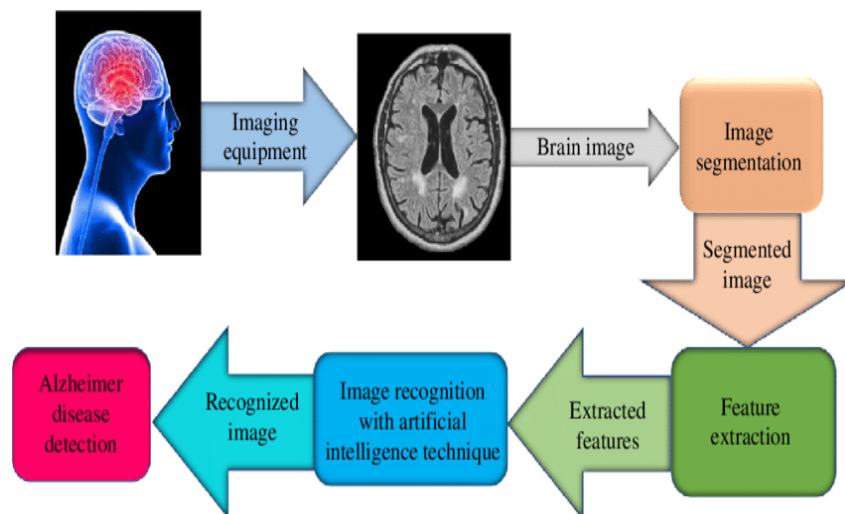


Fig. 3. Frame work for Alzheimer's disease classification and prediction using Artificial intelligence techniques [1]

IV. RELATED WORK

Ebrahimi et al. [17] described the use of (2D) CNNs on magnetic resonance imaging (MRI) scans for AD identification has been used in early Alzheimer's disease detection trials. Lundervold et al [27] presented a quick overview of recent advances in machine learning for medical image processing and analysis, natural language processing, and deep neural networks. Hubar et al [21] proposed the importance of risk analysis and the use of mathematical techniques to assess risk variables in a variety of sectors including technology, public health, insurance, management and ecology. This investigation covers two strategies: direct application of artificial intelligence (AI) techniques like neural networks and dimension reduction, followed by traditional stochastic models. Ullah et al. [36] suggested the CNN model outperforms existing state-of-the-art models in terms of precision, sensitivity, specificity, and F-measure and a collection of 6400 pictures from the Alzheimer's brain MRI dataset was taken from the Kaggle dataset was split into four groups: non-demented, mildly demented, moderately demented and non-demented, by adding random variations to training images utilizing data augmentation techniques. The authors suggested that future work can involve enriching the dataset with authentic MRI images and evaluating new models on the dataset to compare the results with existing models. Khan et al. [23] describe four types of brain disorders, including Alzheimer's disease (AD), brain tumors, epilepsy, and Parkinson's disease, which are being detected using machine learning and deep learning techniques and also concluded that MRI is the preferable type of neuroimaging techniques. Basheer et al. [12] provided a thorough analysis that predicts the onset of dementia using deep neural networks and the OASIS dataset. The authors look into different deep neural network topologies, like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to predict the onset of dementia in patients. In the next study, khan et al. [24] described the development of a classification framework using various machine learning models, including Decision Trees, Random Forests, Naive Bayes, K-Nearest Neighbor, Support Vector Machines, Gradient Boost, Extreme Gradient Boosting, and

Multi-layer Perceptron Neural Networks, using neuroimages of Alzheimer's disease from the Alzheimer's Disorders Neuroimaging Initiative (ADNI). This paper constructs an ensemble based generic kernel model with a master-slave architecture that incorporates extreme gradient boosting in order to improve performance. In this systematic review paper, Grueso et al. [20] concluded the classification accuracy of research combining MRI and PET was higher than that of trials employing just one neuroimaging technology and also showed that SVM is a promising approach for patients with mild cognitive impairment (MCI). Maqsood et al. [28] highlighted the Results from the classification of CN/AD may be done with an accuracy of 85.71% using SVM classifiers.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING METHODS

Authors	Methods used	Accuracy
Grueso et al [20]	MRI and PET data with SVM and CNN	75.4%, 75.5%
Arya et al [10]	CNN, RNN	98.6% 91.2%
Maqsood et al [28]	CNN with binary and multi class	89.6% 92.5%
Amini et al [43]	KNN, SVM, DT, LDA, RF, CNN	77.5%, 85.8%, 91.7% 79.5%, 85.1%, 96.7%
Khan et al [24]	SVM, GLM	84.30%, 88.24%

V. STATE OF THE ART TECHNOLOGIES

Neurodegenerative diseases like Alzheimer's and Parkinson's are characterized by the progressive loss of brain structures and functions, including neuronal death. These diseases can also affect peripheral tissues such as the skin, blood cells, and eyes, leading to metabolic and biochemical dysfunctions. Various peripheral biomarkers have been investigated for the early detection of Alzheimer's and Parkinson's diseases. In the affected part of the brain, this altered protein has a tendency to form and collect intra and extra- cellular protein clumps that may be associated with neuronal death. Puranik et al [31] identified these lumps as biomarkers which include blood cells, skin fibroblasts, proteomics (study of proteins), saliva, olfactory (related to the sense of smell), stomach and colon, heart, peripheral nervous system, etc. The greatest classification outcomes come from combining fluid biomarkers with multimodal neuroimaging but on the other side, there are significant obstacles to finding biomarkers for these conditions. These obstacles include limited access to pathological tissue, the need for invasive procedures like lumbar punctures, uncertainty regarding the sources of biomarkers in central nervous system disorders, difficulties in clinical diagnosis, the complex nature of brain tissue and functions, and a lack of validation models. Brain-derived extracellular vesicles (BDEVs) are released from the central nervous system, and utilized to acquire molecular data from brain tissue in an indirect manner. The molecular data generated by analyzing BDEVs in conjunction with machine learning technologies may assist explain diverse brain occurrences and aid in the discovery of new brain illness biomarkers [30].

VI. FUTURE CHALLENGES

Deep learning-based frameworks for the prediction of neurodegenerative diseases have grown in popularity as a result of the tremendous increase in processing power and the creation of Deep learning tools. Here, we discuss a number of issues with current disease research that will have an impact on the accuracy of disease prediction algorithms.

A. Data unavailability

The use of deep learning in clinical practice faces significant hurdles. The demand for a huge volume of data which might be difficult to obtain for specific medical applications like early brain disease detection is one of the several challenges [15].

B. Data Interpretability

Challenge of understanding and interpreting predictions generated by deep learning models trained on MRI datasets for disease forecasting. [3]. Because these algorithms are prone to overfitting the training data, accurate validation of Deep learning models is critical. Addressing data discrepancies in MRI datasets for ailments prediction is crucial to assuring the accuracy and validity of the results.

C. Generalizability

Different experts' or annotators' inconsistent or subjective classification of MRI images can generate differences in the dataset. Addressing these issues is critical for realizing the full potential of DL in therapeutic settings and promoting its responsible and effective use.

D. Explainability

Deep learning models often get referred to as "black boxes" since they provide no insight into how they make judgments. Explainability is crucial to developing trust and improving clinical decision-making in the context of neurodegenerative disease detection.

VII. CONCLUSION

In order to identify the most prevalent neurodegenerative conditions, such as Parkinson's disease, Alzheimer's disease, brain tumors, and others, in their early stages. This study analyzes the fundamental mechanism of the most recent deep learning models. AI has revolutionized medical science by boosting the predictability and precision of neurological disorder detection. Deep learning models like artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN) outperform conventional methods like logistic regression (LR), support vector machine (SVM) and naïve bayes (NB) when it comes to identifying Alzheimer's disease and mild cognitive impairment (MCI). The ADNI and OASIS longitudinal collections were used for an examination of pretrained convolutional layers. The generalized CNN model performed better than current models and could be employed as a smart decision support tool for Alzheimer's disease diagnosis. convolutional neural networks (CNN) have been created and effectively employed to analyze imaging and genetic data from different neurodegenerative diseases. On the other hand, recurrent neural networks (RNN) have shown promising results when applied to longitudinal clinical data and sensor data. Table 1 shown the findings of analysis of previous studies in this field. This paper highlights the application of deep learning for the early identification of brain problems. Particularly, we identify the key applications, the illnesses involved, the architectures and the data types used. If it comes to future considerations, such as resource efficiency, security and privacy concerns, hardware limitations, and time-consuming image preprocessing still pose problems for deep learning models for diagnosing neurological disorders are summarized in this paper. Interoperability and collaboration are also big concern for brain-related disease detection, for this requirement WHO, WBA can also work together. The overall impact of this study is to early and accurate forecasting of different brain diseases made possible by machine learning and deep learning models. Deep learning models are not meant to replace healthcare professionals, but rather to aid in recognizing illnesses and decision-making. The ultimate goal is to help healthcare providers make more accurate diagnoses and intervene more quickly.

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