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Research Article

A Survey of Machine Learning-Based Approaches for Alzheimer's Disease Prediction

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ARTICLEINFO **ABSTRACT**

MRI has been proven a key role player in the diagnosis of neurological diseases. It was found during the study that differentiation among various neurological disorders is not an easy task due to similarities in symptoms. Novel computation tools based on ML schemes are useful in knowing complex brain functions and diseases. This paper significantly examines and compares the performances of the many ML-based methods to detect neurological disorders—focusing on Alzheimer's disease from MRI data. The development of a novel bioindicator is needed for the prompt diagnosis and prognosis of disorders. The key challenge in this area is to develop a generalized approach for clinical implementation on regular data. The article evaluates and compares the performances of machine - learning based techniques to predict Alzheimer's disease from MRI data. Finally, future research directions are indicated.

Keywords: Alzheimer's disease; brain functions; machine learning; neurological disorder; MR images; bioindicators; clinical implementation; disease prediction.

1 Introduction

A variety of neurological diseases such as Alzheimer's disorder, Parkinson's disease, and Schizophrenia can be predicted and managed using machine learning techniques (Wang et al.,2022; Sharma et al., 2022). Neuroimaging has an important part in the evaluation & assessment of various brain functions and related disorders. High-performance computing practices and Machine Learning methods have provided potential aspects in the treatment of various neurological disorders. A patient with a neurological disorder becomes a liability for his family and society as well.

Alzheimer's disease (AD) is a slow-creeping disease, that causes troubles with memory and behavior. Mild cognitive impairment (MCI) is an intermediary phase between normal adults and AD, having more probability of resulting in AD (Helaly et al.,2022;Bayat et al.,2021). Parkinson's illness is a neurological disease that affects discretional activities. The underlying causes of PD are very important to the planned treatment program. Schizophrenia is a psychiatric disease that is related to functional neurological problems that lead to impairments in cognition and behavior. AD is a serious disorder related to central nerves and is an irrevocable disease with no validated remedy (Bron et al.,2021). AD diagnosis is predictable after stable modifications in brain anatomy. It is therefore essential to identify these disorders at the initial phase so that the development can be retarded, if not entirely blocked. Therefore, the evolution of new biomarkers is vital to the timely recognition and treatment of the disorder. A variety of machine- learning techniques have been applied to classify biomarkers for MCI translation and to evaluate their performances (Yiğit and işik,2020). Image analysis using machine learning techniques has difficulties in gaining adequate classification accuracy (Lodha et al.,2018). The basic process of Alzheimer's disease prediction using machine learning is shown in Figure 1.

2 Machine learning methods

2.1 Random forest classifier

It is a learning method to solve various classification and regression issues. It builds a collection of decision trees into a "forest" where each tree is dependent on information from a random vector. Decision trees are trained using bagging. Bagging combinesdiverse learning models tomaximize the final outcome. It creates numerous decision trees and integrates them to achieve stable forecasts. It has similar hyperparameters as abagging classifier. It detects the best feature among the haphazardcollection of attributes. It is simple to determine the influence of each attribute on the prediction using random forests. Decision trees are sensitive to the data on which they are trained,minor changes can producedifferent tree organizations.

2.2 Logistic regression classifier

It is a supervised learning-based classification model. It is an efficient statistical method for binary classification and can extend to multiclass. It makes predictions by analyzing the relationship between dependent variables. The implementation aspects of this method are comparatively easy. It performs well for linearly separable classes. It enables machine learning processes to categorizearriving input based on preceding data. The additional data allows algorithms to predict better. It can take into consideration multiple input criteria in the account.

2.3 Support vector machines

Support Vector Machine is a learning tool for high dimensionality aspects. It is used to provide solutions in the big data environment. It is considered an outcome of novel development in statistical learning theory. It performs efficiently for both linearly and non-linearly separable datasets. SVM identifies a hyper-plane that establishes a distinction between the various data categories. SVM increases the margin around the hyperplane of separation. The data points that are closest to the decision surface are known as support vectors. In the case of nonlinearly separable data SVM with kernel function is used.This is a measure of similarity between data points.

2.4 Decision tree classifier

It shows the predictions as a series of feature-based splits using a flowchart that resembles a tree structure. Decision trees are labelled learning methodsthat are non-parametric in nature and used for both classification and regression problems. The DT-based model predicts the values based on learning straightforward decision-making regulations inferred from the data attributes. A tree can be considered a segment-wise approximation. In DT each internal node holds a check on a feature, each branch represents the result of the test, and each terminal node denotes a class label. A tree can be formed using recursive partitioning, splitting the source set into subgroups based on an attribute value test, and the procedure is rerunrecursively. Generally, DT classifier shows good accuracy. It is capable of handling multi output problems. The DT-based model can be validated using statistical tests.

2.5 Bayesian classifier

A Naive Bayes classifier is a stochastic learning model used for classification. It can handle both real and discrete data. It is based on Baye's theorem. It is unexpectedly useful because classification decisions are correct even if probability estimation is incorrect. It assumes attributes have independent distributions. The degree of feature dependence does not openly correlate with its accuracy. It is a fast and space-proficient classifier. It is not responsive to inappropriate characteristics.

2.6K-Nearest neighbourclassifier

It is an easy and effective classification technique. It is also called lazy learning. It is one of the precise models that have a highly accurate prediction rate. It depends on the value of the optimal value of k in terms of accuracy.

Figure 1: Alzheimer's disease prediction process using machine learning

It can effortlessly scale to massive datasets. It just stores the dataset during the training of the model. It classifies new data on the basis of previously stored data. It assigns the new data simply to the well-suited category.

2.7Convolutionalneuralnetwork

CNNs are the deep learning modelemployed to resolve challenging image-oriented problems. CNNs are quite similar to ANN which consists of self-optimized neurons using learning. CNNs are used to overcome the weakness of ANN in the area of grid pattern data such as images. CNNs are intended to mechanically and spontaneously learn hierarchies of attributes through back propagation. It uses multiple types of layers such as convolution layers, pooling layers, and fully connected layers. The initial two layers are responsible for attributes mining and the final layer is used for classification. CNNs are considered highly efficient in the case of images because a feature may be obtained anywhere in the images. A linear operation is known as the kernel is used for attribute mining. The input is the array of numbers known as a tensor and a kernel isa small array of numbers that is applied across the input.

3 Machine learning based methods forAlzheimer's disease prediction

Marwa et al. (2023) proposed a research work to identify multi-class Alzheimer's disease using a DNN-based pipeline on brain MR images. The paper has used ROC analysis to verify the procedure's robustness. Srivastava et al. (2023) developed a hybrid CNN-SVM model and achieved an accuracy that stands at 94.57%. The paper shows that the advances in computational intelligence to overcome the obstacles in diagnostic imaging. Gao et al. (2022) proposed a behavior recognition system. An improved fuzzy SVM based on dynamic and static characteristics was used. The paper observed a gain of 2.05% in detection accuracy.Helaly et al. (2022) performed a study for automated left and right hippocampus segmentation to spot Alzheimer's disease. The work is formulated on the U-Net architecture and predicated on MRI data acquired from ADNI and NITRIC datasets.Wang et al. (2022) have aimed to extract significant features from limited imagery dataefficiently and examine the association between brain sections and the successive degeneration of AD. This study has achieved 0.88 accuracy and .95 AUC.Sharma et al. (2022) have proposed a scheme to prepare a consistent and comprehensive analysis of AD at the primary stage of its inception from the data acquired through various modalities of brain imaging. The authors of this paper have achieved 86.60% accuracy. Ron et al. (2021) have performed a study that authenticates the generality of arrangement based on MR images of AD sufferers and controls to an outside data set. The study aims to do the job of the forecast of change to AD in persons with MCI and achieved 76.9% accuracy for SVM.

Kleiman et al. (2021) employed a clinical dementia rating strategy for classifying impairment. Random forests are used to generate the predictions of impairment. The outcomes showed that two class approach has higher sensitivities as compared to three class approach.Gupta et al. (2021) suggested that novel computational tools can be used to predict the association of genes and proteins with AD. A ML-based method was developed with high accuracy. Bayat et al. (2021) have found that GPS driving may be used as a well-organized and precise digital biomarker for spotting pre-symptomatic Alzheimer's disease among elders.Yiğit and işik (2020) suggested a system indicating that the discrimination ability of normal control patients with mild cognitive impairment patients is lesser as compared to healthy individuals having Alzheimer's disease. The study outcomes achieved 83% accuracy for CNN.Li et al. (2020) have indicated that radiomics analysis can be used in the feature extraction method. This paper has estimated accuracy in the range of 90.2–95.9% for SVM and 87.7-92.6% for the random forest.Stamate et al. (2020) have used Multi-Layer Perceptron and Convolutional Bidirectional Long Short-TermMemory models. All methods used were capable to differentiate the various patterns of classes to predict Dementia, MCI, and Normal cognitive stages.Sørensen et al. (2020) proposed a multi-class classifier of NC, MCI, and AD using the features of sMRI. The ensemble technique mixed with bagging for optimal feature selection and accuracy obtained around 70.8% using SVM.Khan and Zubair (2020) proposed a generalized framework established on supervised learning techniques for the analysis of AD and to achieve high accuracy.

Battineni et al. (2020) have suggested a hybrid model that can be used to classify the early phase of dementia in adults with high accuracy. This paper predicts the accuracy of 88.76%, 83.56%, and 96.12% using NB, ANN, and SVM respectively.Liu et al. (2020) proposed a method that can be used to identify AD using a spectrogram for feature extraction. The Logistic Regression model produced high accuracy of 83.3%.Li et al. (2019) presented that radiomic features can diagnose AD and MCI with improved accuracy. They have achieved 91.5% accuracy using SVM.Hao et al. (2019) have proposed a technique that has shown improved classification performance than the other established multimodality methods with enhanced accuracy and AUC. Results show that classification accuracy is 97.60% using MK-SVM.Li et al. (2019) suggested a framework to compare the performance for distinguishing AD from normal patients with different prediction methods on the hippocampal shape and texture attributes and achieved an accuracy of 78.1% using the random forests method.Al-Janabi et. al. (2019) evaluated different prediction techniques used in the field of healthcare and medical diagnosis. The paper observed that the techniques with mathematical basis are fast and powerful.

Naganandhini and Shanmugavadivu (2019) proposed a new tuning technique based on Decision Tree Classification with a hyperparameter for the prediction and to optimize Entropy. This paper has achieved an accuracy of 99.10% using Decision Tree Classifiers.Moscoso et al. (2019) proposed a study on the predictive capability of hippocampal and entorhinal cortex MRI. The outcomes might suffer from survivor prejudice because of long investigations.Fisher et al. (2019) suggested a Machine learning-based generative method to create stochastic simulations and to achieve similar performance on specific and individual models. Results show that R^2=0.82 ± 0.01.Lee et al. (2018) have proposed a model to suggest that with the use of longitudinal multi-domain inputs, better MCI to AD conversion accuracy can be achieved. Feature extraction algorithms need to be modified to preserve the attributes for a single modalityFeng et al. (2018) proposed a method by applying Corpus Callosum Radiomics. Higher classification accuracy can be achieved and the workflow can be implemented in clinical settings. For Alzheimer's disease classification, the Linear Regression classifier showed an accuracy of up to 63%.Wu et al. (2018) proposed a study that evaluated the conversion threat from MCI to AD. The Region of Interest needs to be focused on instead of the regular area

because it can improve the discriminative ability in statistical analysis.Ruiz et al. (2018) proposed a computer-based diagnosis system that estimates the distance per ROI in MR Images. A pre-processing approach based on a histogram was implemented to achieve better results. The accuracies reached 65% for undiagnosed patients.Bäckström et al. (2018) suggested deep learning-based 3D ConvNet architecture that has achieved high classification accuracy. Alarger dataset needs to be used for separate data of patients with partitioning assessments and achieved an accuracy of 98.74% for AD vs NC.
Cui et al. (2018) proposed a CNN AND RNN-based framework to improve disease classification. CNN was used to extricate spatial attributes and RNN for longitudinal features. Structural and functional association systems of the brain for Recurrent Neural Networks can be used for longitudinal analysis. This paper presented an accuracy of 91.33% for AD vs. NC.Feis et al. (2018) suggested a multimodal MRI- classification model that was based on carrier control. It can be used as ameasure to support earlier FTD identification. A framework performed on a larger dataset might encapsulate the heterogeneity required for the clinical generalization of the approach.Li et al. (2018) proposed a framework that demonstrated good classification results. Neurological image study on multimodal data needs to be applied for better results and presented accuracy of 89.5%.Shen et al. (2018) proposed a model that suggested that the decision-making model is prospective to anticipate the transformation possibility from MCI to AD. A Larger data set needs to be used for training of Convolutional Neural Network model.Lodha et al. (2018) proposed a framework that used MR images to get data processed by using ML algorithms. It is observed that the performance of the Neural Network over Random Forest was improved in accuracy. The calculated accuracy is 97.56%, 97.25%, 98.36%, 95%, and 97.86% for SVM, GB, NN, KNN, and RF. Beheshti et al. (2017) have suggested a model that is capable of differentiating between sMCI and pMCI patients and it would be suitable for clinical implementations. This paper presented 93.01% classifying AD/HC.Alam et al. (2017) proposed work using LDA on the principal components that achieved enhanced accuracy with high specificity and sensitivity. This paper also suggested that CNN-based classification algorithms need to be applied to 3D MRI for better predictions. The average accuracy presented is 92.65%.
Hett et al. (2017) proposed a framework using texture-based grading was suggested to represent structural changes due to AD. A novel fusion scheme was proposed to join grading maps and achieved an accuracy of 91.3%.Grassi et al. (2017) suggested a model that used the supervised ML methods Elastic Net and Support Vector Machine to identify the cases with PreMCI and MCI that will convert to AD and produce high performance. The paper has presented thebest-balanced accuracy of 91.3%.Guo et al. (2017) proposed a machine-learning technique that joined numerous features of a hyper network and considered the interactions among brain segments. It achieved an accuracy of 91.60% using a Multi-kernel SVM classifier. This paper also suggested that an optimizing group selection method should be applied for improved accuracy.Hon and Khan (2017) proposed a transfer learning- technique used to detect AD. It provided an enhanced performance on a smaller training set. It also suggested that optimization of the hyperparameters is needed using grid search to achieve improved outcomes.Jha et al. (2017) proposed an automated framework for AD identification using DTCWT, and PCA with FNN. The outcomes produced have displayed that the work has better accuracy. The achieved accuracy is 90.44%.Sørensen et al. (2017) proposed a framework that used a mixture of volumetry, cortical thickness, hippocampal shape, and texture. The paper concluded that novel imaging biomarkers can be incorporated based on other MRI techniques to improve accuracy.Sarraf and Tofighi (2016) performed classification on the AD data with high accuracy using LeNet Convolutional Neural Networks architecture and achieved 96.85% accuracy. The paper suggested additional CNN layers are required to produce more accurate results.
Hwang et al. (2016) proposed their work that has shown the benefits of texture analysis of QSM over that of 3DT1 W images in patients suffering from AD and MCI. This study concluded that the proposed method should be capable to conquer the restrictions of voxel-based analysis.Moradi et al. (2015) proposed a model that combined MRI and cognitive test outcomes and found increased accuracy for the conversion (MCI to AD). The inclusion of MRI with age and cognitive measures can improve the forecast outcomes of translation from MCI to AD.
Payan et al. (2015) suggested a model computed the accuracy of the 2D and 3D architecture and found that the 3D approach has higher performance for 3-way classification and achieved an accuracy of 85.53% and 89.47% for 2D and 3D respectively.Zhang et al. (2012) proposed a framework for texture analysis with a mixed classification accuracy of the hippocampus andentorhinal cortex regions. Inter and Intra viewer variability dimensions should be taken to improve performance. The achieved accuracy is up to 96.4%.

Table I: The summary of machine learning-based methods for Alzheimer's disease prediction

Authorsname	Datadescription	Data source	Machinelearningmethods	Performance	Study objectives
Marwa et al. (2023)	MRI T1-weighted images	ADNI & OASIS	Convolutional Neural Network	Accuracy=99.68%, sensitivity=100%, specificity=100%	This research led to the creation of a DNN-based pipeline that can accurately detect multiple classes of

					Alzheimer's disease.
Helaly et al. (2022)	MRI T1-weighted images	ADNI	Convolutional Neural Network	Accuracy=93.61% for 2D & 95.17% for 3D multiclass AD stage classification.	This paper proposed a framework for AD diagnosis based on U-Net architecture, which automatically segments the left and right hippocampus.
Wang et al. (2022)	MRI T1-weighted images	NA-ADNI	Convolutional Neural Network	Accuracy= 0.88 AUC= 0.95	This study aimed to extract significant features from imagery data and examine the association between brain sections and the successive degeneration of AD.
Sharma et al. (2022)	MRI and PET images	ADNI	Deep Neural Networks, Support Vector Machine	Accuracy AD=86.60% pMCI=73.95%	The key objective of the proposed scheme is to prepare a consistent and comprehensive analysis of AD at the primary stage of its inception from the data acquired through various modalities of brain imaging.
Bron et al. (2021)	T1w images	ADNI	Support Vector Machine & Convolutional Neural Network	Accuracy (SVM)=65.9% (CNN)=65.8%	The study authenticates the generality of arrangement based on MR images of AD sufferers and controls to an outside data set. The study aims to do the job of the forecast of change to AD in persons with MCI.
Kleiman et al. (2021)	MMSE Data	ADNI	Random Forest Classifier	Two Class Sensitivity=94.38%, Specificity=84.42% Accuracy=90.01% Three Class Sensitivity=91.97%, Specificity=86.25% Accuracy=89.44%	The study acknowledged a least attribute set that discriminates between cognitively normal persons from those who are suffering from MCI.
Bayat et al. (2021)	GPS data	GPS Data Logger	Random Forest	F1 Score APOE ε4 status and age =0.85 GPS-based driving indicators=0.82 , APOE ε4 status, and driving=0.91	The findings imply that GPS driving may be used as a well-organized and precise digital biomarker for spotting pre-symptomatic Alzheimer's disease among elders.
Yiğit and işik (2020)	MR Images	OASIS	Convolutional Neural Network	Accuracy =83%	The outcomes of the suggested system indicated

					that the discrimination ability of normal control patients with mild cognitive impairment patients is lesser as compared to the healthy individuals having Alzheimer's disease.
Li et al. (2020)	Amyloid PET	SILCODE project	Support Vector Machine, Random Forest	SVM=90.2–95.9% RF= 87.07-92.6%	The outcomes indicated that radiomics analysis can be used in the feature extraction method.
Stamate et al. (2020)	Clinical data, MRI data, PET data and Genetic data.	ADNI	Multi-Layer Perceptron and Convolutional Bidirectional Long Short-Term Memory Model	Accuracy=82%	All methods used were capable to differentiate the various patterns of classes to predict Dementia, MCI, and Normal cognitive stages.
Sørensen et al. (2020)	T1-weighted structural MRI	ADNI	Support Vector Machines	Accuracy=70.8%	The proposed multi-class classifier of NC, MCI, and AD used the features of sMRI. The ensemble technique is mixed with bagging for optimal feature selection.
Khanand Zubair (2020)	MRI data	OASIS	Multimodal Supervised Learning Methods	RF=86.84% DT=81.6% AB=81.57% LR=81.6% KN=73.7%	A generalized framework was established on supervised learning techniques for the analysis of AD and to achieve high accuracy.
Battineni et al. (2020)	MR Images	ADRC	Naive Bayes, K-Nearest Neighbor, Support-Vector Machines, and Artificial Neural Networks	Accuracy NB=88.76% ANN=83.56% 1NN = 91.32% SVM =96.12%	The suggested hybrid model can be used to classify the early phase of dementia in adults with high accuracy.
Liu et al. (2020)	Speech data	VBSD	Logistic Regression CV	Accuracy=83.3%	The proposed method can be used to identify AD using a spectrogram for feature extraction. The Logistic Regression model produced high accuracy.
Li et al. (2019)	F-FDG PET brain images	ADNI	Support Vector Machine	Accuracy =91.5%	Radiomicfeatures can diagnose AD and MCI with improved accuracy.
Zhou et al. (2019)	Fused MRI/PET brain images	ADNI	Cox Model	Accuracy =84.31%	The proposed framework indicated that the main threat agents attained

					from fused MRI/PET brain images and clinical factors can also predict MCI conversion with improved accuracy.
Hao et al. (2019)	FDG-PET and VBM-MRI	ADNI	MK- Support Vector Machine	Accuracy =97.60%	The proposed technique has shown improved classification performance thanthe other established multimodality methods with enhanced accuracy and AUC.
Li et al. (2019)	MR images	ADNI	Random Forests	Accuracy =78.1%	The proposed framework compared the performance for distinguishingAD from normal patients with different prediction methodson the hippocampal shape and texture attributes.
Naganandhini and Shanmugavadivu (2019)	MR Images	ADNI	Decision Tree Classifier	Accuracy =99.10%	A new tuning technique based on Decision Tree Classification with hyperparameter had proposed for the prediction and to optimize Entropy.
Moscoso et al. (2019)	MR Images	ADNI	Logistic Regression	95% confidence interval for AUC, sensitivity, and specificity.	A study on the predictive capability of hippocampal and entorhinal cortex MRI.
Fisher et al. (2019)	CODR-AD	CAMD	Alzheimer's Disease Assessment Scale–Cognitive Subscale	$R^2 = 0.82 \pm 0.01$	This approach suggested a Machine learning-based generative method to create stochastic simulations and to achieve similar performance on specific models and individual models.
Lee et al. (2019)	Multimodal data	ADNI	Recurrent Neural Network	Single modal Accuracy=75% Multimodal Accuracy=81%	The model suggested with the use of longitudinal multi-domain inputs, better MCI to AD conversion accuracy can be achieved.
Feng et al. (2018)	T1- weighted MR-Images	Zhejiang Provincial People's Hospital	Linear Regression	AUC =0.72 Sensitivity=0.792 Specificity=0 .500 accuracy=0.68	The method suggested that by applying Corpus Callosum radiomics higher

					classification accuracy can be achieved and the workflow can be implemented in clinical settings.
Wu et al. (2018)	MR Images	ADNI	Convolutional Neural Network Architectures (GoogleNet, CaffeNet)	(Three-way discrimination) GoogleNet = 97.58%, 67.33%, and 84.71% CaffeNet= 98.71%, 72.04%, and 92.35%	The proposed work evaluated the conversion threat from MCI to AD.
Ruiz et al. (2018)	T1-weighted MRI images	ADNI	Greedy classifier, Support Vector Machine, and Random Forest	Accuracy= 65%	Proposed a Computer-based diagnosis system that estimates the distance per ROI in MR Images. A pre-processing approach based on a histogram was implemented to achieve better results.
Bäckström et al. (2018)	MRI brain scans	ADNI	Deep 3D ConvNet Architecture	Accuracy = 98.74% for AD vs. NC	Suggested deep learning-based 3D ConvNet architecture has achieved high classification accuracy.
Cui et al.(2018)	T1-weighted structural MRI	ADNI	Convolutional Neural Network AND Recurrent Neural Network based Longitudinal analysis	Accuracy = 91.33% (AD vs. NC)	To improve the disease classification a CNN and RNN based framework is proposed. CNN was used to extricate spatial attributes and RNN for longitudinal features.
Feis et al. (2018)	Anatomical MR Images	Leiden University Medical Centre	Differential classification	-	The suggested multimodal MRI-classification model was based on carrier control. It can be used as a standard to support earlier FTD identification.
Li et al.(2018)	T1-weighted MRIs	ADNI	Dense Convolutional Neural Network (DenseNets).	Accuracy = 89.5%	The Proposed framework demonstrated good classification results.
Shen et al. (2018)	MR Brain Images	ADNI	Convolutional Neural Network and Support Vector Machines	Accuracy Linear kernel=91.0%, Polynomial kernel = 90.0% RBF kernel = 92.33%	The model has suggested that the decision-making model is prospective to anticipate the transformation possibility from MCI to AD.
Lodha et al. (2018)	MRI images	ADNI	Different ML Techniques	Support Vector Machine = 97.56% Gradient Boosting = 97.25% Neural Network = 98.36% K-Nearest Neighbour=	The framework used MR images to get data processed by using ML algorithms. It is observed that the performance of

				95.00% Random Forest = 97.86%	NeuralNetwork over Random Forest was improved inAccuracy.
Beheshti et al. (2017)	T1-weighted images	ADNI	Genetic Algorithm	Accuracy=93.01% classifying AD/HC	The suggested model is capable of differentiating between sMCI and pMCI patients and it would be suitable for clinical implementations.
Alam et al. (2017)	MRI datasets	ADNI	Principal Component Analysis and Linear Discriminant Analysis	Average Accuracy = 92.659%	In this work, using LDA on the principal components achieved enhanced accuracy with high specificity and sensitivity.
Hett et al. (2017)	T1-weighted MRI datasets	ADNI	T1-w grading and texture maps.	Accuracy= 91.3%	A framework using texture-based grading was suggested to represent structural changes due to AD. A novel fusion scheme was proposed to join grading maps.
Grassi et al. (2017)	Structural MRI images	ADRC	Elastic Net and Support Vector Machine	Best Balanced Accuracy = 91.3%	The model used the supervised MLmethods to identifythe cases with PreMCI and MCI will convertto AD and produced highPerformance.
Guo et al. (2017)	fMRI	ADNI	Multi-kernel Support Vector Machines classifier	Accuracy= 91.60%	The proposed machinelearning technique joined numerous features of a hyper networkand considered the interactions among brain segments.
Hon and Khan (2017)	Structural MRI	OASIS	Convolutional Neural Networks (VGG16 and Inception)	Accuracy VGG16 =74.12 % VGG16 = 92.3% Inception V4= 96.25 %	The proposed transfer learning-technique is used to detect AD. It provided an enhanced performance on a smaller training set.
Jha et al. (2017)	MR Images	OASIS	Feed-Forward Neural Network	Accuracy =90.44%	Proposed an automated framework for AD identification using DTCWT, PCA with FNN. The outcomes produced have displayed that the work has better accuracy.
Sørensen et al. (2017)	MR Images	ADNI	Linear Discriminant Analysis	Accuracy =62.7%	The proposed framework has used a mixture of volumetry, cortical thickness,

					hippocampal shape, and texture.
Sarraf and Tofighi (2016)	MRI 3D MP-RAGE sequence	ADNI	Convolutional Neural Networks	Accuracy =96.85%	Performed classification on the AD data with high accuracy using LeNet Convolutional Neural Networks architecture.
Hwang et al. (2016)	3D T1-weighted image	-	Texture Analysis of QSM	-	The proposed work has shown the benefits of texture analysis of QSM over that of 3DT1 W images in patients suffering from AD and MCI.
Moradi, et al.(2015)	T1-weighted MP-RAGE sequence	ADNI	Logistic Regression and Random Forest	Accuracy =90.2%	The proposed model combined MRI and cognitive test outcomes and found increased accuracy for the conversion (MCI to AD).
Payan et al. (2015)	MR Images	ADNI	3D Convolutional Networks	3-way Accuracy (2D) = 85.53% Accuracy (3D) = 89.47%	The suggested model computed the accuracy of the 2D and 3D architecture and found that the 3D approach has higher performance for 3-way classification.
Nemmi et al. (2014)	PET-MRI	Nuclear Medicine physicians	Discriminant Analysis	Specificity =82.4 % Sensitivity = 79.2 % (with grey matter)	The suggested model demonstrated the differential AV-45 binding in white matter between patients with Alzheimer's disease at a premature phase and normal controls.
Zhang et al. (2012)	T1-weighted MRI	Xuanwu Hospital, Beijing	Regularized Dual Averaging, Principal Component Analysis, Linear Discriminant Analysis	Accuracy =64.3% to 96.4%	The proposed framework found a mixed classification accuracy of texture analysis in the hippocampus and entorhinal cortex regions.

4 Resultsdiscussion

The observed results show that the proposed models by various authors are robust and precise. Most of these have achieved high performance in different evaluation measures.

The authors in (Helaly et al, 2022) proposed two architectures for left and right hippocampus segmentation. The first approach uses hyperparameter tuning and the other one uses a transfer learning model. The achieved accuracies are 94.34% and 97%. The proposed method also achieved a high value of sensitivity 95%. In DSC also the methods achieved high values of 94% and 93.5% which are better than other state-of-art methods. Author in (Sharma et al., 2022) established an ML-based AD diagnosis system, many attribute extraction and fusion techniques are elaborated for early and reliable detection of the disorder.

Authors in (Bayat et al., 2022) used in-vehicle GPS data logger for a period of 1 year to distinguish cognitively normal older drivers with preclinical AD and concluded that the system may serve as an operational digital biomarker for detecting AD. The obtained value of the F1 score of RF model was .82 with APOE ε4 status and age and .82 using GPS indicators only. Authors in (YİĞİT et al.,2020) applied the CNN framework on a hybrid dataset obtained from OASIS and MIRIAD. The revealed accuracy in the model is greater than 0.8. Axial, sagittal, and coronal brain projections are obtained from brain images. The model performed well when it trained with all projections. The best result is obtained during axial image evaluation and the poorest during sagittal image evaluation.

Authors in (Stamate et al,2020) have used two frameworks MLP and ConvBLSTM to differentiate the dataset into three classes CN, MCI, and DEM. The first approach has proven more accurate as compared to second one which achieved 86% accuracy. Authors in (Sørensen et al.,2018) have introduced a novel ensemble SVM with bagging and attributed selection to classify dementia, the obtained improved accuracy. The analysis of results shows an accuracy improvement of up to 59.1% by enforcing a leastamount of attributes and growing ensemble classifiers. Authors in (Hao et al., 2020) proposed a model using the MK-SVM approach to obtain better performance in classification. The paper achieved high accuracy and AUC values on AD vs NC, MCI vs NC, and on MCI-C vs MCI-NC. The author showed that MK-SVM outperforms RF and KNN classifiers.

The achieved results have high accuracy. Authors in (Fisher et al., 2019) introduced an unsupervised learning model CRBM to model 44 commonly measured variables in trials and found ADAS-Cog and MMSE scores are weakly related to each other. Authors simulated 18-month patient trajectories trained on a baseline ADAS-Cog11 score of 10 to know about the understanding of fast and show progressing patients. Authors in (Alam et al.,2017) proposed a new framework based on dual-tree complex wavelet transforms for distinguishing NC from AD and achieved comparatively superior accuracy, specificity, and sensitivity. They applied TSVM using linear discriminant DTCWT principal components as input attributes. The time complexity of the extraction of DTCWT and DWT coefficients from a 2D MRI image slice are 0.5148 and 0.5109, respectively. Authors in (Sarraf et al.,2016) used the LeNet-5 Convolutional Neural Network model to classify fMRI data of AD and achieved an accuracy of 96.85%. The 5-fold cross-validation is used to achieve robustness and reproducibility. CNN is used as a feature extractor to extract high level features from images.

Extensive research has been carried out on the future status of the patient. Earlier models are based on neuroimaging as a data source but the recent focus is on multimodal data. The biggest challenge is the generalization of studies and bringing these methods into clinical practices.

5 Conclusion

A study was performed to discover the role of machine learning methods in the diagnosis and classification of neurological disorders. Most of the research work has been accomplished in the prediction of the subsequent state of the patient. Promising results have been obtained in many neurological disorders such as AD, MCI, epilepsy, psychiatric conditions, movement disorders, and multiple sclerosis. Inceptive work was concentrated on neuroimaging as a primary source of the data, recent studies are integrating multimodal sources including clinical data, genomic data, and data obtained from other corners. ML techniques are already implemented in the diagnosis of AD, MCI, and other neurological disorders but still, there seems plenty of scope for research from these computer-based diagnostic techniques to the clinical realization. The process of investigation includes the acquisition of imaging data, attribute extraction, and attribute selection and classification or forecasting. The lead of radiomics analysis is that its attributes are interrelated with clinical measures related to AD and MCI.

References

1. Alam, S., Kwon, G.R., Kim, J.I. and Park, C.S., 2017. Twin SVM-based classification of Alzheimer's disease using complex dual-tree wavelet principal coefficients and LDA. Journal of healthcare engineering, 2017.
2. Al-Janabi, S. and Mahdi, M.A., 2019. Evaluation prediction techniques to achievement an optimal biomedical analysis. International Journal of Grid and Utility Computing, 10(5), pp.512-527.
3. Bäckström, K., Nazari, M., Gu, I.Y.H. and Jakola, A.S., 2018, April. An efficient 3D deep convolutional network for Alzheimer's disease diagnosis using MR images. In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (pp. 149-153). IEEE.
4. Battineni, G., Chintalapudi, N., Amenta, F. and Traini, E., 2020. A comprehensive machine-learning model applied to magnetic resonance imaging (mri) to predict alzheimer's disease (ad) in older subjects. Journal of Clinical Medicine, 9(7), p.2146.
5. Bayat, S., Babulal, G.M., Schindler, S.E., Fagan, A.M., Morris, J.C., Mihailidis, A. and Roe, C.M., 2021. GPS driving: a digital biomarker for preclinical Alzheimer disease. Alzheimer's Research & Therapy, 13(1), pp.1-9.
6. Beheshti, I., Demirel, H., Matsuda, H. and Alzheimer's Disease Neuroimaging Initiative, 2017.

Classification of Alzheimer's disease and prediction of mild cognitive impairment-to-Alzheimer's conversion from structural magnetic resource imaging using feature ranking and a genetic algorithm. Computers in biology and medicine, 83, pp.109-119.

7. Bron, E.E., Klein, S., Papma, J.M., Jiskoot, L.C., Venkatraghavan, V., Linders, J., Aalten, P., De Deyn, P.P., Biessels, G.J., Claassen, J.A. and Middelkoop, H.A., 2021. Cross-cohort generalizability of deep and conventional machine learning for MRI-based diagnosis and prediction of Alzheimer's disease. NeuroImage: Clinical, 31, p.102712.
8. Cui, R., Liu, M. and Alzheimer's Disease Neuroimaging Initiative, 2019. RNN-based longitudinal analysis for diagnosis of Alzheimer's disease. Computerized Medical Imaging and Graphics, 73, pp.1-10.
9. Feis, R.A., Bouts, M.J., Panman, J.L., Jiskoot, L.C., Dopper, E.G., Schouten, T.M., de Vos, F., van der Grond, J., van Swieten, J.C. and Rombouts, S.A., 2018. Single-subject classification of presymptomatic frontotemporal dementia mutation carriers using multimodal MRI. NeuroImage: Clinical, 20, pp.188-196.
10. Feng, Q., Chen, Y., Liao, Z., Jiang, H., Mao, D., Wang, M., Yu, E. and Ding, Z., 2018. Corpus callosum radiomics-based classification model in Alzheimer's disease: a case-control study. Frontiers in neurology, 9, p.618.
11. Fisher, C.K., Smith, A.M. and Walsh, J.R., 2019. Machine learning for comprehensive forecasting of Alzheimer's Disease progression. Scientific reports, 9(1), pp.1-14.
12. Gao, D. and Yu, H., 2022. The use of optimised SVM method in human abnormal behaviour detection. International Journal of Grid and Utility Computing, 13(2-3), pp.164-172.
13. Grassi, M., Perna, G., Caldirola, D., Schruers, K., Duara, R. and Loewenstein, D.A., 2018. A clinically-translatable machine learning algorithm for the prediction of Alzheimer's disease conversion in individuals with mild and premild cognitive impairment. Journal of Alzheimer's Disease, 61(4), pp.1555-1573.
14. Guo, H., Zhang, F., Chen, J., Xu, Y. and Xiang, J., 2017. Machine learning classification combining multiple features of a hyper-network of fMRI data in Alzheimer's disease. Frontiers in neuroscience, 11, p.615.
15. Gupta, G., Gupta, N., Gupta, A., Vaidya, P., Singh, G.K. and Jaiswal, V., 2021. Prediction of Alzheimer associated proteins (PAAP): a perspective to understand Alzheimer disease for therapeutic design. International Journal of Bioinformatics Research and Applications, 17(4), pp.363-374.
16. Hao, X., Bao, Y., Guo, Y., Yu, M., Zhang, D., Risacher, S.L., Saykin, A.J., Yao, X., Shen, L. and Alzheimer's Disease Neuroimaging Initiative, 2020. Multi-modal neuroimaging feature selection with consistent metric constraint for diagnosis of Alzheimer's disease. Medical image analysis, 60, p.101625.
17. Helaly, H.A., Badawy, M. and Haikal, A.Y., 2022. Toward deep mri segmentation for alzheimer's disease detection. Neural Computing and Applications, 34(2), pp.1047-1063.
18. Hett, K., Ta, V.T., Manjón, J.V., Coupé, P. and Alzheimer's Disease Neuroimaging Initiative, 2017. Adaptive fusion of texture-based grading: application to Alzheimer's disease detection. In Patch-Based Techniques in Medical Imaging: Third International Workshop, Patch-MI 2017, Held in Conjunction with MICCAI 2017, Quebec City, QC, Canada, September 14, 2017, Proceedings 3 (pp. 82-89). Springer International Publishing.
19. Hon, M. and Khan, N.M., 2017, November. Towards Alzheimer's disease classification through transfer learning. In 2017 IEEE International conference on bioinformatics and biomedicine (BIBM) (pp. 1166-1169). IEEE.
20. Hwang, E.J., Kim, H.G., Kim, D., Rhee, H.Y., Ryu, C.W., Liu, T., Wang, Y. and Jahng, G.H., 2016. Texture analyses of quantitative susceptibility maps to differentiate Alzheimer's disease from cognitive normal and mild cognitive impairment. Medical physics, 43(8Part1), pp.4718-4728.
21. Jha, D., Kim, J.I. and Kwon, G.R., 2017. Diagnosis of Alzheimer's disease using dual-tree complex wavelet transform, PCA, and feed-forward neural network. Journal of healthcare engineering, 2017.
22. Khan, A. and Zubair, S., 2022. An improved multi-modal based machine learning approach for the prognosis of Alzheimer's disease. Journal of King Saud University-Computer and Information Sciences, 34(6), pp.2688-2706.
23. Kleiman, M. J., Barenholtz, E., Galvin, J. E., & Alzheimer's Disease Neuroimaging Initiative. (2021). Screening for early-stage Alzheimer's disease using optimized feature sets and machine learning. Journal of Alzheimer's Disease, 81(1), 355-366.
24. Lee, G., Nho, K., Kang, B., Sohn, K.A. and Kim, D., 2019. Predicting Alzheimer's disease progression using multi-modal deep learning approach. Scientific reports, 9(1), p.1952.
25. Li, F., Liu, M. and Alzheimer's Disease Neuroimaging Initiative, 2018. Alzheimer's disease diagnosis based on multiple cluster dense convolutional networks. Computerized Medical Imaging and Graphics, 70, pp.101-110.
26. Li, H., Habes, M., Wolk, D.A., Fan, Y. and Alzheimer's Disease Neuroimaging Initiative, 2019. A deep learning model for early prediction of Alzheimer's disease dementia based on hippocampal magnetic resonance imaging data. Alzheimer's & Dementia, 15(8), pp.1059-1070.
27. Li, T.R., Wu, Y., Jiang, J.J., Lin, H., Han, C.L., Jiang, J.H. and Han, Y., 2020. Radiomics analysis of

magnetic resonance imaging facilitates the identification of preclinical Alzheimer's disease: an exploratory study. Frontiers in Cell and Developmental Biology, 8, p.605734.

28. Li, Y., Jiang, J., Lu, J., Jiang, J., Zhang, H. and Zuo, C., 2019. Radiomics: a novel feature extraction method for brain neuron degeneration disease using 18F-FDG PET imaging and its implementation for Alzheimer's disease and mild cognitive impairment. Therapeutic advances in neurological disorders, 12, p.1756286419838682.
29. Liu, L., Zhao, S., Chen, H. and Wang, A., 2020. A new machine learning method for identifying Alzheimer's disease. Simulation Modelling Practice and Theory, 99, p.102023.
30. Lodha, P., Talele, A. and Degaonkar, K., 2018, August. Diagnosis of alzheimer's disease using machine learning. In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA) (pp. 1-4). IEEE.
31. Marwa, E.G., Moustafa, H.E.D., Khalifa, F., Khater, H. and AbdElhalim, E., 2023. An MRI-based deep learning approach for accurate detection of Alzheimer's disease. Alexandria Engineering Journal, 63, pp.211-221.Helaly, H. A., Badawy, M., &Haikal, A. Y. (2022). Toward deep mri segmentation for alzheimer's disease detection. Neural Computing and Applications, 34(2), 1047-1063.
32. Moradi, E., Pepe, A., Gaser, C., Huttunen, H., Tohka, J. and Alzheimer's Disease Neuroimaging Initiative, 2015. Machine learning framework for early MRI-based Alzheimer's conversion prediction in MCI subjects. Neuroimage, 104, pp.398-412.
33. Moscoso, A., Silva-Rodríguez, J., Aldrey, J.M., Cortés, J., Fernández-Ferreiro, A., Gómez-Lado, N., Ruibal, Á., Aguiar, P. and Alzheimer's Disease Neuroimaging Initiative, 2019. Prediction of Alzheimer's disease dementia with MRI beyond the short-term: Implications for the design of predictive models. NeuroImage: Clinical, 23, p.101837.
34. Naganandhini, S. and Shanmugavadivu, P., 2019. Effective diagnosis of Alzheimer's disease using modified decision tree classifier. Procedia Computer Science, 165, pp.548-555.
35. Nemmi, F., Saint-Aubert, L., Adel, D., Salabert, A.S., Pariente, J., Barbeau, E.J., Payoux, P. and Péran, P., 2014. Insight on AV-45 binding in white and grey matter from histogram analysis: a study on early Alzheimer's disease patients and healthy subjects. European journal of nuclear medicine and molecular imaging, 41, pp.1408-1418.
36. Payan, A. and Montana, G., 2015. Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks. arXiv preprint arXiv:1502.02506.
37. Ruiz, E., Ramirez, J., Górriz, J. M., Casillas, J., & Alzheimer's Disease Neuroimaging Initiative. (2018). Alzheimer's disease computer-aided diagnosis: histogram-based analysis of regional MRI volumes for feature selection and classification. Journal of Alzheimer's Disease, 65(3), 819-842.
38. Sarraf, S. and Tofighi, G., 2016. Classification of alzheimer's disease using fmri data and deep learning convolutional neural networks. arXiv preprint arXiv:1603.08631.
39. Sharma, S. and Mandal, P.K., 2022. A comprehensive report on machine learning-based early detection of alzheimer's disease using multi-modal neuroimaging data. ACM Computing Surveys (CSUR), 55(2), pp.1-44.
40. Shen, T., Jiang, J., Li, Y., Wu, P., Zuo, C. and Yan, Z., 2018, July. Decision supporting model for one-year conversion probability from MCI to AD using CNN and SVM. In 2018 40th annual international conference of the IEEE engineering in Medicine and biology society (EMBC) (pp. 738-741). IEEE.
41. Sørensen, L., Igel, C., Pai, A., Balas, I., Anker, C., Lillholm, M., Nielsen, M. and Alzheimer's Disease Neuroimaging Initiative, 2017. Differential diagnosis of mild cognitive impairment and Alzheimer's disease using structural MRI cortical thickness, hippocampal shape, hippocampal texture, and volumetry. NeuroImage: Clinical, 13, pp.470-482.
42. Sørensen, L., Nielsen, M. and Alzheimer's Disease Neuroimaging Initiative, 2018. Ensemble support vector machine classification of dementia using structural MRI and mini-mental state examination. Journal of neuroscience methods, 302, pp.66-74.
43. Srivastava, R. and Kumar, P., 2022. A CNN-SVM hybrid model for the classification of thyroid nodules in medical ultrasound images. International Journal of Grid and Utility Computing, 13(6), pp.624-639.
44. Stamate, D., Smith, R., Tsygancov, R., Vorobev, R., Langham, J., Stahl, D. and Reeves, D., 2020. Applying deep learning to predicting dementia and mild cognitive impairment. In Artificial Intelligence Applications and Innovations: 16th IFIP WG 12.5 International Conference, AIAI 2020, Neos Marmaras, Greece, June 5–7, 2020, Proceedings, Part II 16 (pp. 308-319). Springer International Publishing.
45. Wang, C., Li, Y., Tsuboshita, Y., Sakurai, T., Goto, T., Yamaguchi, H., Yamashita, Y., Sekiguchi, A., Tachimori, H. and Alzheimer's Disease Neuroimaging Initiative http://orcid. org/0000-0001-5252-1965 Wang Caihua 7 http://orcid. org/0000-0003-2490-4867 Li Yuanzhong 7 http://orcid. org/0000-0002-4814-8093 GotoTsubasa 7, 2022. A high-generalizability machine learning framework for predicting the progression of Alzheimer's disease using limited data. NPJ digital medicine, 5(1), p.43.
46. Wu, C., Guo, S., Hong, Y., Xiao, B., Wu, Y., Zhang, Q. and Alzheimer's Disease Neuroimaging Initiative, 2018. Discrimination and conversion prediction of mild cognitive impairment using convolutional neural networks. Quantitative imaging in medicine and surgery, 8(10), p.992.
47. YİĞİT, A. and Işik, Z., 2020. Applying deep learning models to structural MRI for stage prediction of

Alzheimer's disease. Turkish Journal of Electrical Engineering and Computer Sciences, 28(1), pp.196-210.

48. Zhang, J., Yu, C., Jiang, G., Liu, W. and Tong, L., 2012. 3D texture analysis on MRI images of Alzheimer’s disease. Brain imaging and behavior, 6, pp.61-69.
49. Zhou, H., Jiang, J., Lu, J., Wang, M., Zhang, H., Zuo, C. and Alzheimer’s Disease Neuroimaging Initiative, 2019. Dual-model radiomic biomarkers predict development of mild cognitive impairment progression to Alzheimer’s disease. Frontiers in neuroscience, 12, p.1045.