**A Complete survey on Alzheimer’s disease**

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**ABSTRACT**

Alzheimer’s disease (AD) is a disorder that is neurodegenerative ,it slowly affects your cognitive functions resulting in the significant decline of the memory gradually.It mostly affects older adults. There is no cure for this disease as of now , some drugs can be taken that will alleviate the symptoms .So, the machine learning models are increasingly used to for the early detection and diagnosis of Alzheimer’s. This research paper focuses on providing with the different machine learning algorithms used mores0 prevalently , the most important data used by the ML models for giving the accurate result. This research has reviewed literature from 1906 to 2024. The important data used for the detection in most of the literature reviewed are Magnetic Resonance Imaging(MRI), Positron Emission Tomography(PET), Functional Magnetic Resonance Imaging(fMRI), cognitive testing and biomarkers like cerebrospinal fluid etc. The most commonly used techniques were random forests, k-nearest neighbours(KNN), Support Vector Machine(SVM), Decision trees, Logistic Regression (LR) and Convolutional Neural Networks(CNN). These techniques were used because they could work with both numerical and categorical data , it is fast and efficient even with large volumes of data and results in good accuracy. This research suggests that using the different techniques and combining different kind of data like genetic, imaging and cognitive testing scores, that is by following a multimodal approach, there is a higher accuracy rate for the early detection and classification of Alzheimer’s Disease Stages.  
  
 Keywords: Alzheimer’s Disease ,Machine Learning, Multimodal approach, Early Detection ,MRI ,Cognitive testing , PET, fMRI, Biomarkers, Random Forest , k-Nearest Neighbours (KNN),Support Vector Machine(SVM),Decision Trees , Logistic Regression , Convolutional Neural Networks ( CNN)

**INTRODUCTION**

Alzheimer’s Disease(AD) is one of the most significant types of dementia , it accounts to majority of the cases of dementia worldwide that is 60% to 80%.This disease gradually impairs yours cognitive function , your capacity to do you simple daily activities is declined and this neurological condition worsens your memory . Alzheimer’s is mainly affects elderly section of the society. Amyloid -beta plaques, and the buildup of tau protein - based neurofibrillary tangling are the main reasons for the extensive neuronal death and which in turn becomes the significant reason for Alzheimer’s disease. Serious problems are faced by global healthcare systems due to the rise of this disease along with life expectancy. If there is no cure or preventive measure found by 2050 the current estimate of 50 million will triple among the dementia patients .

Main risk factors of this disease include age , smoking , environmental variables , heredity and nutrition. This disease is detected in people who are above 65 indicating that age is a reliable risk factor among the mentioned risk factors. Genetic factors are linked to early onset of Alzheimer’s disease. It is still not clear what are the factors that lead to the beginning stage and development of AD even though a fair amount of study has been done on these risk factors .

One of the most important problem with the condition is its late diagnosis. The clinical symptoms like cognitive impairment and memory loss are the conventional diagnostic techniques we mainly rely on to identify this illness but by the time these symptoms are identified considerable and irreversible brain damage would already have been occurred. The therapeutic measures that has a chance to slow down or reverse this disease course will have a little or no effect at this point .It is imperative that we make a early and precise diagnosis, as this would us to provide with better patient care , more prompt therapies and better outcomes that leads in delaying the progression of the disease.

In conditions like Alzheimer's disease where early detection is very critical , the recent developments in ML and AI holds a significant potential to make transformations in medical diagnostics. They can spot patterns in large and complex data using ML algorithms which the conventional analysis would mostly miss in providing . This capability is helpful in the faster diagnosis of AD in their early stages as it enables the integration of multimodal data which includes genetic profiles, neuroimaging and cognitive test results .

PET, fMRI, MRI are the neuroimaging methods that are frequently used to find the functional and structural alterations in the brain that is linked to AD. Hippocampus atrophy and accumulation of amyloid plaque are the identifying signs we achieve through these scans , which occurs during the preclinical stages of this disease . Cerebrospinal fluid (CSF) proteins like amyloid beta and tau are the biomarkers that are employed .To asses cognitive function in the areas that are suspected ,cognitive tests like Mini-Mental State Examination (MMSE) are conducted to provide with additional information

Since the ML models has been trained on a variety of data the early stage detection accuracy has significantly increased. Differentiating AD patients from healthy persons using CNN and DL models utilizing neuroimaging data has shown improved performance in the differentiation .Method like KNN , SVM and random forests are some among the other algorithms that are popular in performing well with both numerical and categorical data . The researchers have been able to attain higher diagnosis accuracy depending on the data collected and the ML approached utilized.

There exists a number of obstacles even though there is developments in this field, To integrate different modalities like PET , cognitive tests, MRI and genetic data on massive datasets it takes strong algorithms . This kind of integration of modals are computationally demanding . The ability to generalize among a range of populations is the clinical applicability of these models . It makes it challenging to understand how some of these predictions are made due to the interpretability problem which arises due to the black box structure of the ML models which makes interpretability a crucial skill.

In conclusion , thanks to the existing diagnostic techniques which helps in detecting AD before its too late for effective intervention . Machine learning is a viable choice that evaluates complicated and large dataset that helps in spotting the early symptoms of the disease. More study in this area is important and necessary to increase the accuracy of these models and to make it suitable for use in clinical settings .If this is successful it can revolutionize the ways in which AD is diagnosed and treated in the future .

**LITERATURE REVIEW**

**Chang et al,(1912)** identified preclinical AD using cognitive testing and ML techniques to differentiate memory strategies between individual at high risk and those at low risk. The Rey Auditory Verbal Learning Test was utilized and ML methods, including stochastic gradient descent, were applied to exploit subtle differences in memory strategies. The results showed significant differences in memory performance, providing better separation between the 2 risk groups than the traditional methods. The dataset includes results from 879 high risk and 355 low risk individuals (Chang, 1912)

**Boyd et al,(1936)** talks about a typical case of AD, characterized by complex mental disintegration, speech disorders and apraxia. Tissue examination via biopsy confirmed the diagnosis with a key symptom being the inability to calculate. The patient showed significant memory impairment and reduced comprehension on abstract tasks. Despite the extensive case analysis, the writer concludes that it is not possible to diagnose Alzheimer’s solely based on psychological examination, as it can be confused with other diffuse disease of the cortex (Boyd, 1936)

**Terry et al,(1963)**examined the intricate details of neurofibrillary tangles in Alzheimer's disease using electron microscopy. He found that the tangles are made up of paired helical filaments (PHFs), which cause structural disruption to the inside of the neuron. PHFs are mainly composed of tau protein. His research indicated that tau protein could be a target for therapeutic intervention by connecting the formation of these tangles to neuronal dysfunction and cell death, underscoring their crucial role in the development of Alzheimer's disease. (D., 1963)

**Kidd et al,(1963)** identified paired helical filaments in Alzheimer's disease and described them as a characteristic characteristic of neurofibrillary tangles using electron microscopy. The study linked the presence of these twisted structures to cognitive decline by observing them in degenerating neurons within the cortex and hippocampus. This study recommended more research into the mechanisms underlying PHF formation and emphasized the significance of PHFs in understanding the pathology of Alzheimer's disease. (Kidd, 1963)

**Blessed et al,(1968)** discovered a strong correlation between the degree of dementia and the amount of neurofibrillary tangles and senile plaques in elderly subjects. Their research established tangles and plaques as important indicators of cognitive decline and provided early evidence for the pathological basis of Alzheimer's disease. It also quantitatively showed that individuals with more severe dementia had higher levels of these pathological features, particularly in the hippocampus and temporal cortex. (Blessed, 1968)

**Crapper et al,(1973**)Aluminum exposure produced similar tangles in rabbits, indicating a possible role in the pathophysiology of Alzheimer's disease. Although the study could not establish causation, it did demonstrate a correlation between aluminum and neurodegeneration, which led to more research into aluminum's involvement in the illness. (Crapper, 1973)

**Hopper et al , (1976)** examined the hippocampus and amygdala as key components of the limbic system in Alzheimer's disease. In these areas, they found significant neuronal loss, neurofibrillary tangles, and gliosis. They linked the damage to memory loss and emotional abnormalities that are characteristic of Alzheimer's disease. Their research connected the limbic system to the emotional and cognitive deficiencies seen in patients, highlighting the limbic system's crucial role in disease pathology. (Hopper, 1976)

**Katzman et al,(1976)** According to Katzman , Alzheimer's disease is a major cause of death for the elderly due to its high prevalence and fatal nature. According to his research, Alzheimer's was frequently mislabeled as general senility, and the disease's malignant progression needed to be acknowledged. In addition to highlighting the need for improved diagnosis and treatment, Katzman's paper established Alzheimer's as a primary cause of death for the elderly population and raised awareness of the disease as a significant public health concern. (Katzman R. , 1976)

**Perl et al,(1980)** X-ray spectrometry was utilized by Perl and Brody to identify increased aluminium concentrations in Alzheimer's patients' neurons that had neurofibrillary tangles. Although the study was unable to determine whether aluminium causes or results from the disease, the results point to a potential connection between aluminium and the formation of tangles, which suggests more research into the role of metals in neurodegeneration. (Perl, 1980)

**Glenner and Wong,(1984)** isolated and characterized a novel amyloid protein that was subsequently identified as amyloid-beta from cerebrovascular plaques in Alzheimer's patients. According to their research, this tiny protein forms insoluble fibrils that build up in brain blood vessels and contribute to the pathophysiology of Alzheimer's disease and the formation of amyloid plaques. This important finding laid the groundwork for the development of the amyloid cascade theory and provided insight into the pathophysiology of Alzheimer's disease. (Glenner, 1984)

**Hyman et al,(1984)** The higher levels of neurofibrillary tangles and neuronal decline was found in the subiculum and CA1 region in the hippocampi on the cell-specific study in AD patients .The impairments in the early memory of the patients are partly because of the degeneration of these regions , since these regions are essential for proper functioning of the memory. The results obtained from this study points out how AD progresses due to the pathology of certain specific cells. (Hyman, 1984)

**Yamamoto et al,(1986)** Upon the ultrastructural study, it was found that paired helical filaments are the primary factor in the neurofibrillary tangles in AD .The research pointed out how paired helical filaments are different from the filaments in other diseases that are neurodegenerative .This study tells that PHF might be the factor that contributes to neurodegeneration as its buildup would disrupt the regular cellular processes . (Yamamoto, 1986)

**Katzman et al, (1991)** This study tells how giving importance to cellular alterations , genetic factors , clinical implications and molecular alterations have helped in increasing progress in studying this disease.They mostly emphasis on the pathological characters such as amyloid plaques ,neurotransmitter deficiencies and neurofibrillary tangles. This study highlights the recent genetical discoveries such as how the connection between amyloid precursor protein and chromosome can help in creating more specialized treatment . (Katzman, 1991)

**Pericak-Vance MA et al,( 1991)** They discovered that in the families that were afflicted by this disease there found the evidence that there is a genetic correlation between the chromosome 19 and Alzheimer’s disease through their linkage analysis .They found that APOE played a significant role as a genetic risk factor in AD .This study was revolutionary since it opened doors to further investigation of the genetic locus linked to Alzheimer’s. (Pericak-Vance MA, 1991)

**Tsai et al,(1994)** The study established that apoliproprotein E is a significant factor in the genetic risk of AD disease . It also verified that one or more alleles of this protein is one of the causes for increased risk in AD . The screening of this ApoE genotype helps in identifying the individuals that are at the risk of this disease . (Tsai, 1994)

**Näslund et al, (1994)**  In this study the aging people were examined along with finding the abundance of amyloid beta variants presence in the brain of people with AD .They found that Aβ42 is contributing more towards the AD patients . This study urges that more investigation must be done on the role of these peptides in the development rate of AD. (Näslund, 1994)

**Lehericy et al, (1994)** Using MRI they measured the amygdala and hippocampal volumes in AD patients .It demonstrated that there is a decline in the brain regions , which are essential for memory and emotion .They suggested that MR volumetric analysis will help in tracking AD and for providing early diagnosis.They suggested more studies must be conducted in larger populations to confirm the results . (Lehericy, 1994)

**Besthorn et al,(1994)** This study looks towards the variance in the EEG of AD patients .The EEG measures the functional connectivity between the different brain regions .The results showed that in the parietal and temporal lobes , the increase in the EEG coherence is linked to the decline in cognitive of AD .Impaired synchronization in brain was found as the marker for the advancement of AD.The study suggests more research should be done in future on how the coherence of EEG is significant in the early diagnosis of AD . (Besthorn, 1994)

**Schellenberg et al, (1995)** This study highlights the heterogeneity in the genetic complexity in AD.This paper describes how ApoEa and APP along with several other genes contribute to the course and onset of AD. This study investigates the identification of risk factors and genetic mutations of AD using genetic mapping and molecular analysis .This paper tells that a good understanding of the genetic basis will help in the personalized treatment and early diagnosis of AD. (Schellenberg, 1995)

**Finch et al, (1997)** This paper studied the connections between digestion system , maturing and AD. They found that metabolic changes in maturing , modifications in glucose digestion system and expanded oxidative push mainly contribute to improving AD. They found that mature handle along with metabolic dysregulation increases the drive to cognitive decrease. The study highlights the requirement to inquire more about the metabolic pathways in maturing and AD. (Finch, 1997)

**Perry et al, (1998)** This paper studies on the role of ROS in the damage of cells in AD.It shows that oxidative stress causes deterioration in neurons in AD patients further contributing to the progression of this disease .This study tells that addressing oxidative damage could be a strategy for slowing AD progression .The study suggests to further investigate on the antioxidant effects in AD treatment . (Perry, 1998)

**Smith et al, (1998)**  This paper discusses in details about underlaying mechanisms , treatment approaches and clinical features of AD.This review suggested that oxidative damage is significant factor in the development of the disease .It tells that amyloid -beta , oxidative stress and tau protein are the main causes . This review emphasis the need for fresh ideas in regard to therapeutic intervention. (Smith, 1998)

**McGeer et al,(1998)** It tells that the major factor contributing to the pathophysiology of AD is neuroinflammation , majorly the activation of microglia and astrocytes.It tells that persistent inflammation worsens the neuronal damage and cognitive decline .The study tells that there can be therapeutic benefits for the anti-inflammatory medications. (McGeer, [23]"The importance of inflammatory mechanisms in Alzheimer disease." Experimental Gerontology, 33(5), 371-378., 1998)

**Blacker et al ,(1998)** The study tells that genes like PSEN2, PSEN1,APOE and APP are linked to the both sporadic and familial forms of the disease .The study tells how discovering the genetic connections is creating new opportunities for creating treatments for this disease.The study recommends that to improve more gene based treatments and to find more risk genes . (Blacker, 1998)

**Gao S et al*,* (1998)** This meta-analysis looks at the relationship between sex and age on the prevalence of AD and dementia. This study evaluates the diagnoses of dementia between the age group and genders aggregating data from several epidemiological studies.The study tells that the risk of this disease increases with age and that women are more likely to get it than men mainly in older age groups. This study tells that more focus should be given for researching on the age and sex specific factors. (Gao S, 1998)

**Younkin et al,(1998)** The study tells the important role amyloid beta 42 peptide plays in the neurodegeneration and plaques development which is related to AD.This study describes how the increase in this peptide has contributed in the cognitive decline in patients. Further research is necessary to fully explore the therapeutic avenues, the author suggests that targeting Aβ42 with therapies could potentially slow down the progression of the disease. (Younkin, [26]"The role of Aβ42 in Alzheimer's disease." Journal of Physiology-Paris, 92(3-4), 289-292., 1998)

**Markesbery, (1999)** This study tells how oxidative stress is playing a important role in AD.It tells how amyloid-beta and tau protein changes aggregation will ultimately result in the death of neurons.This paper suggests antioxidant therapies as a tactic to verify how effectively we can delay the course of AD. (Markesbery, [28] "The role of oxidative stress in Alzheimer disease." Archives of Neurology, 56(12), 1449-1452., 1999)

**Johnson et al, (1999)** The paper tells that there is a frontal variant of AD that can be distinguished by the identifying the dysfunction of frontal lobes. In the executive function and personality disorders , the variation is linked to behavioral deficits and specific cognitive function The paper suggests that more awareness and knowledge of this variant is needed to manage and improve the diagnosis. (Johnson, 1999)

**Haroutunian V et al, (1999)** This study examines the neurofibrillary tangles in elderly people with mild Alzheimer’s disease and without it . They discovered that NFT’s are common in those with mild AD..They said that NFT’s might appear before dementia symptoms , that can act as precursor to this disease .The study suggests that more research should be done on the NFT formation. (Haroutunian V, 1999)

**Grundman et al, (2000)** This studytells how vitamin E can impede the advancement of AD.They suggests clinical trials should be done to investigate if vitamin E as a therapeutic option, they cited several research demonstrating their antioxidant qualities.The study tells that vitamin E slow down the decline in cognitive function in AD patients and may help in shielding the neurons from oxidative damage . (Grundman, 2000)

**Gillette-Guyonnet et al,(2000)** Thestudy found thatweight loss in AD patients has been linked to AD progression and the metabolic process disruption. They examine the relation between cognitive decline and weight loss to highlight the importance of efficiency in nutritional management .The research tells that by maintaining the nutritional status may slow down the cognitive decline and enhance the quality of life (Gillette-Guyonnet, 2000)

**Christen ,(2000)** This study by Yves Christen focuses on how oxidative stress contributes to Alzheimer's disease. It goes over how amyloid-beta accumulation and neurofibrillary tangles—two pathological hallmarks of Alzheimer's disease—are exacerbated by oxidative damage. The study notes that additional research is necessary to validate the use of antioxidants as a potential intervention to slow the progression of disease. The review emphasizes that one important, albeit poorly understood, component of Alzheimer's pathology is oxidative stress (Christen, 2000)

**Nourhashémi, F et al, (2000)** This study examines a number of lifestyle variables, such as food, exercise, and cognitive engagement, that are protective against Alzheimer's disease. According to the study, upholding a healthy lifestyle that includes a Mediterranean diet and frequent exercise may lower the chance of developing Alzheimer's disease. However, because the available data is still developing, the authors urge additional longitudinal research to validate these protective associations. (Nourhashémi, 2000)

**Milien et al, (2000)** In their review of possible pharmacological interventions for Alzheimer's disease, they put particular emphasis on recently developed therapies that target neuroinflammation, cholinergic dysfunction, and amyloid-beta accumulation. Because of the disease's complexity and the importance of early intervention, the authors talk about the difficulties in creating effective treatments. They draw attention to knowledge gaps regarding the specific mechanisms of drug action while highlighting the significance of continuing research to improve patient outcomes and treatment strategies. (milien, 2000)

**El-Baz et al,(2001)** used deep learning techniques, specifically CNN to classify AD using MRI and FMRI data. The datasets were collected from the ADNI database. Their deep learning based model achieved an accuracy of 95.4% in distinguishing Alzheimer’s patients from healthy controls. Comparatively, traditional ML algorithms like SVM showed lower accuracies around 85%. (El-Baz, 2001)

**Dickerson et al,(2001)** used MRI to study brain atrophy in the entorhinal cortex and hippocampus in early AD. they compared healthy elderly controls, patients with cognitive complaints and very mild Alzheimer’s cases. Entrohinal cortex volume was found to be the best predictor with accuracy from non converters with 83% accuracy, hippocampus atrophy was better in distinguishing mild alzheimer’s patients from non-demented individuals classifying 75% correctly . They have used logistic regression algorithm indicated that EC bollume was more accurate for predicting AD risk in early stages. (Dickerson, 2001)

**Kantarci et al, (2002)**  have compared different MRI methods, including hippocampal volumetry, MR spectroscopy and diffusion weighted imaging to distinguish AD, MCI and normal aging. Identified MCI with 79% accuracy and AD with 86% accuracy. Combining MR techniques improved sensitivity for detecting AD (Kantarci, 2002)

**Chetelat et al,(2003)** uses MRI scans for studying AD progression. They focus on the hippocampus and related brain structures, analyzing their atrophy. The dataset consists of individuals who are in the developing stage of Alzheimer’s disease because of healthy aged subjects and memory impairments. The researchers have applied volumetric measurements and compared them to visual assessments, finding hippocampal atrophy as a key indicator of early Alzheimer’s. Their models achieved an accuracy of 70% in differentiating AD patients from healthy individuals (Aël Chetelat, 2003)

**Jeong et al,(2004)** used EEG dynamics to examine brain activity in Alzheimer’s patients, focusing on EEG abnormalities. They used EEG data from patients with Alzheimer’s , analysing linear and nonlinear changes in brain dynamics. The study found that alzheimer’s patients had less complex brain wave activity, which was linked to neuronal loss and cortical disconnection. Showed EEG as a useful tool for early diagnosis with 80% accuracy (Jeong, 2004)

**Adeli et al, (2005)** used multimodal approaches such as imaging, EEG feature extraction and neural model to predict and classify AD. The dataset used involved neuroimaging data, anatomical images and EEG recordings. They applied various ML models like Ai neural networks for classification and feature extraction. They’ve reported that ANNs gave better classification accuracy compared to traditional methods such as discriminant analysis and clustering (Adeli, 2005)

**Devanand et al, (2007)** have used MRI scans to predict the conversion from MCI to AD. They have analyzed brain regions like the hippocampus and entorhinal cortex, which are known to shrink in the early stages of AD. The Study involved 139 MCI patients and 63 healthy controls. Using a combination of brian volume measurements and cognitive tests, they found that smaller hippocampal and entorhinal cortex volumes predicted the progression to AD. The MRI data were collected from patients at the New York State Psychiatric Institute and Columbia-Presbyterian Medical center. Achieved an overall accuracy of 85% by combining memory tests, age and brain volume (Devanand, 2007)

**Venneri et al,(2009)** used ADNI and included 130 healthy controls, 122 subjects with MCI and 130 AD patients. Their study focused on how cognitive reserve, indicated by education level, affects the ability to predict the progression from MCI to AD. they developed a Normalized thickness Index to measure cortical thickness and found that it could predict conversion to AD with an accuracy of 85% through cross validation. The NTI was particularly effective in identifying progressive MCI achieving a predictive value of 76%. (Querbes, 2009)

**Gerardin et al,(2009)** developed a method to distinguish AD and MCI from healthy aging using hippocampal shape features. They used data from the ADNI and applied spherical harmonics for shape modeling SVM for classification. Their method achieved 94% accuracy for AD vc controls and 83% for MCI vs controls outperforming traditional volumetry and showing comparable results to other recent svm methods (Gerardin, 2009)

**Hu et al, (2010)** used multimodal predictors, including neuropsychological assessments , structural MRI & cerebrospinal fluid biomarkers to differentiate AD from frontotemporal lobar degeneration in patients with primary progressive aphasia . combining neuropsychological testing with MRI atrophy patterns improved prediction accuracy, achieving 90% specificity for AD and 100 % sensitivity for predicting pathology (Hu, 2010)

**Ewers et al, (2011)** Used MRI, PET scans with tracers like Pittsburgh Compound-B(PiB), and FDG-PET to track amyloid-beta deposits and brain glucose metabolism in subjects at risk for Alzheimer’s disease. Their study involves cognitively normal elderly individuals , patients with MCI and AD. For detecting early Alzheimer's a comparison of the algorithms resulted that PET scans especially PiB-PET were more sensitive. MRI provided structural brain changes like hippocampal atrophy, while FDG-PET highlighted metabolic dysfunction. This combination of techniques gave an accuracy of approximately 80% in predicting progress from MCI to AD (Ewers, 2011)

**Wolz et al, (2011)** have used combination of MRI based features like hippocampal volume, cortical thickness, tensor based morphometry and manifold based learning to improve the early diagnosis of Alzheimer’s disease. The data was collected from the ADNI. they used linear discriminant Analysis and support vector machines for classification, achieving 93% sensitivity and 85% specificity for Alzheimer’s vs healthy controls. (Wolz, 2011)

**Zhang et al, (2012)** uses multimodal data, which includes MRI, PET and cerebrospinal fluid to improve predictions of Alzheimer’s disease and mild cognitive impairment . They employed multi-task learning with support vector machines and features selection techniques to predict both regression (mini-mental state examination & AD assessment scale-cognitive subscale) and classification tasks (AD , MCI , healthy controls) . their method achieved a correlation of 0.697 for MMSE and 0.739 for ADAS-cog, with classification accuracies of 93% for AD vs.healthy controls and 83% for MCI vs healthy controls (Zhang D. S., [48]Multi-modal multi-task learning for joint prediction of multiple regression and classification variables in Alzheimer's disease. NeuroImage, 59(2), 895-907., 2012)

**Zhang et al, (2012)** have used data from AD neuroimaging initiative database including MRI and FDG-PET imaging data along with clinical scored to predict future clinical changes in patients with MCI . they developed a method that combines longitudinal feature selection and multi-kernel support vector machines for improved prediction . their approach achieved a correlation coefficient of 0.786 for predicting future MMSE scores and 0.777 for ADAS-cog scores at teh 24 month mark, they’ve also achieved a classification accuracy of 78.4% in predicting the conversion of MCI to AD, demonstrating the effectiveness of using longitudinal multimodal data for enhanced prediction (Zhang D. S., 2012)

**Dai et al,(2012)** used multi modal imaging and a multi level characterization method, combining structural MRI and resting-state functional MRI(R-fMRI) to differentiate Alzheimer’s patients from healthy controls. Their approach names M3 method, applied features likely gray from MRI and functional characteristics like amplitude of low frequency fluctuations , Regional homogeneity, Regional Functional connectivity Strength. They achieved a classification accuracy of 89.47% using these multi classifier models. (Dai, 2012)

**Westman et al ,(2012)** used data from ADNI to improve AD classification and predict MCI conversion. They combined model resonance imaging and cerebrospinal fluid measures. Their combined model achieved an accuracy of 91.8% for distinguishing AD from healthy controls, compared to 87.0% for MRI alone and 81.6% for CSF alone. This study shows that using both MRI and CSF together is more effective than using separately (Westman, 2012)

**Young et al, (2013)** have used multimodal data which includes brain imaging & biomarkers, to enhance prediction of Alzheimer’s disease in patients with mild cognitive impairment. They’ve applied Gaussian Process classification to generate probabilistic predictions , which correlated very well with conversion to Alzheimer’s. Their model achieved high accuracy in distinguishing between patients who would develop Alzheimer’s and those who would remain stable (Young, 2013)

**Gray et al, (2013)** have used data from ADNI , including MRI, FDG-PET, CSF biomarker measures, and genetic data to improve AD classification . They applied Random Forest Classifiers and used pairwise similarity measures to combine features from different modalities. Their approach achieved an 89% accuracy for Alzhiemer’s vs healthy controls and 75% accuracy for MCI vs Healthy controls. (Gray, 2013)

**Segovia et al,(2013)** developed a method for the early diagnosis of AD using single photon emission computed tomography(SPECT) images. They used data from 97 SPECT images collected from patients at the virgen de las Nieves hospital in spain. Theri approach combined partial least squares for feature extraction and SVM for classification. The system achieved over 90% accuracy, sensitivity and specificity, outperforming other recent methods for diagnosing AD (Segovia, 2013)

**Thung et al,(2013)** have used data from the AD neuroimaging initiative dataset, including MRI , PET and CSF data to identify AD patients. They have applied matrix completion algorithm on a shrunk version of the feature matrix. This approach allows them to predict missing feature values and clinical scores. It has 2 methods involved 1st , they apply matrix completion to fill in the missing values. The results showed an accuracy of around 88% in identifying AD patients. Their approach not only increases accuracy but also speeds up the identification process of AD using incomplete multimodal data (Thung, 2013)

**Shaffer et al,(2013)** used data from the ADNI, which includes cerebrospinal fluid, MR imaging, and Fluorine 18 FDG PET biomarkers to predict Alzheimer’s disease conversion. They applied independent component Analysis on these multi modal datasets to improve prediction models. This combination of model achieved a misclassification rate of 28.4%. (Shaffer, 2013)

**Eskildsen et al,(2013)** utilized data from the ADNI, which includes MRI-based cortical thickness measurements, to predict Alzheimer’s disease in subjects with MCI. The study used surface based cortical thickness analysis to identify regions of the brain affected by atrophy in different stages. They achieved accuracy from 70% to 76%. (Eskildsen, 2013)

**Ziming Zhang et al,(2014)** studied how to predict AD using different types of data. They looked at MRI, cerebrospinal fluid and genetic data. They tested 3 methods to choose important features from this data. They used MRI , PET, CSF and genetic data to test them . Multiple kernel learning , high order graph matching based feature selection and sparse multimodal leaning . PET images showed most accurate for prediction and SNP data helped improving it and HGM-FS was best among the 3 methods. (Zhang, 2014)

**Li et al,(2014)** used data from the ADNI including MRI and PET images, to improve Alzheimer’s prediction. Their 3D CNNs significantly surpasses traditional approaches like KNN and zero filled methods. These conventional techniques were less effective in estimating the missing PET data. The CNN achieved 88.68% accuracy in predicting AD vs NC, comparable to the 89.82% with real PET data. Combining MRI with the completed PET data further boosted classification accuracy (Li, 2014)

**Razlighi et al,(2014)** developed a new algorithm using data from two cohorts to predict how long Alzheimer's disease patients would need to live, require full-time care or be placed in a nursing home. The data came from the “Predictors” study, which followed over 500 patients across 3 centers for 10 years. Their algorithm achieved accurate predictions and showed strong results even when key data was missing, with accuracy falling within the 95% confidence interval for all tested scenarios (Razlighi, 2013)

**Hinrichs et al, (2014)** have used data from ADNI database which included MRI, PET scans for prediction of AD progression. They have developed a method called Multi kernel learning to combine different types of data for better accuracy. Their results showed that this method improved accuray by 3% to 4% compared to traditional methods. They found that their multi-modal disease marker can distinguish between MCI patients who progressed to AD and who remained stable over 3 years. The classification accuracy by 3 % to 4 % compared to traditional methods (Hinrichs, 2011)

**Suk et al ,(2014)** used deep learning to improve the diagnosis of Alzheimer’s and MCI by using both MRI and PET images which are taken from the ADNI database for testing. They used a Deep Boltzmann Machine to automatically find important patterns in small 3D patches of brain scans. Their model was more accurate compared to other methods, achieving a 95.35% accuracy for alzhiemer’s vs healthy controls and 85.67% for MCI (Suk, 2014)

**Ortiz et al,(2014)** used data from the ADNI database , which included both PET and MRI scans.. They applied a method that combines these two types of brain images to better diagnose AD. their technique called Sparse Representation Classifiers, merges information from both MRI and PET images, helping to improve diagnosis accuracy. Their model achived 94% accuracy, which was better than using just one type of image (Ortiz, 2014)

**Liu et al,(2014)** used deep learning techniques for early diagnosis of AD using neuroimaging data from MRI and PET scans. They developed a framework that included CNN to extract high-level features from the images, focusing on classifying different stages of AD. it has achieved better performance distinguishing between healthy individuals and AD patients. It reports that their deep learning model for early alzheimer’s diagnosis achieved an accuracy of 96.85% (Liu S. L., 2014)

**Lebedev et al,(2014)** studies how to detect and predict AD using random forest classifiers. They used data from the ADNI and the AddNeuroMed consortium, which included MRI scans from 185 AD patients and 225 healthy controls. Their best model achieved a sensitivity of 88.6% and specificity of 92.0% for distinguishing AD from healthy controls. They found that their random forest model was more accurate than a linear SVM classifier (Lebedev, 2014)

**Liu et al,(2014)** used data from the ADNI database , which included neuroimaging modalities such as MRI and PET for AD diagnosis. They implementd deep learning models, partucularyl stacked autoencoder, combined with a softmax logistic regression for classification. Their model achieved a multiclass classification of Alzheimer’s stages with an accuracy of 91.4% for binary classification tasks and 53.79% for multiclass classification. (Liu, 2014)

**Mehdi Rahim et al,(2015)** used spatial TV-l1 prior, PET-informed prior and ridge regression on the fluorodeoxyglucose positron emission tomography (FDG - PET) and resting -state functional magnetic resonance imaging (fMRI) data from the ADNI dataset to build a model integrating priors for the functional characterization of alzheimer’s disease. The ridge classifier gives the highest accuracy of 88%. (Rahim, 2015)

**Kerstin Ritter et al,(2015)** utilized classification algorithms such as support vector machines (SVM) , random forest and a single classification tree on the clinical data ,genetics ,biospecimen ,neuropsychology ,PET and MRI data retrieved from ADNI database for the predictions based on incomplete biomarkers for Alzheimer’s disease. Support vector machines (SVM) gave the highest accuracy of 73.44%. (Ritter, 2015)

**Tingyan Wang et al,(2018)** utilized logistic regression(LR),support vector machine(SVM),decision tree(DT),random forests (RF) and long short-term memory RNN model on the data that includes patients demographics , physical information ,health history, geriatric depression scale (GDS) , elements of the clinical dementia rating (CDR) scale and functional activities questionnaire (FAQ) on the dataset collected from the US National Alzheimer’s Coordinating Center(NACC) for building a model that predicts the progression of alzheimer’s disease. When compared to other models long short-term memory RNN gives a highest accuracy of 99%. (Wang, 2018)

**Daniel Stamate et al,(2019)** uses XGBoost , random forest, deep learning on the data including MRI ,PET, details on the subjects, clinical and cognitive data and measurements of AD pathological markers from ADNI database for diagnosing Alzheimer in blood. XGBoost has the highest accuracy of 87% (Stamate, 2019)

**S.Naganandhini et al,(2019)** uses decision tree classifier with hyper parameters tuning (DTC-HPT) model on the data including age ,gender,fMRI,PET ,MMSE,CDR from OASIS dataset for diagnosis of alzheimers disease.DTC-HPT gives the highest accuracy of 99.10%. (Naganandhini, 2019)

**Taeho Jo et al,(2019)** utilized stacked auto-encoder(SAE) , RNN and CNN on the MRI ,PET and FDG-PET data retrieved from the ADNI database for the prognostic and diagnostic classification using neuroimaging data for Alzheimer’s disease. Stacked auto-encoders (SAE) gave the highest accuracy of 98.8%. (Jo, 2019)

**Garam Lee et al,(2019)** uses RNN, SVM, Gaussian process, Hierarchical ensemble, Deep neural networks combining demographic information, neuroimaging phenotypes measured by MRI, longitudinal cerebrospinal fluid(CSF) and cognitive performance biomarkers etc from the ADNI dataset for predicting Alzheimer disease .Deep neural networks had a highest accuracy of 82%. (Lee G. N., 2019)

**Garam Lee et al,(2019)** uses RNN networks which includes GRU and LSTM , they used cognitive performance ,cerebrospinal fluid, demographic data and MRI data from the ADNI dataset to build a deep learning based multimodal framework. When compared with other algorithms like LR,RF and SVM the proposed model had a highest accuracy of 95%. (Lee, 2019)

**Xian-an Bi et al,(2020)** used Clustered evolutionary random forest(CERF), Random forest, Random SVM cluster (RSVMC), Canonical correlation analysis(CCA),Discriminant correspondence analysis (DCA), t-test on the ADNI dataset using the functional magnetic resonance imaging (fMRI) and single nucleotide polymorphism (SNP) to analyze the data of alzheimer’s disease.The highest accuracy achieved by clustered evolutionary random forest is 86%. (Bi, 2020)

**Solale Tabarestani et al,(2020)** used algorithms like ridge regression , elastic lasso ,temporal group lasso (TGL) , convex fused sparse group lasso (cFSGL) , non-convex fused sparse group lasso (nFSGL) , parameter-free least lasso,l2,1norm and subspace regularized sparse multitask learning on the MRI , PET , other biological markers and clinical and neuropsychological assessments from the ADNI database for alzheimer disease prediction in a longitudinal study . The convex fused sparse group lasso has the highest p-value of 0.501 (Tabarestani, 2020)

**Gopi Battineni et al,(2020)** utilized naïve bayes,SVM, k-nearest neighbor and artificial neural networks(ANN) on the data including MRI , gender , age, CDR score, ASF, eTIV etc from the assessment conducted at the Alzheimer’s Disease Research Center (ADRC) of Washington University for predicting Alzheimer’s in older patients. . Hybrid or joint modelling with limited features had the highest accuracy rate of 98%. (Battineni G. C., 2020)

**Juan Felipe Beltran et al,(2020)** utilized classification and regression tree(CART),gradient boosting , random forest and SVM on data including MRI, PET, cerebral spinal fluid measurements, genetic tests , demographics and vital signs from the ADNI database for predicting Alzheimer’s using ML. Random forest gives the highest accuracy of 75%. (Beltran, 2020)

**Gloria Castellaazzi et al, (2020)** used ANN, SVM and adaptive neuro-fuzzy inference system (ANFIS) on data including resting -state fMRI(rs-fMRI) and diffusion tensor imaging (DTI) from dataset from Neurological Institute IRCCS Mondino Foundation (Pavia, Italy) .ANFIS gives the highest accuracy of 83.50%. (Castellazzi, 2020)

**Janani Venugopalan et al, (2021)** used deep learning , convolutional neural networks, stacked denoising auto encoders which is used to analyze and extract features from clinical and genetic data to give a early prediction of Alzheimer’s disease. They used Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset that contained SNP(single nucleotide polymorphisms) ,clinical and neurological test data,MRI imaging and demonstrated that shallow models such as random forests , SVM, kNN ,and decision trees outperform deep learning models .They got 88% as the highest accuracy for the combination deep learning models( EHR+SNP data) and SVM. Their limitation was the small sample size of the dataset. (Venugopalan, 2021)

**Shaker El-Sappagh et al,(2021)** used machine learning algorithms such as random forest , kNN , SVM ,decision tree and logistic regression to predict Alzheimer disease progression.They used ADNI database .The model is a fusion of information of cognitive scores , comorbidities and medications for patient diagnosis .Additional informations such as gender , years of education ,demographics , age of the patient is considered .Random forest algorithm has the highest accuracy of 90.51%. (El-Sappagh S. S., 2021)

**Zhen Pang et al,(2021)** uses multi-task learning algorithm DT,RF,SVM along with XGBoost classification algorithm on the ADNI dataset using data such as PET and MRI images , cognitive testing ,genetics etc for the prediction of final stage of alzheimer’s using these ML methods .Uses random forest algorithm on PET and MMSE data sets to achieve highest accuracy of 75%. (Pang, 2021)

**Gopi Battineni et al,(2021)** utilized algorithms such as random forest ,gaussian naïve bayes , SVM, logistic regression , gradient boosting and AdaBoost on the MRI data taken from the dataset from Open Access Series of Imaging Studies (OASIS) for improving the detection of alzheimers using MRI. The gradient boosting algorithm resulted in the highest accuracy of 97.58% outperforming the other models . (Battineni, 2021)

**Shaker El-Sappagh et al,(2021)** used random forest,SVM,KNN,DT,Naïve Bayes algorithms on the ADNI dataset with 11 modalities like demographics, cognitive scores etc for making a detection and prediction model for alzheimer’s.When compared with other algorithms random forest had the highest accuracy of 93.33%. (El-Sappagh S. A., 2021)

**Mohammed Abdelaziz et al,(2021)** utilized CNN , multi-task feature learning (MTFL) , principle component analysis (PCA) ,locality preserving projection (LPP) and Shallow Wide Deep Neural Networks(SWDNN) on the data which includes PET, MRI, clinical scores and SNP’s which is retrieved from ADNI dataset to build a model to diagnose Alzheimer’s disease .The proposed model which used CNN had the highest accuracy of 98.22%. (Abdelaziz, 2021)

**Juan E.Arco et al,(2021)** utilizes Searchlight and Principal component analysis (PCA) on neuropsychological tests and MRI from the ADNI database for prediction of alzheimer’s disease from data fusion on searchlight analysis.Searchlight gave the best result with the highest accuracy rate of 80.9%. (Arco, 2021)

**Morshedul Bari Antor et al,(2021)** utilized SVM, logistic regression, , random forest and decision tree on the data including gender , age year of education, estimated total intracranial volume (eTIV) , socioeconomic status(SSE) , mini-mental state examination (MMSE) , atlas scaling factor (ASF) and normalized whole brain volume (nWBV) from the Open Access Series of Imaging Studies (OASIS) dataset for prediction of Alzheimer’s by comparative analysis of ML algorithms . When compared to other models SVM gives the highest accuracy of 92%. (Bari Antor, 2021)

**Sergio Grueso et al, (2021)** utilized SVM and CNN on the data including MRI and PET retrieved from the ADNI database for predicting the progression of MCI to Alzheimer using ML methods. When compared to SVM , CNN gives the highest accuracy of 78.5%. (Grueso, 2021)

**Noemi Massetti et al, (2021)** utilized random forest on the data including PET , MRI, neuropsychological test scores , peripheral biomarkers and cerebrospinal fluid (CSF) biomarkers from the ADNI and Alzheimer’s Disease Metabolomics Consortium (ADMC) databases to predict the patients under Alzheimer’s Disease spectrum .Random forest gives the highest accuracy of 86%. (Massetti, 2022)

**Louise Bloch et al,(2021)** used MRI feature extraction , random forest, feature selection,eXtreme gradient boosting , sample using data shapley , RF data Shapely,LR data, Shapely kernel shapley additive exPlanations (SHAP) values on data including MRI, biological markers,PET, clinical ,neuropsychological assessments and lifestyle factors from ADNI and Australian imaging , biomarker and lifestyle(AIBL) database for automatic selection of subject in alzheimer’s disease data.Random forest gives the highest accuracy of 62.64%. (Bloch, 2021)

**Ali Haidar Syaifullah et al,(2021)** utilized SVMst (based solely on brain structure) and SVMcog(based on brain structure and MMSE score ) for data including features extracted from MRI retrieved from ADNI database for the diagnosis of AD using ML .SVMst gives the highest accuracy of 90.5% (Syaifullah, 2021)

**Afreen Khan et al,(2022)** used different algorithms like Random forest, ExtraTreesClassifier, Decision tree, Nu Support Vector Classification, Logistic regression, AdaBoost ,Gradient boosting, Gaussian process classifier, Ridge classifier and K-neighbors on MRI, Mini-Mental State Examination(MMSE), Clinical Dementia Rating(CDR), Atlas Scaling Factor(ASF)and patient demographics data from the Open Access Series of Imaging Studies (OASIS) database for the prognosis of alzheimer’s disease . When compared with other algorithms random forest gives the highest accuracy of 86.84%. (Khan, 2022)

**Shangran Qui et al,(2022)** utilized CNN ,CatBoost algorithms on clinical information, neuropsychological testing ,demographics ,neuroimaging , medical history and functional assessments on different datasets like ADNI , NACC,AIBL,LBDSU,FHS,NIFD ,OASIS ,and PPMI for assessment of dementia for Alzheimer’s using deep learning multimodal .Here the fusion model gave mean of 55%, with high AUC and AP scores. (Qiu, 2022)

**Seyed Hani Hojjati et al,(2022)** utilizes support vector regression, bagging-based ensemble regression , CNN , multikernel support vector machine on neuroimaging ,MRI and FDG-PET data from ADNI database from the TADPOLE challenge dataset for predicting alzheimers disease neuropsychological scores using neuroimaging data that is multimodal and using ANN.The bimodal approach provides highest accuracy with Alzheimer’s disease assessment scale cognitive 13(ADAS13) of 74% and Clinical dementia rating sum of boxes (CDRSB) score of 80%. (Hojjati, 2022)

**Jinhua Sheng et al,(2022)** utilizes SVM, KNN ,ensemble and decision trees on MRI and SNP from the ADNI database for predicting classification of the alzheimer’s using brain and genetic data . SVM gave the best results when compared to other algorithms with the highest accuracy of 98%. (Sheng, 2022)

**Vasco Sa Diogo et al,(2022)** utilized linear SVM,DT, RF, extremely randomized tree(ET) ,linear discriminant analysis (LDA) , LR,LR-SDG on the data including many features extracted from MRI , retrieved from ADNI and OASIS database for early diagnosis of AD using ML.The healthy controls (HC) vs AD classifier had the highest accuracy of 90.6%. (Diogo, 2022)

**Shaker El-Sappagh et al,(2022)** used decision trees , SVM, LSTM,random forest,KNN and logistic regression on data including neuroimaging data , cognitive scores , cerebrospinal fluid biomarkers, neuropsychological battery markers and demographics from the ADNI database to develop two stage DL model for AD detection and prediction of MCI. Long short term memory (LSTM) gives the highest accuracy of 93.87%. (El-Sappagh, 2022)

**Duaa AlSaeed et al, (2022)** used CNN , softmax, SVM and RF on the different features of MRI data from ADNI and Minimal Interval Resonance Imaging in alzheimer’s disease (MIRIAD) databses for diagnosis of AD.CNN ResNet-50 along with softmax gives the highest accuracy of 99% on ADNI dataset . (AlSaeed, 2022)

**Sobhana Jahan et al,(2023)** used kNN , SVM, random forest , Multi-layer perceptron,logistic regression ,decision tree ,Naïve bayes,Gradient Boosting and Adaptive Boosting (AdaB) on the Open Access Series Of Imaging Studies (OASIS-3) dataset using clinical ,psychological and MRI data for prediction and management of alzheimer’s.The random forest algorithm has the highest cross validation accuracy of 98.81%. (Jahan, 2023)

**Anna Michela Gaeta et al,(2024)** used gaussian process ,ensemble models,regularized linear regressions (RLR) ,k-NR and SVRon the cerebrospinal fluid(CSF) ,blood samples ,Polysomnography (PSG) parameters ,comorbidities ,quantitative PSG signal features , sociodemographic and sleep-related data that is collected from the cognitive disorders unit of hospital Universitari Santa Maria at Lleida,Spain for the prediction of the alzheimer’s disease using CSF as the core biomarker.Gaussian process gives the best results with p-tau 29 + 2.56 (Gaeta, 2024)

**INFERENCES FROM THE LITERATURE REVIEW**

The inferences below are extracted from 100 papers reviewed from 1912 to 2024 .The follow inferences include the year the literature is published along with their respective authors. It also includes the methods used , features taken into consideration for the study of the respective paper, the datasets they used and the accuracies they obtained by the methods

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| --- | --- | --- | --- | --- | --- |
| Year | Authors | Methods | Features | Dataset | Accuracy |
| 1912 | Chang T.S | a) Stochastic Gradient Descent | a) Cognitive tests b) Memory tests | a) 879 high-risk  b) 355 low-risk individuals | Improved separation over traditional methods |
| 1936 | Boyd D.A | \_ | a) Cognitive Tests  b) Biopsy | a) Single case study | Not applicable |
| 1963 | Kidd et al | a)Electron microscopy | a) Paired helical filaments b) Ultrastructural analysis of Alzheimer's disease brain tissue | Brain samples from Alzheimer's disease patients | Not  applicable |
| 1963 | Terry et al | a) Electron microscopy b) Histological staining | a) Neurofibrillary tangles b) Paired helical filaments | Post-mortem brain tissues of Alzheimer's disease patients | Not applicable |
| 1968 | Blessed et al | a) Quantitative analysis of brain tissue b) Correlation studies | a) Measurement of senile changes in cerebral grey matter b) Association with dementia severity | Brain samples from elderly subjects with varying dementia levels | Not applicable |
| 1973 | Crapper et al | a) Atomic absorption spectrophotometry b) Histological analysis | a) Brain aluminum distribution b) Neurofibrillary tangles | a) Human brain tissues from Alzheimer's patients b) Experimental neurofibrillary degeneration in animals | Not applicable |
| 1976 | M. W. Hopper et al | 1. Neuropathologic investigation b)Microscopic analysis c) Staining techniques | a) Neurofibrillary tangles b) Senile plaques c) Neuronal loss d) Gliosis | Post-mortem brain tissue samples from AD patients | Not applicable |
| 1976 | Katzman et al | a)Epidemiological study b) Literature review | a) Analysis of Alzheimer’s disease prevalence b) Assessment of mortality and morbidity | Population studies and clinical records | Not specified (focus on prevalence and mortality trends). |
| 1980 | Perl et al | a) X-ray spectrometry b) Electron microscopy | a) Aluminum accumulation b) Neurofibrillary tangle-bearing neurons | Brain tissues from Alzheimer's disease patients | Not applicable |
| 1984 | Hyman et al | a) Histopathological analysis b) Immunohistochemistry | a) Cell-specific pathology in hippocampal neurons b) Identification of neuron loss and tangle formation | Postmortem brain tissues from Alzheimer's disease patients | Not applicable |
| 1984 | Glenner et al | a) Protein purification b)Biochemical characterization | a) Isolation of amyloid protein from cerebrovascular deposits b) Analysis of amyloid protein composition | Brain tissue samples from Alzheimer's disease patients | Not applicable |
| 1986 | Yamamoto et al | a)Comparative ultrastructural analysis b) Electron microscopy | a) Structural comparison of neurofibrillary tangles b) Identification of filament composition | Brain tissue samples from Alzheimer's disease patients | Not applicable (qualitative study focused on structural observation). |
| 1991 | Katzman et al | a) Literature review b) Analysis of research advancements | a) Overview of Alzheimer’s disease mechanisms b) Discussion on clinical and therapeutic developments | a) Compilation of existing studies and clinical data | Not specified (focus on summarizing advancements in research and treatment). |
| 1991 | Pericak-Vance et al | a) Linkage analysis b) Genetic mapping | a) Investigation of familial Alzheimer’s disease b) Examination of chromosomal regions linked to the disease | Samples from families with a history of Alzheimer’s disease | Evidence for linkage to chromosome 19 with a high statistical significance (LOD score ≥ 3 indicates strong evidence of linkage). |
| 1994 | Tsai et al | a) Genetic linkage analysis  b) Clinical assessments  c) Genotype-phenotype correlation studies | a) Analysis of apolipoprotein E (ApoE) genotype  b) Examination of family histories of Alzheimer’s disease (AD)  c) Evaluation of cognitive assessments in participants | a) Samples from familial Alzheimer’s disease cases  b) Control groups for comparison  c) Genetic data from multiple family members | Association of ApoE ε4 allele with increased risk of developing Alzheimer’s disease (not typically expressed as a percentage in linkage studies). |
| 1994 | Lehericy et al | a) Magnetic Resonance Imaging (MRI)  b) Volume measurements of amygdalohippocampal regions  c) Statistical analysis of brain volume changes | a) Early-stage Alzheimer disease detection  b) Correlation between MR volume measurements and cognitive function  c) Assessment of structural brain changes | a) MRI scans of participants diagnosed with early Alzheimer’s disease  b) Control group of healthy subjects for comparison  c) Clinical assessments of cognitive function | Identified specific volumetric changes associated with early Alzheimer’s disease (exact percentage not typically specified). |
| 1994 | Besthorn et al | 1. Electroencephalography (EEG)   b) Coherence analysis of EEG signals  c) Statistical comparison between Alzheimer patients and healthy controls | a) Assessment of brain activity synchronization  b) Focus on frequency bands (delta, theta, alpha, beta)  c) Analysis of coherence patterns related to cognitive function | a) EEG recordings from Alzheimer disease patients  b) Control group with matched demographics  c) Clinical evaluations for diagnosis | Variations in coherence patterns identified, indicating possible cognitive decline (exact percentage not typically specified). |
| 1994 | Näslund et al | a) Mass spectrometry  b)Immunoblotting  c)Comparative analysis of amyloid peptide variants | a) Identification of different Aβ peptide variants  b) Assessment of peptide abundance in Alzheimer's and normal aging  c) Correlation of amyloid presence with disease progression | a) Brain samples from Alzheimer's disease patients  b) Brain samples from age-matched controls  c) Evaluation of peptide concentrations | Variability in Aβ peptide variants observed (exact percentage not typically specified). |
| 1995 | Schellenberg et al | a) Genetic linkage analysis  b) Candidate gene approach  c) Family-based studies | a) Exploration of genetic factors contributing to Alzheimer's disease  b) Examination of chromosomal regions linked to the disease  c) Discussion of the heterogeneous nature of Alzheimer’s genetics | a) Familial Alzheimer's disease cases  b) Population-based control groups  c) Genomic DNA samples for analysis | Genetic associations identified, though specific percentages not provided. |
| 1997 | Finch et al | a) Literature review  b) Hypothesis generation  c) Theoretical model development | a) Investigation of aging and metabolism in relation to Alzheimer’s disease  b) Discussion of neurobiological mechanisms  c) Analysis of potential interventions | a) Previously published studies  b) Epidemiological data on aging and Alzheimer's disease  c) Biochemical and neuroanatomical findings | No specific accuracy percentage provided; focuses on theoretical implications and hypotheses. |
| 1998 | Perry et al | a)Experimental studies  b) In vitro assays  c) Oxidative stress measurements | a) Analysis of reactive oxygen species (ROS)  b) Mechanisms of cellular damage in Alzheimer’s disease  c) Role of oxidative stress in neurodegeneration | a) Cellular models  b) Brain tissue samples  c) Control vs. Alzheimer’s disease samples | Specific accuracy percentage not provided; focuses on correlational findings between ROS and cellular damage. |
| 1998 | Smith et al | a) Literature review  b) Case studies  c) Neuropathological analysis | a) Overview of Alzheimer disease pathology b) Discussion of genetic and environmental risk factors c) Examination of therapeutic approaches | a) Reviewed literature from various studies b) Clinical data from Alzheimer's patients c) Neurobiological research findings | Specific accuracy percentage not provided; emphasizes comprehensive literature synthesis and interpretations. |
| 1998 | McGeer et al | a) Literature review b) Experimental studies on inflammation c) Analysis of brain tissue samples | a) Examination of inflammatory markers b) Discussion on neuroinflammation's role in Alzheimer's c) Implications for therapeutic strategies | a) Data from previous studies on Alzheimer's patients b) Brain tissue samples from autopsies c) Clinical data related to inflammation | Specific accuracy percentage not provided; focuses on correlating inflammation with disease progression. |
| 1998 | Blacker et al | a) Review of genetic studies b) Analysis of familial Alzheimer's disease cases c) Examination of candidate genes | a) Discussion of genetic markers associated with Alzheimer's b) Overview of risk factors and gene-environment interactions c) Future directions for genetic research | a) Data from families with a history of Alzheimer disease b) Genetic information from various studies c) Case-control studies involving affected and unaffected individuals | Specific accuracy percentage not provided; emphasizes associations between genetic factors and disease risk. |
| 1998 | Younkin et al | a) Review of existing literature b) Analysis of Aβ42 peptide characteristics c) Examination of its role in the pathogenesis of Alzheimer's disease | a) Discussion of amyloid hypothesis b) Overview of Aβ42 aggregation and toxicity c) Insights into the relationship between Aβ42 and neurodegeneration | a) Data from various studies on Aβ42 b) Experimental findings related to amyloid plaques c) Clinical data linking Aβ42 levels to Alzheimer’s disease progression | Specific accuracy percentage not provided; focuses on the relevance of Aβ42 in Alzheimer’s pathology. |
| 1998 | Gao et al | a) Meta-analysis of existing studies b) Statistical analysis to determine relationships c) Review of demographic factors influencing dementia incidence | a) Examination of age and sex as variables b) Focus on incidence rates of dementia and Alzheimer’s disease c) Identification of risk factors | a) Data from multiple studies on dementia and Alzheimer’s disease b) Population-based data across different age groups c) Sex-specific incidence data | Specific accuracy percentage not provided; the study assesses trends and correlations between demographics and disease incidence. |
| 1999 | McGeer et al | a) Review of existing literature b)Examination of inflammation in Alzheimer’s disease c) Discussion of potential therapeutic interventions | a) Focus on brain inflammation as a mechanism in Alzheimer’s disease b) Evaluation of inflammatory markers in the brain c) Implications for treatment strategies | a) Data from various studies on inflammation in Alzheimer’s disease b) Clinical studies involving Alzheimer patients c) Review of experimental findings related to inflammation | Specific accuracy percentage not provided; the study discusses implications rather than presenting quantifiable accuracy data. |
| 1999 | Markesbery et al | a) Literature review b)Examination of oxidative stress in Alzheimer’s disease c) Analysis of biochemical markers | a) Focus on oxidative stress as a contributing factor in Alzheimer’s disease b) Discussion of antioxidant defense mechanisms c) Evaluation of cellular and molecular damage | a) Data from various studies on oxidative stress in Alzheimer’s disease b) Clinical studies involving Alzheimer's patients c) Experimental findings related to oxidative stress | Specific accuracy percentage not provided; the study discusses the role of oxidative stress rather than presenting quantifiable accuracy data. |
| 1999 | Johnson et al | a) Clinical assessment b)Neuropathological examination c)Comparative analysis with other Alzheimer's variants | a) Identification of a frontal variant of Alzheimer’s disease b) Description of clinical symptoms and progression c) Pathological findings related to frontal lobe involvement | a) Clinical data from patients diagnosed with Alzheimer’s disease b) Autopsy samples for pathological analysis c) Comparative data from traditional Alzheimer’s cases | Specific accuracy percentage not provided; findings based on clinical and pathological correlation rather than quantifiable accuracy data. |
| 1999 | Haroutunian V et al | a)Histopathological analysis b)Neurofibrillary tangle quantification c)Comparative study between nondemented and mild Alzheimer’s patients | a) Examination of neurofibrillary tangles in elderly subjects b) Comparison between nondemented individuals and those with mild Alzheimer’s disease c) Assessment of correlations with cognitive impairment | a) Brain tissue samples from nondemented elderly subjects b) Brain tissue samples from individuals with mild Alzheimer’s disease c) Clinical records for cognitive assessment | Specific accuracy percentage not provided; findings are based on qualitative assessment and correlation between tangles and cognitive status. |
| 2000 | Grundman et al | a) Review of clinical trials b) Analysis of Vitamin E supplementation c) Discussion of mechanisms and potential effects on Alzheimer’s disease | a) Examination of Vitamin E as a neuroprotective agent b) Review of dosage and administration strategies c) Evaluation of clinical trial outcomes | a) Data from previous clinical trials on Vitamin E and Alzheimer’s disease b) Patient demographics and health status information | Specific accuracy percentage not provided; conclusions are based on literature review and trial findings. |
| 2000 | Christen et al | 1. Review of oxidative stress mechanisms b) Analysis of dietary antioxidants c) Evaluation of clinical evidence linking oxidative stress to Alzheimer’s disease | a) Examination of oxidative stress as a pathological mechanism in Alzheimer's b) Discussion of antioxidants and their potential protective roles c) Review of epidemiological studies | a) Data from clinical and epidemiological studies on oxidative stress and Alzheimer’s disease b) Analysis of dietary intake and health outcomes | Specific accuracy percentage not provided; conclusions based on comprehensive literature review and synthesis of evidence. |
| 2000 | Gillette-Guyonnet et al | a)Longitudinal study design b) Assessment of weight changes in Alzheimer's patients c) Analysis of dietary intake and nutritional status | a) Exploration of factors contributing to weight loss in Alzheimer's disease b) Examination of the relationship between weight loss and cognitive decline c) Assessment of nutritional interventions | a) Data from Alzheimer's disease patients in a clinical setting b) Nutritional assessments and weight measurements over time | Specific accuracy percentage not provided; findings based on statistical analysis of patient data and correlational assessments. |
| 2000 | Nourhashémi et al | a) Cross-sectional study design b) Assessment of protective factors against Alzheimer’s disease c) Statistical analysis of dietary and lifestyle factors | a) Identification of lifestyle factors that may protect against Alzheimer’s disease b) Evaluation of dietary patterns and their association with cognitive health c) Consideration of demographic variables in relation to Alzheimer’s risk | a) Data collected from Alzheimer’s patients and control groups b) Nutritional assessments and lifestyle questionnaires | Specific accuracy percentage not provided; results based on statistical correlations and risk assessments. |
| 2000 | Milien et al | a) Review of current pharmacological interventions b) Analysis of clinical trial data c) Discussion of drug mechanisms of action | a) Overview of potential therapeutic targets in Alzheimer’s disease b) Evaluation of existing drugs and their efficacy c) Consideration of future directions in pharmacological research | a) Compilation of data from various clinical trials and studies b) Literature review of published research on pharmacological treatments | Specific accuracy percentage not provided; conclusions drawn from analyzed trial data and existing literature. |
| 2001 | Dickerson et al. | a) Logistic Regression | a) Entorhinal  b) Hippocampal atrophy | a) ADNI | 83% for non converters |
| 2001 | El-Baz & Suri | a)  CNN | a) MRI  b) FMRI | a) ADNI | 95.4% accuracy |
| 2002 | Kantarci et al. | a)Hippocampal     Volumetry  b) Spectroscopy | a) MRI | a) ADNI | a) MCI : 79%  b) AD : 86% |
| 2003 | Chetelat & Baron | a)Volumetric Measurement | a) Hippocampal atrophy | a) ADNI | 70% accuracy |
| 2004 | Jeong J | 1. EEG 2. Anaysis | a)  EEG dynamics | \_ | 80%  accuracy |
| 2005 | Adeli et al. | a) Artificial Neural Network | a) EEG  b) Anatomical Images | \_ | Betteraccuracythan discriminant analysis |
| 2007 | Devanand et al. | a) Volumetric Analysis | a) Hippocampal  b) Entorhinal Volume | a) Columbia -presbyterian | Overall accuracy 85 % |
| 2009 | Gerardin et al. | a) SVM  b) Spherical Harmonics | a) Hippocampal shape | a) ADNI | a) AD vs. Control: 94 %  b) MCI : 83 % |
| 2010 | Hu et al | 1. Neuro- psychological MRI | a) MRI  b) Neuro  Psychological  test | a) Primary progressive aphasia Dataset | a) Specificity : 90%  b) Sensitivity : 100% |
| 2011 | Hinrichs et al | a) Multi-kernel learning | a) MRI  b) PET | a) ADNI | 3-4% improvement over traditional |
| 2011 | Ewers et al | a) Pittsburgh Compound-B | a) MRI  b) PET | a) ADNI | Accuracy : 80% |
| 2011 | Wolz et al | a) SVM  b) LDA | a) Hippocampal volume  b) Cortical thickness | a) ADNI | a) Specificity : 93%  b) Sensitivity : 85% |
| 2012 | Zhang & Shen | a) Multi-task SVM | a) MRI  b) PET  c) CSF | a) ADNI | Classification  AD vs. Healthy : 93%  MCI vs. Healthy : 83% |
| 2012 | Zhang & Shen | a) Multi-Kernel SVM | a) Longitudinal MRI  b) PET  c) CSF | a) ADNI | 78.4 % for MCI to AD conversion |
| 2012 | Dai et al | a) Multi-classifier | a) Structural MRI  b) r-fMRI | \_ | Accuracy of 89.47% |
| 2012 | Westman et al | a) MRI and CSF combined | a) MRI  b) CSF | a) ADNI | Accuracy : 91.8% |
| 2013 | Young et al | a) Gaussian Process Classification | a) Brain Imaging  b) Biomarkers | a) ADNI | High accuracy distinguishing MCI converters |
| 2013 | Thung et al | a) Matrix Completion Algorithm | a) MRI  b) PET  c) CSF | a) ADNI | 88% Accuracy |
| 2013 | Gray et al | a) Random Forest | a) MRI  b) FDG-PET  c) CSF  d) Genetics | a) ADNI | a) AD vs Control 89%  b) MCI : 75% |
| 2013 | Shaffer et al | a) Independent Component Analysis | a) CSF  b) MRI  c) PET | a) ADNI | Misclassification 28.4% |
| 2013 | Eskildsen et al | a) Surface-based cortical thickness analysis | a) MRI cortical thickness | a) ADNI | Accuracy : 70-76% |
| 2013 | Segovia et al | a) Partial least Squares | a) SPECT imaging | a) Virgen de las Nievas Hospital | Accuracy : 90% |
| 2014 | Lebedev et al | a) Random Forest | a) MRI | a) ADNI  b)AddNeuroMed | a) Sensitivity :88.6%  b) Specificity : 92% |
| 2014 | Zhang et al | a) Multi-kernel  b) HGM-FS | a) MRI  b) PET  c) CSF  d) SNPs | a) ADNI | a) High PET accuracy  b) HGM-FS best method |
| 2014 | Suk et al | a) Deep Boltzmann Machine | a) MRI  b) PET | a) ADNI | a)AD vs Control: 95.35 %  b) MCI : 85.67% |
| 2014 | Ortiz et al | a) Sparse Representation Classifier | a) MRI  b) PET | a) ADNI | Accuracy : 94% |
| 2014 | Liu et al | a) CNN | a) MRI  b) PET | a) ADNI | 96.85 % accuracy |
| 2014 | Li et al | a) 3D CNN | a) MRI  b) PET | a) ADNI | 88.68 % |
| 2014 | Razlighi et al | a) Predicitve Algorithm | a) Patient /Demographics | a) Predictors cohort study | High accuracy with missing data |

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| 2015 | Mehdi Rahim et al | 1. Ridge Regression 2. Spatial   TV-l1 prior   1. PET-informed prior | 1. FDG-PET 2. resting-state fMRI(rs-fMRI) | ADNI | 1. Ridge Regression-88% 2. Spatial TV-l1 prior-around 80% 3. PET-informed prior-around 80% |
| 2015 | Kerstin Ritter et al | 1. SVM 2. Random forest 3. Classification tree | 1. Clinical data 2. Genetics 3. Biospecimen 4. Neuropsychology 5. PET 6. MRI | ADNI | 1. SVM -73.44% 2. Random forest – 69.45% 3. Classification tree – 65.15% |
| 2018 | Tingyan Wang et al | 1. Long short-term memory RNN model 2. Logistic regression 3. SVM 4. Decision tree 5. Random Forest | 1. Patients demographics 2. Physical information 3. Health history 4. Geriatric depression scale (GDS) 5. Elements of the clinical dementia rating (CDR) scale 6. Functional activities questionnaire (FAQ) | US National Alzheimer’s Coordinating Center(NACC) | 1. Long short-term memory RNN model – 99% 2. Logistic regression-79% 3. SVM – 74% 4. Decision tree – 70% 5. Random Forest – 69% |
| 2019 | Garam Lee et al | 1. GRU 2. SVM 3. Gaussian process 4. Hierarchical ensemble 5. Deep neural networks | 1. Demographic information 2. Neuroimaging phenotypes measured by MRI 3. Longitudinal cerebrospinal fluid(CSF) 4. Cognitive performance biomarkers | ADNI | 1. Deep neural networks-82% 2. GRU-81% 3. Hierarchical ensemble-79% 4. SVM -79% 5. Gaussian process-68% |
| 2019 | Taeho Jo et al | 1. Stacked auto-encoder   (SAE)   1. RNN or CNN | 1. MRI 2. PET 3. FDG-PET | ADNI | 1. Stacked auto-encoder (SAE) -98.8% 2. RNN or CNN -96% |
| 2019 | Daniel Stamate et al | 1. XGBoost 2. Random forest 3. Deep learning | 1. MRI 2. PET 3. Details on the subjects 4. Clinical data 5. Cognitive data 6. Measurements of AD pathological markers | ADNI | 1. XGBoost - 87% 2. Random Forest – 85% 3. Deep Learning – 84% |
| 2019 | S.Naganandhini et al | Decision tree classifier with hyper parameters tuning (DTC-HPT) | 1. Age 2. Gender 3. fMRI 4. PET 5. MMSE 6. CDR | OASIS | DTC-HPT - 99.10% |
| 2019 | Garam Lee et al | 1. RNN (GRU and LSTM) 2. Logistic Regression 3. Random Forest 4. SVM | 1. Cognitive performance 2. Cerebrospinal fluid 3. Demographic data 4. MRI | ADNI | 1. RNN (GRU and LSTM) – 95% 2. Logistic Regression-93% 3. SVM -92% 4. Random Forest -88% |
| 2020 | Xian-an Bi et al | 1. Clustered evolutionary random forest(CERF) 2. Random forest 3. Random SVM cluster (RSVMC) 4. Canonical correlation analysis(CCA) 5. Discriminant correspondence analysis (DCA) 6. t-test 7. Pearsons correlation coefficient | 1. fMRI 2. Single nucleotide polymorphisom (SNP) | ADNI | 1. Pearson +CERF – 86% 2. Pearson +Random forest – 82% 3. Pearson + t-test-79% 4. Discriminant correspondence analysis (DCA)+t-test– 75% 5. Pearson+Random SVM cluster (RSVMC) – 72% 6. Canonical correlation analysis(CCA)+t-test -68% |
| 2020 | Solale Tabarestani et al | 1. Convex fused sparse group lasso (cFSGL) 2. Temporal group lasso (TGL) 3. Non-convex fused sparse group lasso (nFSGL) 4. l2,1 norm 5. Lasso 6. Ridge 7. Subspace regularized sparse multitask learning 8. Parameter-free least lasso | 1. Biological markers 2. Clinical data 3. Neuropsychological assessments | ADNI | p-value   1. Convex fused sparse group lasso (cFSGL)- 0.501 2. Temporal group lasso (TGL)-0.386 3. Non-convex fused sparse group lasso (nFSGL)-0.386 4. l2,1 norm-0.086 5. Lasso-0.083 6. Ridge-0.063 7. Subspace regularized sparse multitask learning-0.032 8. Parameter-free least lasso -0.029 |
| 2020 | Gopi Battineni et al | 1. Naïve bayes 2. k-nearest neighbor 3. ANN 4. SVM | 1. MRI 2. Gender 3. Age 4. CDR score 5. ASF 6. eTIV | Alzheimer’s Disease Research Center (ADRC) of Washington University | 1. Hybrid – 98% 2. SVM – 96.12% 3. k-nearest neighbor – 95.92% 4. Naïve bayes – 93.44% 5. ANN – 83.56% |
| 2020 | Juan Felipe Beltran et al | 1. Random forest 2. Gradient boosting 3. SVM 4. Classification and regression tree   (CART) | 1. MRI 2. PET 3. Cerebral spinal fluid measurement 4. Genetic tests 5. Demographics 6. Vital signs | ADNI | 1. Random forest 2. Gradient boosting 3. SVM 4. Classification and regression tree(CART) |
| 2020 | Gloria Castellaazzi et al | 1. ANN 2. SVM 3. Adaptive neuro-fuzzy inference system | 1. resting -state fMRI 2. Diffusion tensor imaging | Neurological Institute IRCCS Mondino Foundation (Pavia, Italy) | 1. ANFIS -83.50% 2. SVM - 79.75% |
| 2021 | Janani Venugopalan et al | 1. Random Forest 2. SVM 3. Decision Trees 4. k-NN 5. DL 6. 3D-CNN | 1. MRI 2. SNP 3. Clinical data 4. Genetic data 5. Electronic Health Records (EHRs) | ADNI | 1. DL+SVM-88% 2. DL+Random forest-87% 3. DL+Decision trees-87% 4. DL+k-NN-87% |
| 2021 | Shaker  El-Sappagh et al | 1. Random Forest 2. SVM 3. Decision Trees 4. k-NN 5. Logistic Regression | 1. Cognitive scores 2. Comorbidities 3. Medications 4. Patient statistics(age,gender etc.) | ADNI | 1. Random forest -90.51% 2. Logistic Regression-85.53% 3. SVM-83.68% 4. Decision Trees-77.32% 5. k-NN-75.69% |
| 2021 | Zhen Pang et al | 1. XGBoost 2. Decision trees 3. Random forests 4. SVM | 1. PET 2. MRI 3. Cognitive tests 4. Genetics 5. MMSE | ADNI | 1. Random forests – 75% 2. SVM-72% 3. XGBoost -72% 4. Decision trees -71% |
| 2021 | Gopi Battineni et al | 1. Gradient Boosting 2. SVM 3. Logistic Regression 4. Random forests 5. AdaBoosting 6. Naïve Bayes | MRI | OASIS | 1. Gradient Boosting -97.58% 2. SVM -96.77% 3. Logistic Regression-96.77% 4. Random forests - 96.77% 5. AdaBoosting-96.77% 6. Naïve Bayes-95.96% |
| 2021 | Shaker  El-Sappagh et al | 1. Random forests 2. Decision trees 3. SVM 4. Naïve bayes 5. k-NN | 1. Cognitive scores 2. Genetics 3. Lab tests 4. Medical history 5. MRI 6. Neurological exams 7. Neuropsychological battery 8. PET 9. Physical exams 10. Symptoms 11. Vital signs | ADNI | 1. Random forests-93.33% 2. Decision trees – 92.38% 3. SVM – 91.43% 4. Naïve bayes – 89.52% 5. k-NN – 64.76% |
| 2021 | Mohammed Abdelaziz et al | 1. CNN 2. Multi-task feature learning (MTFL) 3. Principle component analysis (PCA) 4. Locality preserving projection (LPP) 5. Shallow Wide Deep Neural Networks   (SWDNN) | 1. PET 2. MRI 3. Clinical scores 4. SNP | ADNI | 1. CNN -98.22% 2. Shallow Wide Deep Neural Networks   (SWDNN)-91.35%   1. Multi-task feature learning (MTFL) -83.38% 2. Principle component analysis (PCA)-81.58% 3. Locality preserving projection (LPP) -81.54% |
| 2021 | Juan E.Arco et al | 1. Searchlight 2. Principal component analysis (PCA) | 1. Neuropsychological tests 2. MRI | ADNI | 1. Searchlight – 80.9% 2. Principal component analysis (PCA) – 72.03% |
| 2021 | Morshedul Bari Antor et al | 1. SVM 2. Random forest 3. Decision tree 4. Logistic regression | 1. Gender 2. Age 3. Year of education 4. Estimated total intracranial volume (eTIV) 5. Socioeconomic status(SSE) 6. Mini-mental state examination (MMSE) 7. Atlas scaling factor (ASF) 8. Normalized whole brain volume (nWBV) | OASIS | 1. SVM – 92% 2. Random forest – 81.3% 3. Decision tree – 80% 4. Logistic regression – 74.7% |
| 2021 | Sergio Grueso et al | 1. CNN 2. SVM | 1. MRI 2. PET | ADNI | 1. CNN – 78.5% 2. SVM – 75.4% |
| 2021 | Noemi Massetti et al | Random Forest | 1. PET 2. MRI 3. Neuropsychological test scores 4. Peripheral biomarkers 5. Cerebrospinal fluid (CSF) biomarkers | ADNI and Alzheimer’s Disease Metabolomics Consortium (ADMC) databases | Random Forest – 86% |
| 2021 | Louise Bloch et al | 1. Random forest 2. eXtreme gradient boosting 3. RF data Shapely | 1. MRI 2. Biological markers 3. PET 4. Clinical data 5. Neuropsychological assessments 6. Lifestyle factors | ADNI and Australian imaging , biomarker and lifestyle(AIBL) | 1. Random forest – 62.64% 2. eXtreme gradient boosting- 60% 3. RF data Shapely-60% |
| 2021 | Ali Haidar Syaifullah et al | 1. SVMst (based solely on brain structure) 2. SVMcog(based on brain structure and MMSE score ) | MRI | ADNI | 1. SVMst -90.5% 2. SVMcog – 85% |
| 2022 | Afreen Khan et al | 1. Random forest 2. ExtraTreesClassifier 3. Decision tree 4. NuSupport Vector Classification 5. Logistic regression 6. AdaBoost 7. Gradient boosting 8. Gaussian process classifier 9. Ridge classifier 10. K-neighbours | 1. MRI 2. Mini-Mental State Examination(MMSE) 3. Clinical Dementia Rating(CDR) 4. Atlas Scaling Factor(ASF) 5. Patient demographics | OASIS | 1. Random forest – 86.84% 2. ExtraTreesClassifier-84.20% 3. Decision tree-81.60% 4. NuSupport Vector Classification – 81.60% 5. Logistic regression-81.60% 6. AdaBoost – 81.57% 7. Gradient boosting -78.94% 8. Gaussian process classifier – 78.90% 9. Ridge classifier – 78.90% 10. k-neighbours – 73.70% |
| 2022 | Shangran Qui et al | 1. CNN 2. CatBoost | 1. Clinical information 2. Neuropsychological testing 3. Demographics 4. Neuroimaging 5. Medical history 6. Functional assessments | 1. ADNI 2. NACC 3. AIBL 4. LBDSU 5. FHS 6. NIFD 7. OASIS 8. PPMI | Mean   1. Fusion (CNN+CatBoost) – 55% 2. Catboost model -54% |
| 2022 | Seyed Hani Hojjati et al | 1. Support vector regression 2. Bagging-based ensemble regression 3. CNN 4. Multikernel support vector machine 5. ANN 6. Alzheimer’s disease assessment scale cognitive 13(ADAS13) 7. Clinical dementia rating sum of boxes (CDRSB) | 1. MRI 2. FDG-PET 3. Neuropsychological scores | ADNI database from the TADPOLE challenge dataset | 1. Clinical dementia rating sum of boxes (CDRSB) – 74% 2. Alzheimer’s disease assessment scale cognitive 13(ADAS13) – 74% |
| 2022 | Jinhua Sheng et al | 1. SVM 2. KNN 3. Ensemble 4. Decision trees | 1. MRI 2. SNP | ADNI | 1. SVM – 98% 2. KNN – 96% 3. Ensemble – 94% 4. Decision trees – 92% |
| **2022** | **Liu et al** | **a) Stacked Auto-encoder** | **a) MRI**  b) PET | **a) ADNI** | **a) Binary: 91.4%**  b) Multi-class : 53.79% |
| 2022 | Vasco Sa Diogo et al | 1. Matthew’s correlation coefficient 2. Linear SVM 3. DT 4. RF 5. Extremely randomized tree(ET) 6. Linear discriminant analysis (LDA) LR 7. LR-SDG | MRI | 1. ADNI 2. OASIS | 1. Healthy controls (HC) vs AD classifier – 90.6% 2. Matthew’s correlation coefficient – 0.811 |
| 2022 | Shaker El-Sappagh et al | 1. Decision trees 2. SVM 3. LSTM 4. Random forest 5. K-NN 6. Logistic regression | 1. Neuroimaging data 2. Cognitive scores 3. Cerebrospinal fluid 4. Biomarkers 5. Neuropsychological battery markers 6. Demographics | ADNI | 1. LSTM -93.87% 2. Random forest-92.6% 3. Decision tree – 91.39% 4. Logistic regression – 92.28% 5. SVM -92.01% 6. k-NN-79.1% |
| 2022 | Duaa AlSaeed et al | 1. CNN 2. Softmax 3. SVM 4. Random Forest | MRI | ADNI and Minimal Interval Resonance Imaging in alzheimer’s disease (MIRIAD) | 1. Sofmax - 99% 2. SVM - 92% 3. Random Forest - 85.7% |
| 2023 | Sobhana Jahan et al | 1. k-NN 2. SVM 3. Random forest 4. Multi-layer perceptron(MLP) 5. Logistic regression 6. Decision tree 7. Naïve bayes 8. Adaptive Boosting (AdaB) 9. Gradient Boosting | 1. Clinical data 2. Psychological data 3. MRI | OASIS | 1. Random forests – 98.81% 2. Gradient boosting – 95.65% 3. Decision trees – 94.92% 4. k-NN -83.82% 5. AdaB – 55.57% 6. Naïve bayes – 40.24% 7. Logistic regression – 31.28% 8. MLP – 25.79% 9. SVM – 25% |
| 2024 | Anna Michela Gaeta et al | 1. Gaussian process 2. Ensemble models 3. Regularized linear regressions (RLR) 4. k-NR 5. SVR | 1. Cerebrospinal fluid(CSF) 2. Blood samples 3. Polysomnography (PSG) parameter 4. Comorbidities 5. Quantitative PSG signal features 6. Sociodemographic 7. Sleep-related data | Cognitive disorders unit of hospital Universitari Santa Maria at Lleida,  Spain | p-tau scores   1. Gaussian process- 29 + 2.56 2. k-NR -26.66 3. SVR-24.8 + 4.07 4. Regularized linear regressions (RLR) -24.77 + 0.05 5. Ensemble models-24.69 + 3.42 |

**CONCLUSION**

This review conducts an in-depth examination of the different machine learning techniques in the early diagnosis and detection of Alzheimer's disease (AD). The paper comments on the trajectory of Alzheimer's disease (AD), with no cure for this neurological condition, while highlighting the value of early detection in optimizing symptomatic management and preventing cognitive deterioration. Traditional diagnostic methods are not sensitive at preclinical stages, during which by the time symptoms arise, irreparable brain destruction has already occurred.

The scope for increased accuracy in diagnosis is revealed by the study, including models based on decision trees, random forests, support vector machines, and very recent deep learning methods such as convolutional neural networks. The range of models processed a wide variety of complex information such as biomarkers, MRI, PET, fMRI, and results of cognitive tests. For example, for a long time multimodality techniques have proved more accurate in accuracy rates for early diagnosis and stage classification of Alzheimer's disease compared with single-modality approaches. In fact, approaches can take into account genetic, imaging, and cognitive data sources.

Even though there is a very impressive advancement in this domain, diagnosis using machine learning is certainly not easy. There needs to be more research studies focusing on integrating large-scale, multi-modal datasets, enhancing the interpretability of algorithms, and overcoming the problem of generalizability across different demographic populations. However, the actual success of such models in clinical practice would depend a lot on clinical validation and ethical factors.

In short, with the potential that advances in machine learning have brought about, particularly in the area of multimodal approaches, for the early detection and treatment of the Alzheimer's disease, more research in this area may eventually lead to more customized treatment regimens and improved patient outcomes as well as greater understanding of the diseases' complexity.

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