Journal of Research High School

Vol. 2025 (12) 1035 – 1045
ISSN 2688-3651 [online]

Accessibility and Cost-Effectiveness of Machine Learning Algorithms in Neuro-imaging for Early Alzheimer's Disease Detection

Zhengyu Huang[1] *

[1] Crean Lutheran High School, Irvine, CA, USA
*Corresponding Author: 20061214huangzhengyu@gmail.com

Advisor: Arij Daou, arijdaou@gmail.com

Received August 11, 2025; Revised September 8, 2025; Accepted September 23, 2025

Abstract

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that leads to memory loss, cognitive decline, and behavioral changes. Early detection is important for effective intervention and management of the disease. This paper reviews the diagnostic role of neuroimaging machines —MRI, PET, CT, and fMRI—and checks how Machine Learning (ML) and Deep Learning (DL) techniques improve early detection and prognostication for AD. Convolutional Neural Networks (CNNs) have high accuracy in identifying early signs of the disease from brain scans. This paper also discusses combining imaging and ML with other information, such as biomarkers, to enhance prediction and support personalized care. Even while these methods initially demand a large financial outlay, this article also identifies accessibility issues that lead to uneven adoption across healthcare systems, such as the scarcity of sophisticated scanners and costly infrastructure requirements. The cost-effectiveness of ML-assisted early detection is also taken into account. Although imaging and computational resources are costly up front, early and precise diagnosis can reduce overall costs by lowering long-term dementia care costs and focusing treatments on the people who will benefit from them the most. This study offers a more thorough understanding of how ML and imaging technologies might enhance Alzheimer's disease diagnosis and care by combining technical performance with accessibility and financial considerations.

Keywords: Alzheimer's disease, Machine learning, Imaging technologies

1. Introduction

AD is a progressive neurodegenerative disorder characterized by gradual decline in memory, impaired reasoning, language deficits, and eventual deterioration of physical ability. The two hallmark pathological features of AD are amyloid plaques, which are protein clumps between brain cells, and neurofibrillary tangles, which are twisted protein fibers inside neurons. (Lane et al., 2018). Both biomarkers can be used to detect AD in its early stages.

The progression of AD is generally categorized into several stages: stages 0–2 show no clear symptoms; stage 3 brings early memory issues and measurable deficits on cognitive assessments; stage 4 involves increasing memory loss and difficulty with daily tasks; and stages 5–6 are marked by severe decline, in which patients may lose the ability to walk, eat, or communicate (Rasmussen & Langerman, 2019). The number of people with AD is rising rapidly. For example, the Alzheimer's Association estimates that more than 6 million Americans are currently living with the disease, and this number is projected to double by 2050 if no effective treatments are developed (Alzheimer's Association, 2024). These trends underscore the urgency of early detection, which allows patients and families more preparation time, reduces medication costs, and improves quality of life (Rasmussen & Langerman, 2019). Moreover, interventions are generally more effective in the early stages of AD.

In parallel with rising healthcare demands, advancements in Artificial Intelligence (AI) and ML are transforming medicine. ML, which allows computers to identify patterns and make predictions from complex datasets, has shown

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strong potential in assisting with the early detection of AD. In healthcare applications, ML algorithms can recognize imaging features and biomarkers that may indicate early stages of the disease, enabling clinicians to make faster and more accurate diagnoses (Rasmussen & Langerman, 2019).

The aim of this paper is to evaluate the accessibility, cost-effectiveness, and diagnostic performance of ML algorithms used in AD detection through brain imaging technologies: MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), fMRI (functional MRI), and CT (Computed Tomography). This study compares traditional diagnostic approaches with ML methods, examines the algorithms used in recent research, and assesses whether these technologies provide clear advantages for improving diagnosis and care.

2. Methodology

The literature reviewed in this paper was identified through searches of PubMed, Google Scholar, and IEEE Xplore, covering biomedical, clinical, and computational research. The search mainly focused on studies published between 2016 and 2025, while several earlier landmark works (e.g., Minoshima et al., 1997) were included to provide historical context. Articles were selected based on their relevance to AD, neuroimaging modalities (MRI, PET, CT, and fMRI), and the application of ML and DL algorithms for early detection. In addition, economic and accessibility studies were incorporated to address the broader implications of these technologies. This review is presented as a narrative review, rather than a systematic review, with the aim of synthesizing recent findings and making them accessible to a high school audience.

3. Literature Review

AD is the most common cause of dementia in the world today, with significant economic impacts (Wittenberg et al., 2019). Although development of imaging techniques such as MRI *(Magnetic Resonance Imaging)*, PET *(Positron Emission Tomography)*, and CT *(Computed Tomography)* have improved early detection, these methods are costly and not widely accessible. For example, large-scale PET images require annual investments over £100 million in the UK (Wittenberg et al., 2019).

Neuroimaging machines play an important role in detecting AD. Structural MRI is widely used to measure hippocampal atrophy, which correlates with disease progression (Lane et al., 2018). While CT provides basic structural information, it has limitations in sensitivity (Scheltens et al., 2016). fMRI can detect ongoing changes in brain activity patterns over time, which may reveal trends before visible atrophy occurs (Scheltens et al., 2016). PET measures glucose metabolism and shows hypometabolism in the temporoparietal regions, helping identify characteristics of AD (Lane et al., 2018). However, these imaging modalities require professional equipment and skilled operators, making them expensive and less available in many healthcare systems (Wittenberg et al., 2019).

In recent years, ML algorithms have shown great improvement in helping the healthcare system analyze brain images and detect AD more accurately (Khan et al., 2021). Early studies examined supervised techniques such as support vector machines, *algorithms separating data into categories,* and random forests*, the ensembles of decision trees*, which helped classify imaging data but did not always produce perfect results (Klöppel et al., 2008). More recently, DL methods, especially convolutional neural networks (CNNs) *(neural networks for analyzing images)*, have been more successful. Some studies report CNNs can correctly identify early AD in over 85% of cases (Basaia et al., 2019; Khan et al., 2021). Combining multiple data types, like MRI and PET, and using transfer learning, the learning *uses a model trained on one task to improve another, which* has also worked well for early detection, but these approaches require

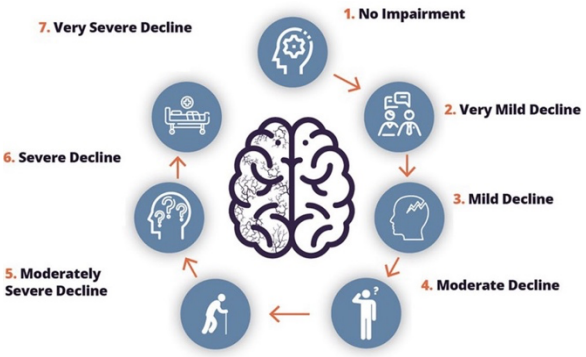

Figure 1. Stages of cognitive decline in AD. Progression from no impairment to very severe decline. Adapted from Rasmussen & Langerman (2019).

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significant computing power and technical expertise to set up (Rasmussen & Langerman, 2019).

Recent studies suggest that ML-based tools have great potential to improve early detection by making image analysis faster and more accurate but still face unsolved issues before they can be used widely (Scheltens et al., 2016).

4. AD Diagnosis with MRI, PET, CT, fMRI

All ML algorithms, whether supervised or unsupervised, need data. In AD diagnosis, this data comes from neuroimaging techniques capturing detailed brain images that are fed into the ML algorithms to detect early pathological signs. Two major imaging modalities in this process are MRI and PET (Chouliaras & O'Brien, 2023).

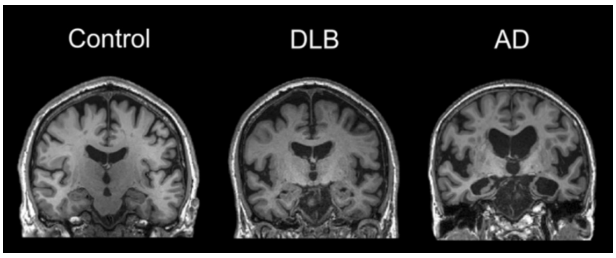

Figure 2. MRI brain scans of Control, DLB, and AD patients. The Control MRI shows a healthy brain with normal hippocampal and medial temporal lobe size, while the AD MRI displays clear atrophy, especially in the medial temporal regions. DLB shows intermediate patterns between Control and AD. Adapted from Chouliaras & O'Brien (2023)

4.1 MRI

MRI is a non-invasive imaging technique that uses magnetic fields and radiofrequency pulses to produce high-resolution images of the brain's soft tissues. It is effective at revealing structural abnormalities such as atrophy, tissue shrinkage, swelling, and microbleeds—tiny areas of bleeding (Chouliaras & O'Brien, 2023). Research by Scheltens et al. (2016) shows MRI can detect degeneration in hippocampal neurons before cognitive symptoms appear, making it valuable for early-stage detection.

Beyond identifying hippocampal atrophy, or the loss of volume in the memory region, MRI can also measure the thickness and volume of the cerebral cortex, the outer layer of the brain that supports higher-level thinking, which shrinks as AD progresses (Aghdam et al., 2025). MRI is further used to rule out other causes of dementia symptoms, including strokes, tumors, or normal-pressure hydrocephalus, a condition in which fluid builds up in the brain (Lane et al., 2018). Advanced MRI techniques such as diffusion tensor imaging (DTI), which can map white matter connections, are useful for evaluating how brain connectivity deteriorates in AD (Aghdam et al., 2025). Because MRI does not use ionizing radiation, it is suitable for repeated scans in long-term studies to track disease progression or treatment effects (Singh et al., 2024).

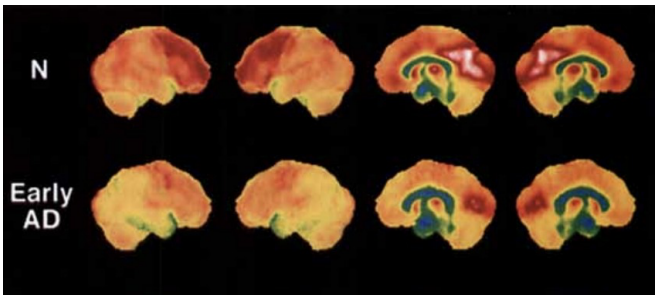

Figure 3. PET scans comparing glucose metabolism in normal and early AD brains.

The normal brain (top row) shows widespread high metabolic activity in red and yellow regions, while the early AD brain (bottom row) demonstrates reduced activity in the parietal and temporal lobes, shown as more green and blue regions (Minoshima et al. 1997).

4.2 PET

Like MRI, PET is also non-invasive but is used to visualize metabolic and molecular processes inside the brain. PET scans require injection of a small radioactive tracer, which acts as a chemical marker to detect biomarkers directly linked to AD pathology. Several types of PET are relevant to AD: FDG-PET measures glucose metabolism and often shows reduced activity in affected brain regions (Chouliaras & O'Brien, 2023); amyloid PET detects beta-amyloid plaques, which are protein clumps located outside neurons; and tau PET identifies tau protein tangles, which are abnormally twisted fibers inside neurons. Both MRI and PET can reveal abnormal protein buildup and metabolic changes before clinical symptoms appear, making them highly effective for early diagnosis (Scheltens et al., 2016).

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Panels A and B are MRI scans. Panel A shows small dark spots consistent with microbleeds, while Panel B shows bright regions that may indicate inflammation. Panels C and D are PET scans. Panel C highlights amyloid plaques in red, and Panel D shows reduced brain activity in blue regions, both characteristic features of AD (Sengoku et al. 2014).

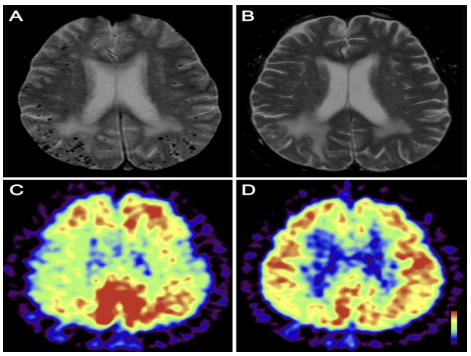

Figure 4. MRI and PET images showing brain abnormalities associated with AD.

4.3 CT

Computed tomography (CT) is a type of scan that uses X-rays to create cross-sectional images of the brain, and it remains one of the most widely available neuroimaging methods. CT is often used in the early detection of patients with suspected cognitive impairment or other initial signs of AD (Scheltens et al., 2016). It provides anatomical images of the brain that can help identify abnormalities such as tumors, subdural hematomas, which are areas of bleeding beneath the outer covering of the brain, and large infarcts, which represent tissue death caused by a lack of blood supply. CT can also reveal patterns of cortical atrophy, or thinning of the brain's cortex, particularly in the medial temporal lobes, which are important for memory, and the hippocampi, the primary structures responsible for memory processing. These regions are also examined with MRI (Lane et al., 2018). However, CT has limited soft-tissue contrast resolution, which makes it less sensitive for detecting subtle neuronal changes.

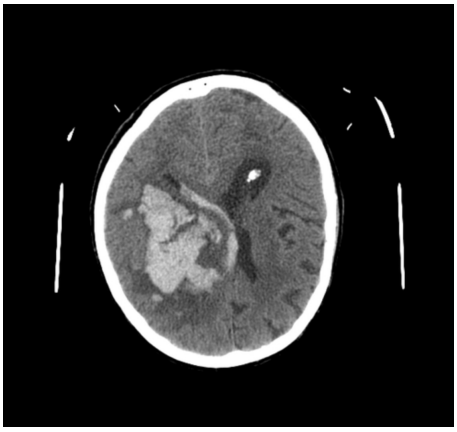
Figure 5. CT scan showing intracerebral hemorrhage. The image displays a large, irregular hemorrhage on the right side of the brain, measuring approximately 75 mm across. The bleeding involves the basal ganglia region and is accompanied by swelling and several smaller hemorrhages nearby (Radiopaedia.org (n.d.)).

Despite these limitations, CT offers advantages such as rapid acquisition and lower cost compared with MRI or PET (Wittenberg et al., 2019). More recently, researchers have explored the use of ML algorithms to improve the diagnostic utility of CT scans. For example, Khan et al. (2021) noted that deep learning models can detect subtle patterns of atrophy that are often missed with traditional analysis. Nonetheless, most ML research in this field continues to focus on MRI and PET. Future studies are needed to determine whether ML-assisted CT can provide meaningful improvements in sensitivity and specificity (Rasmussen & Langerman, 2019).

4.4 FMRI

Functional Magnetic Resonance Imaging (fMRI) is an important tool for studying how brain function changes in AD. Unlike structural MRI, which shows brain shrinkage, fMRI measures changes in blood oxygen levels that reflect brain activity. One issue observed in AD is that the brain's default mode network, a resting-state network closely related to memory, becomes disrupted at an early stage (Aghdam et al., 2025). These disruptions often appear before visible atrophy, which makes fMRI a promising early biomarker. In recent years, researchers have also combined fMRI with other imaging methods such as structural MRI and PET to obtain a more comprehensive picture of the brain and to improve diagnostic accuracy (Chamakuri & Janapana, 2025).

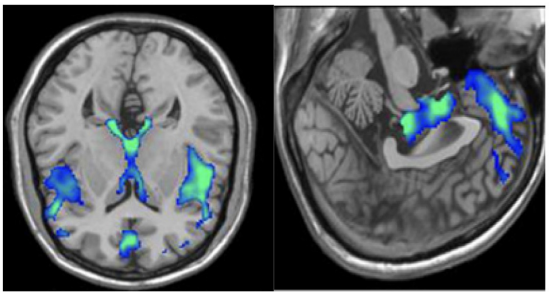
Figure 6. fMRI scans showing altered brain activity in AD. The colored blue and green regions indicate changes in brain activity or functional connectivity, reflecting differences in blood oxygen levels Jackson et al. (2013).

In general, fMRI is divided into two main types: resting-state fMRI and task-based fMRI. Resting-state

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fMRI is often used in patients with cognitive problems who may have difficulty following instructions (Singh et al., 2024). Researchers use this approach to assess whether critical networks such as the default mode, attention, and executive control networks lose connectivity as the disease progresses. Task-based fMRI, by contrast, focuses on brain regions activated during activities such as memory or language tasks, helping to show which areas become less active over time (Aghdam et al., 2025). Despite its advantages, fMRI also has limitations. It is highly sensitive to motion artifacts caused by patient movement and to physiological noise from heartbeat and breathing. As a result, interpreting neuronal activity from blood oxygen signals requires careful analysis (Chamakuri & Janapana, 2025).

5. Role of ML in medicine

The development of ML makes substantial benefits to modern medicine. Unlike traditional detection, ML can analyze vast, complex data, uncover hidden patterns, identify correlations, and make predictions that are difficult for humans. This is valuable in healthcare because decisions are always based on large amounts of detailed information such as medical imaging and detection of small abnormalities (Rahmani et al., 2021).

One role of ML is helping clinicians to do faster and more accurate detection (An et al., 2023). For example, ML algorithms can detect subtle changes in CT scans that the human eye might miss. Today, ML tools are typically used to predict secondary review layer to support clinical decisions. They do not replace human judgment but provide additional confirmation (An et al., 2023).

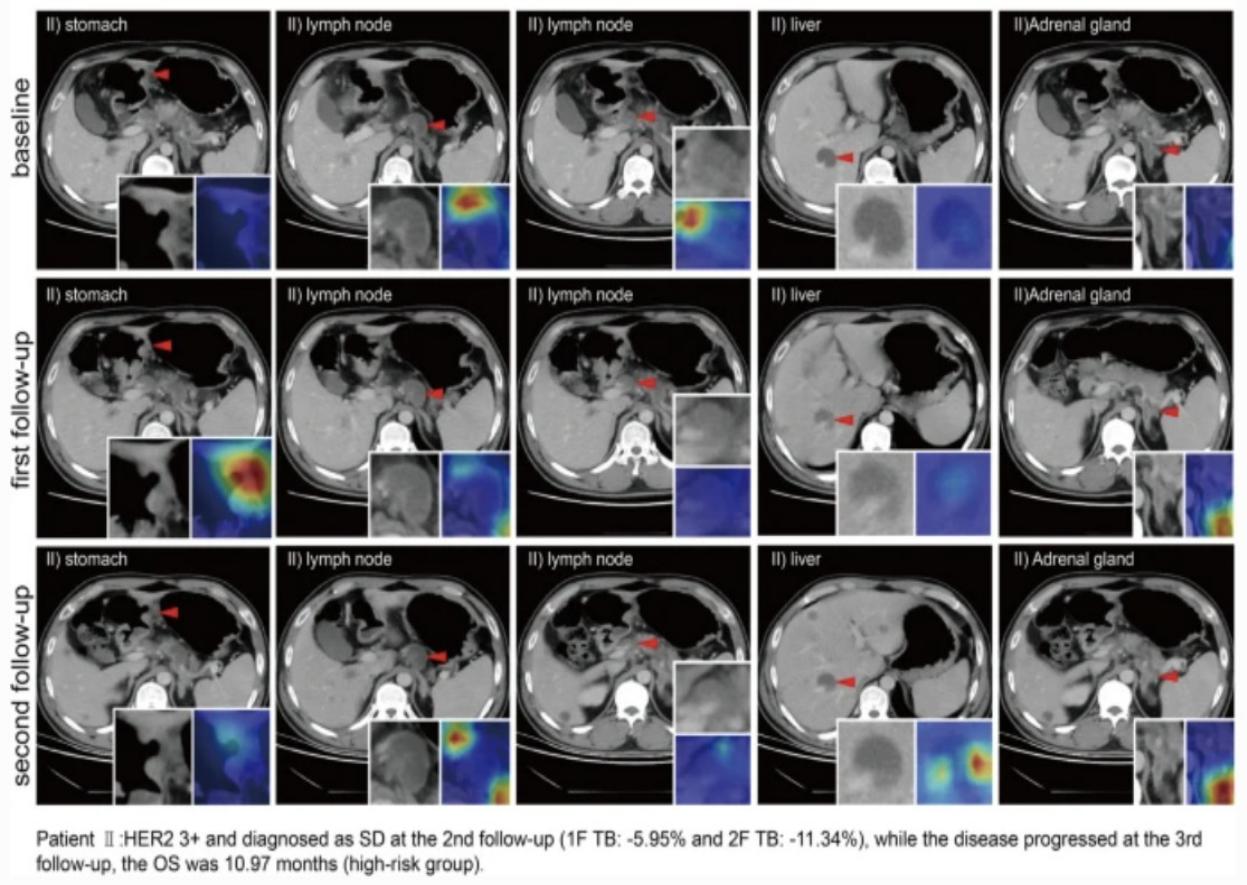

Figure 7: it shows how a ML model applied GRad-CAM visualization to highlight critical tumor regions from CT scans image. This model closely matches to label all known lesion areas and varies across different stages, can help doctors to track disease progression and make predictions (He et al., 2024).

Beyond early diagnosis, ML can also predict the likelihood of future health events, such as hospital readmissions, extended length of stay, discharge diagnoses, and the progression of chronic conditions (Figure 8). By analyzing historical data, ML models can estimate individual risk profiles and propose tailored preventive strategies for each

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patient (An et al., 2023). These predictions support early intervention, improve long-term outcomes, and help reduce the pressure on both healthcare systems and patients.

On the other hand, ML plays an important role in better personalized medicine. Rather than applying uniform treatments to all patients, ML systems can help identify which treatments are most likely to be effective for specific individuals. By combining diverse data sources—such as genetic information, lifestyle habits, and prior treatment responses—these models enable more customized and targeted care (An et al., 2023).

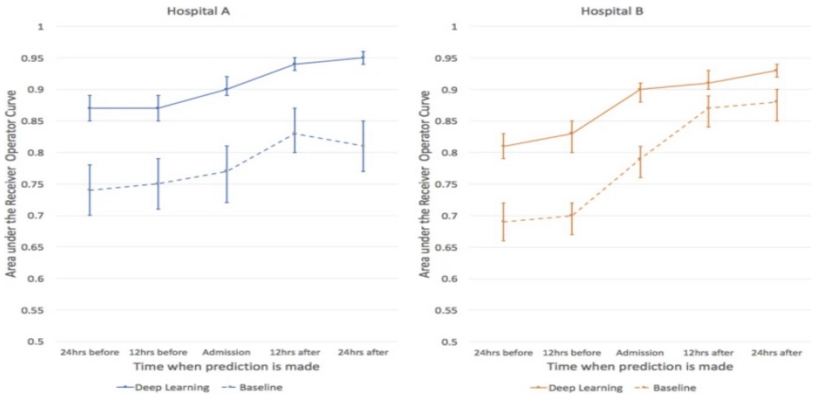

Figure 8. Comparison of DL and baseline models across two hospitals.The figure plots the area under the receiver operating characteristic curve (AUROC) for predictions made from 24 hours before admission through 24 hours after admission (Rajkomar et al. 2018).

6. Different types of ML algorithms

ML is often divided into four main categories, and each of them has been applied in different ways to AD research. In this section, the focus is on how these categories are being used in neuroimaging studies, rather than repeating their detailed definitions.

6.1 Supervised Learning

Supervised learning is one of the most common approaches in medical imaging. In the case of AD, algorithms such as support vector machines (SVMs), random forests (RFs), and neural networks have been applied to MRI and PET scans to separate patients with mild cognitive impairment (MCI) from those with AD and to predict disease progression. These methods often achieve relatively high accuracy, especially when trained with large, well-labeled datasets (Woodman & Mangoni, 2023).

6.2 Unsupervised Learning

Unsupervised learning is helpful when dealing with large datasets that lack labels. In AD studies, clustering methods have been used to group patients into subtypes that show different patterns of decline. Techniques such as principal component analysis (PCA) and visualization tools like t-SNE also help simplify complex imaging data and highlight features that could serve as biomarkers (Verbeeck et al., 2020).

6.3 Semi-supervised learning

Since labeled imaging data are often limited and expensive to obtain, semi-supervised learning has become especially useful in AD research. By combining a small amount of labeled scans with a larger number of unlabeled ones, models can reach better performance than supervised methods alone. Approaches include self-training (where a model labels more data for itself over time), co-training (where two models exchange labels), and graph-based methods that spread information across connected data points (Sarker, 2021).

6.4 Reinforcement Learning

Reinforcement learning (RL) is less common in AD studies but has shown promise in healthcare more broadly. RL works by receiving feedback from trial-and-error decisions, which makes it suitable for tasks such as optimizing

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treatment schedules or drug dosing. The two main approaches are value-based methods, such as Q-learning, which estimate future rewards, and policy-based methods, which directly learn how to act. While RL is not yet widely used in AD detection, it has potential to support the development of more personalized long-term care strategies in the future (Tufail et al., 2023).

6.5 Deep Learning

In recent years, deep learning (DL) has become one of the most promising tools for detecting AD from neuroimaging and clinical data. Unlike traditional ML methods that rely on carefully designed handcrafted features, DL models can automatically learn hierarchical representations from raw input, such as MRI and PET scans (Chamakuri & Janapana, 2025). Among these, CNNs are the most widely used, as they can identify subtle structural and functional brain changes that may signal AD onset (Aghdam et al., 2025). These models are capable of detecting slight patterns of cortical thinning and hippocampal damage that traditional analysis might miss. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have also been applied to longitudinal imaging studies to capture temporal dynamics and track disease progression over time (Rezaie & Banad, 2024). In addition, combining CNNs with other algorithms in ensemble models has produced higher accuracy and stronger performance, making DL a central component of computer-aided diagnosis systems (Aghdam et al., 2025)

Despite its successes, the application of DL to AD diagnosis still faces several challenges. One major issue is limited generalizability, meaning that models trained on a single dataset often perform poorly when applied to new populations. Their accuracy tends to decrease when patients differ in demographics, scanning equipment, or clinical conditions (Aghdam et al., 2025). DL methods also require large amounts of labeled data to achieve reliable accuracy. This issue is compounded by the fact that research centers use different protocols for preparing and scanning images, leaving no universally standardized approach (Rezaie & Banad, 2024). Another important concern is the “black box” nature of many DL models, which limits interpretability and reduces clinician trust in their results. To address these limitations, researchers are developing hybrid models that combine DL with feature selection, attention mechanisms that highlight the most relevant parts of the data, and explainability frameworks designed to make outputs more transparent (Chamakuri & Janapana, 2025). Overcoming these challenges is necessary for DL to be adopted as a reliable tool in routine AD diagnosis.

7. Application of ML in AD

ML and DL techniques are used as tools for early detection and diagnosis of AD,making a solution for the issue of the limitations of traditional clinical assessments. Traditionally, doctors make treatments and decisions from memory tests and neurological exams, but these usually identify AD only when the brain already has significant damage, under this situation, the treatments would be less effective (Aghdam et al., 2025). To overcome this challenge, researchers try to use ML models together with brain scans such as structural MRI, fMRI, and PET to detect early signs of disease in the brain. Combining imaging with genetic and cognitive assessments, this new way can capture complex and nonlinear patterns of disease when the signs of it have just appeared, which traditional approaches always fail to detect (Rezaie & Banad, 2024).

Of the different DL approaches, CNNs were the most common ones that can automate the extraction of diagnostic features from imaging data. Unlike conventional ML techniques, which need handcrafted feature engineering and expert segmentation, CNNs can learn hierarchical representations from oscans directly. This progress can reduce subjectivity and improve reproducibility(AlSaeed & Omar, 2022). This ability is important for distinguishing mild cognitive impairment (MCI), progressive MCI, and stable MCI, which is the early stage of memory problems; PMCI is MCI progress to AD in a few years; sMCI used to describe patients whose MCI remains stable) (Aghdam et al., 2025; Singh et al., 2024). Also, it plays an important role on risk stratification and early prediction (Singh et al., 2024).

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Another important development of ML is the use of unsupervised and multimodal learning to check hidden disease subtypes and progression patterns. For example, clustering methods, using multimodal data, is used to identify patient subgroups with distinct trajectories of cognitive decline (Rezaie & Banad, 2024). The feedback can be used to make personalized treatment and help to identify the individuals for early intervention trials (Rezaie & Banad, 2024). Additionally, generative adversarial networks (GANs) and graph-based neural networks have been used to model complex brain connectivity and to make realistic imaging data, in other way to improve the field of predictive modeling in AD research (Singh et al., 2024). A generator creates fake data and a discriminator evaluates it, and both compete in a game that improves the generator's ability to produce outputs. (Singh et al., 2024). These advanced ML methods can group patients more accurately and model how the disease changes over time, which may help predict outcomes better and create more personalized treatments(Singh et al., 2024).

Figure 10. Main data sources used in Alzheimer's disease research. The figure summarizes nine types of data commonly used to support ML models in AD research, including genetic data, CSF and blood plasma biomarkers, cognitive assessments, neuroimaging (PET, MRI, CT, fMRI), EEG, electronic health records, and longitudinal and cross-sectional data. Adapted from Rezaie & Banad (2024).

Ensemble learning, which combines multiple models, and hybrid methods, which integrate different algorithmic approaches, can improve the ability of models to predict AD by drawing on complementary strengths. For example, studies show that using Random Forests, CNNs, and SVMs together allows researchers to benefit from the clear interpretability of tree-based models as well as the strong feature extraction capabilities of deep networks (Rezaie & Banad, 2024). Ensemble systems can also integrate structural MRI and PET brain scans with biomarkers derived from cerebrospinal fluid and results from cognitive tests to improve the accuracy of early-stage AD detection (Chamakuri & Janapana, 2025). Transfer learning offers another promising approach by applying pre-trained models to new AD datasets with limited labeled examples. This strategy can improve performance across different patient groups and reduce the need for extensive manual labeling (Aghdam et al., 2025). However, reproducibility remains a concern, as models often lose accuracy when applied to datasets collected using different scanning procedures (Aghdam et al., 2025).

8. Cost-effectiveness

The economic impact of expanding large-scale early AD detection, particularly among people with mild cognitive impairment, is significant but must be weighed against the high costs of dementia care. In the UK, for example, increasing amyloid PET scans by 100,000 per year would cost approximately £113 million annually, while adding the same number of cerebrospinal fluid (CSF) tests would cost about £63 million in the first year, with lower costs in subsequent years as training expenses decline (Wittenberg et al., 2019). Although these amounts are considerable, they remain lower than the long-term costs of dementia care and the projected prices of future disease-modifying treatments. Accurate early diagnosis can also help ensure that expensive therapies are provided only to patients most likely to benefit, thereby improving health outcomes and reducing avoidable care costs (Wittenberg et al., 2019).

Economic modeling by Handels et al. (2017) further shows that adding biomarker tests such as CSF analysis to standard assessments improves both accuracy and cost-effectiveness, particularly in groups with a higher risk of developing AD. However, the wider adoption of biomarker testing will require substantial investment in trained staff, equipment, and laboratory infrastructure, as well as careful management to avoid shortages and delays that could increase costs. Although expanding early diagnostic testing will create high initial expenditures, these investments may ultimately be justified if they provide earlier access to effective treatments and help slow disease progression, leading to both economic savings and improved quality of life at the community level.

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9. Discussion.

The findings emphasize the potential of combining advanced imaging techniques with ML. It can improve the early detection of AD. Traditional imaging methods, including MRI and PET, do good work when showing structural and metabolic changes in the brain but have limitations such as high costs, restricted access, and requiring the expert interpretation. ML, especially CNN, can analyze imaging data and identify subtle patterns that can't be captured by human observers. Some studies show that CNNs can classify early AD with accuracy rates above 85%, which is a significant advantage compared to earlier tools.

However, there are still some challenges waiting to be overcome. Many DL models require large, high-quality datasets to train, and their ability may decrease when applied to new populations or different scanning equipment. Another concern is the "black box" issue—these models can be difficult to interpret, which lead clinician can't really use them to make decisions . Moreover, combining these tools into daily clinical making treatments will demand investments in technology, staff training, and clear guidelines for use.

Economic modeling shows that scaling up diagnostic testing—biomarker analysis and imaging—requires high investment at the beginning . For example, expanding amyloid PET and CSF testing programs can cost tens of millions of pounds annually. However, early detection has the potential to improve care planning and find the patients who really need costly treatments, potentially reducing long-term dementia care expenditures.

10. Conclusion

Early detection of AD is important to improving treatment and reducing the pressure on patients and healthcare systems. This paper talks about how combining neuroimaging methods with ML algorithms, especially DL models like CNNs, can improve diagnostic precision. However, these advances come with important challenges related to accessibility and cost. To combine such technologies requires high investment at the beginning, data infrastructure, and professional training, so it is difficult to spread to all healthcare systems. Moreover, the interpretability and consistent performance on different populations is another issue for using ML in this process that needs to be overcome before widely using.

Future research should focus not only on improving model accuracy but also on developing strategies that make these tools more affordable and accessible in different situations. Evaluating real-world cost-effectiveness and ensuring that the benefits of ML in neuroimaging are available to a wide patient population. While combining ML with advanced imaging makes a big improvement for early Alzheimer's detection, to make this working widely, it needs coordinated efforts across research, policy, and clinical practice.

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