AI-Based Neuroimaging Techniques for Diagnosing Alzheimer's Disease

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Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that is becoming an increasingly urgent public health challenge due to aging populations worldwide (Alzheimer's Disease International, 2017). Despite its profound social and economic impact, there remains no cure for AD, and current diagnostic methods often detect the disease only after significant brain damage has already occurred. Traditional diagnostic tools, such as cognitive testing and standard imaging, lack the precision and sensitivity to reliably identify early-stage Alzheimer's in asymptomatic individuals (NIH, 2022). This diagnostic delay limits the potential for early intervention, preventive strategies, and clinical trial enrollment. As the prevalence of AD continues to rise, the urgent need for more accurate and timely diagnostic methods has never been greater — but there are limitations in the field. These limitations include low predictive accuracy in earlier diagnosis, the frequent presence of other brain pathologies, and difficulties in detecting the disease in its early stages. Hence, the application of AI-based neuroimaging techniques have begun to be discussed more in clinical environments in regards to AD.

Artificial intelligence (AI) offers a promising pathway to revolutionize the early diagnosis of AD by leveraging advanced data analysis and pattern recognition capabilities. AI-based algorithms, particularly those using machine learning and deep learning, can be trained on large-scale neuroimaging datasets such as MRI, PET scans, and functional imaging to detect subtle brain changes that may precede clinical symptoms by years (Coursera, 2025). These techniques can identify complex patterns in brain structure and function that are often imperceptible to human radiologists, improving diagnostic accuracy and enabling earlier detection. Beyond imaging, AI can integrate multimodal data — including genetics, biomarkers, and cognitive test results — to create comprehensive diagnostic models.

This paper will first provide a basic understanding of both AD, its causes and symptoms, as well as explain the concept of utilizing AI algorithms, particularly deep learning networks, such as Convolutional Neural Networks (CNNs), and their potential future applications into clinical workspaces. Then, I will present three different AI algorithms and evaluate their function, strengths, limitations, and then choose a single AI algorithm that is most likely to have the most effective impact on diagnosing AD earlier and more accurately, while simultaneously offering several areas of improvement to the model. The goal of this research will be to evaluate the extent to which AI algorithms will be able to be effectively clinically implemented to provide care for diverse patients in a more accurate manner. Ultimately, this paper can provide a more thorough understanding

on how the use of AI in AD could help improve future research on both AI in neurology applications and medicine broadly.

Alzheimer's Disease

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the most prevalent form of dementia, characterized most prominently by a declining memory and remembering recent events despite experiencing them in the past. This is followed by dramatic mood swings (outbursts of anger, anxiety, and depression), physical problems (like odd gait or coordination), feeling confused or frustrated (especially at night), feeling disoriented or getting lost easily, and difficulty doing ordinary activities (Alzheimer's Association, 2025) (Figure 1). As of 2020, over 55 million people globally live with dementia, and approximately 10 million new AD cases are diagnosed each year, and nearly all diagnoses being elderly people of 65 or older, demonstrating its continued problems towards public health. For example, in 2025 an estimated 7.2 million Americans aged 65 and older are living with AD, a number expected to grow significantly, with deaths from AD having doubled since 2000, demonstrating its continued public health challenge (Alzheimer's Disease International, 2017).

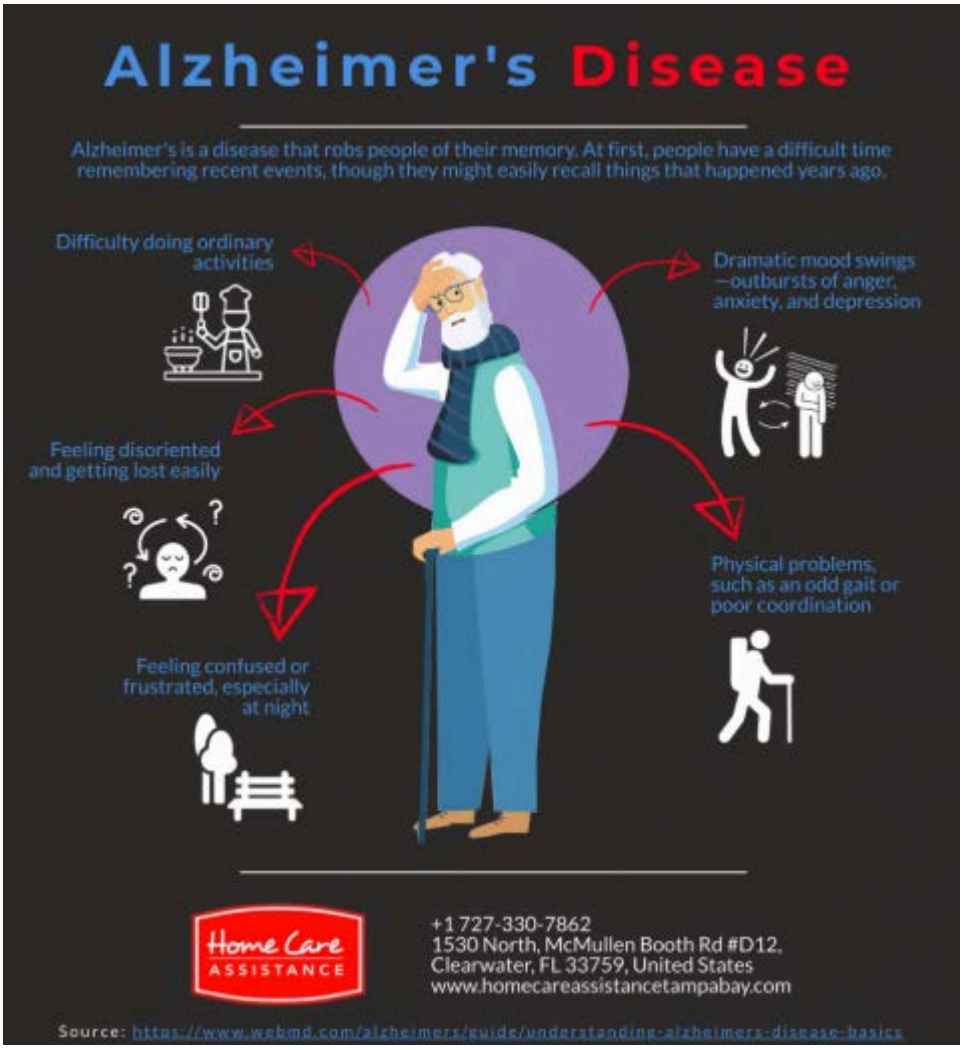

Figure 1: *Symptoms of Alzheimer's Disease (AD)*. Highlights all the symptoms commonplace among people suffering from AD, including dramatic mood swings, difficulty doing ordinary activities, feeling disconnected and getting lost easily, feeling confused and frustrated at night, and physical problems such as a lack of coordination. (Home Care Assistance, 2020).

Pathogenesis of Alzheimer's Disease

The pathogenesis of AD is strongly associated with the accumulation of amyloid beta (Aβ) plaques. These plaques are dense, insoluble clumps of beta-amyloid (Aβ) proteins that accumulate outside nerve cells in the brain. The amyloid cascade hypothesis, which proposes that Aβ deposition in the brain triggers a cascade of events leading to a buildup of tau proteins in the brain. Over time, this buildup of amyloid plaques and tau tangles trigger inflammation between synapses which proceeds to block internal transport systems, damage the cells, and eventually contribute to cell death, which contributes to cognitive decline. This hypothesis is widely accepted as the primary

explanation for the biological mechanisms underpinning the development of AD, though the actual cause of AD remains unknown (Zhang et al, 2023) (Figure 2). Furthermore, AD primarily affects key brain regions like the hippocampus, frontal, temporal, and parietal lobes—resulting in memory losses, impaired reasoning, and language difficulties. This highlights the importance of early detection can help minimize the irreversible neuronal damage (MyHealth Alberta, 2024) (Figure 3).

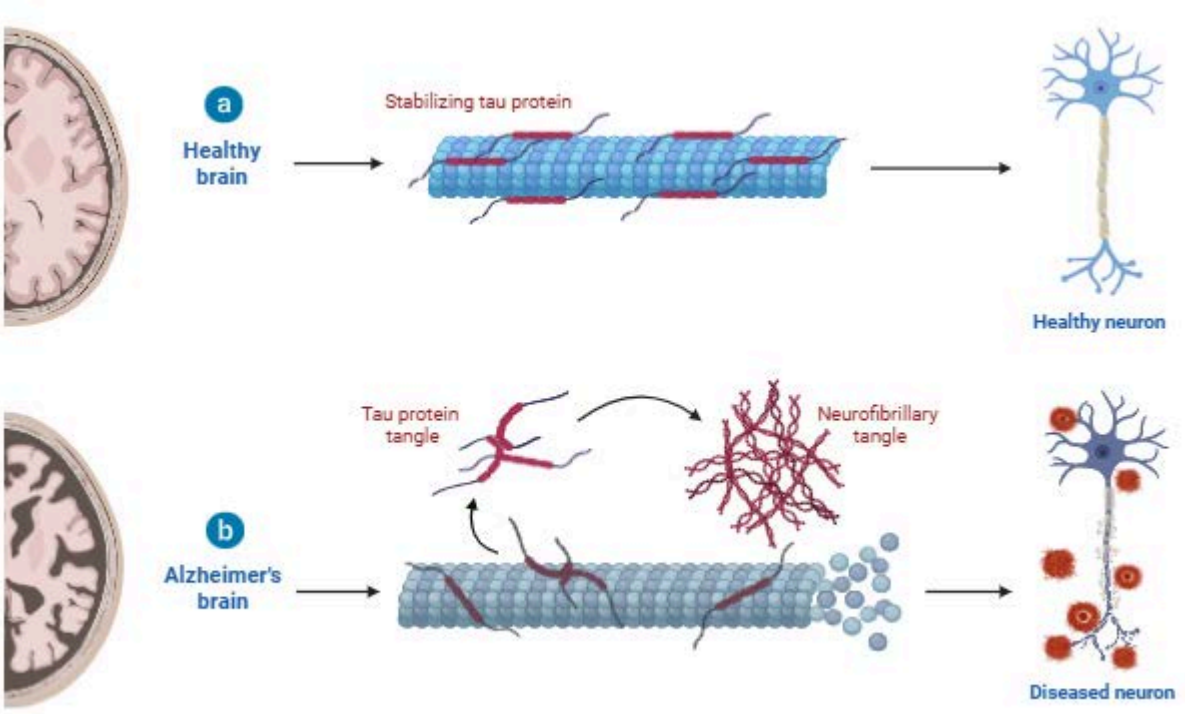

Figure 2: *Pathology of Healthy and AD brain*. Depictions of the development of a healthy brain and the development of a diseased (AD) brain, showing the formation of Tau proteins on the AD brain compared to the healthy brain. Red is the tau protein and amyloid plaques (BioRender, 2025).

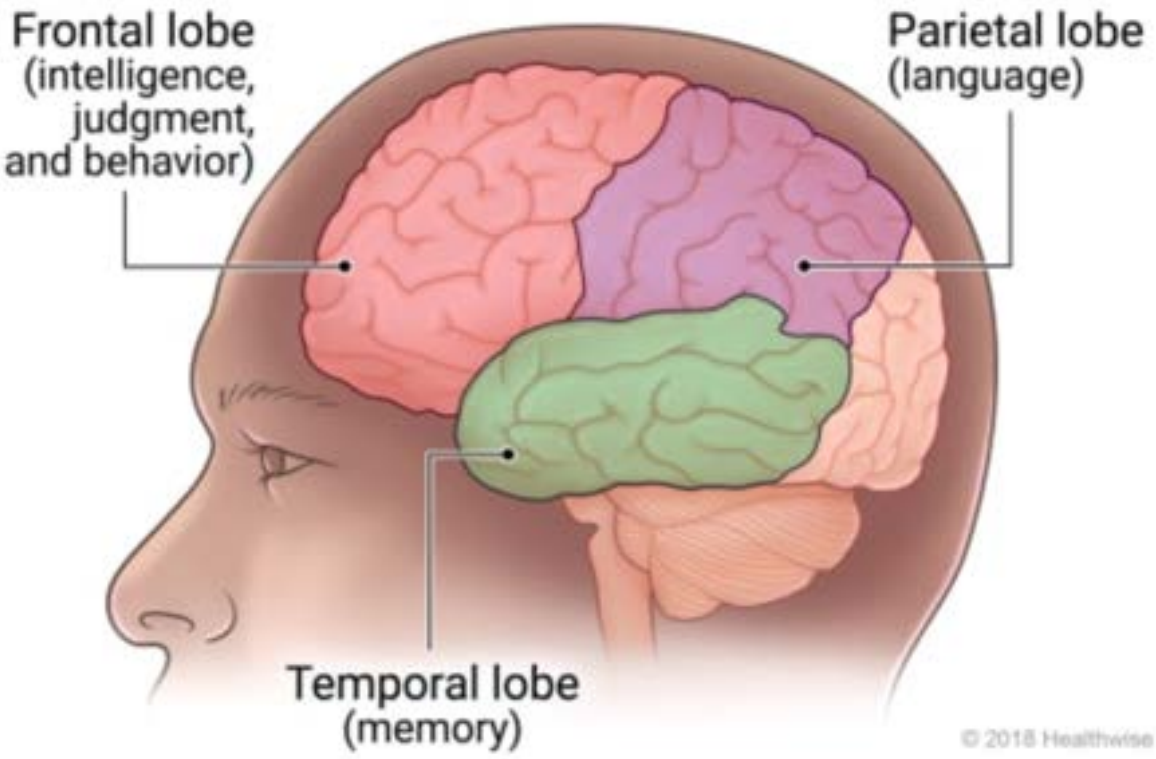

Figure 3: *Affected regions of the brain.* Shows the 3 main parts of the brain that control the functions of a person/what they control as well as being the three parts that are affected by AD development (Healthwise, 2018).

Heterogeneity in Alzheimer's Disease

Alzheimer's disease (AD) is highly heterogeneous, meaning that it does not present the same way in all individuals. Patients may show different patterns of memory decline, language impairment, or behavioral changes, and the rate of progression can vary widely from slow deterioration over decades to rapid decline within a few years. Subtypes such as early-onset AD, which is often linked to rare genetic mutations (e.g., in *APP*, *PSEN1*, or *PSEN2*), differ from the more common late-onset form, which is influenced by risk genes like *APOE ε4*. Beyond genetics, environmental and lifestyle factors also contribute to disease risk and expression—examples include head trauma, cardiovascular health, diet, physical activity, education level, and exposure to toxins. Additionally, having a family history of AD increases the likelihood of developing the disease, but sporadic cases without any familial link are also common (Avalar-Pereira et al, 2022).

Traditionally Diagnosing Alzheimer's Disease

Currently, diagnoses typically rely on cognitive assessments, brain imaging (CT, MRI, PET). However, these traditional methods are expensive, time-consuming, and often take several months to years, as well as require specialist expertise, limiting accessibility. Current treatments, from cholinesterase inhibitors to recently approved IV infusions like lecanemab, offer relief and modest disease modification but are only temporary solutions (NIH, 2022) (Figure 4). Thus, accurate and early diagnosis, ideally in the preclinical stage before visible symptoms emerge, is critical for effective treatment planning, safety in prescribing medications, and improving patient quality of life.

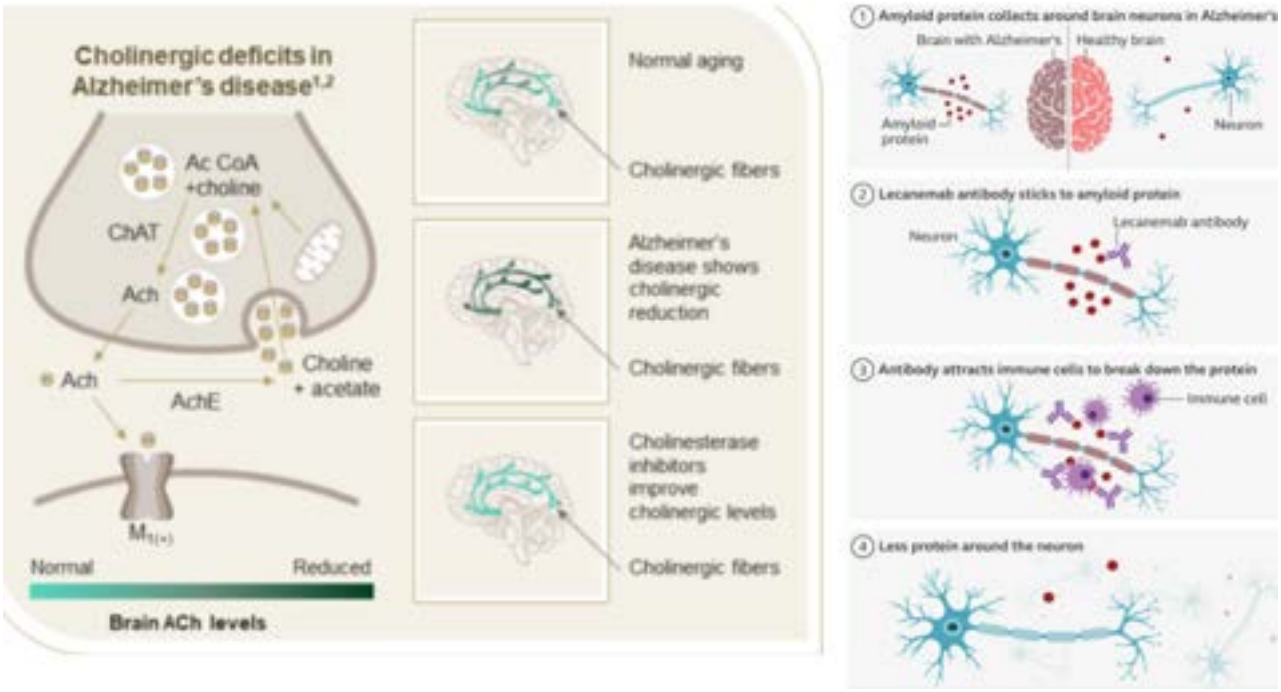

Figure 4: *Temporary solutions to AD*. The left image shows how cholinesterase inhibitors work. In people with AD, cholinergic neurons are progressively lost, reducing levels of acetylcholine. By targeting cholinesterase enzymes (AChE and BuChE) and inhibit the breakdown of acetylcholine (a major neurotransmitter). This increases the availability of acetylcholine at the cholinergic synapses. The right image shows a lecanemab IV infusion of the antibodies that stimulate the attraction of immune cells that can break down the amyloid proteins around the neurons, thus minimizing the damage caused by the buildup of the amyloid beta plaques (Neurotorium, 2023) (BBC Research, 2022).

However, clinical trials continue to face challenges due to late intervention, incorrect dosing, and incomplete understanding of AD's pathophysiology, aggravated by the disease's varying genetic and pathological origins in different populations. This variability requires larger patient populations to detect treatment effects, increases the cost and duration of trials, and can lead to treatments that appear ineffective because they only work for specific patient subgroups. These gaps highlight the need for innovative approaches such as neuroimaging-based AI techniques to revolutionize early and accurate AD diagnosis. (Alzheimer's Association, 2025).

Population targets for AI powered diagnostic screening

For early diagnosis of AD, the populations that should be prioritized are those at highest risk due to age, genetics, or medical conditions. The most prominent group is elderly individuals, particularly those 65 years and older, as this is the age range when symptoms typically become most apparent, with prevalence rising steeply compared to younger groups.

Another critical population is those with a family history of AD, since having a parent or sibling with the disease increases one's risk significantly. Genetic predispositions are especially important to consider—mutations in the APP, PSEN1, and PSEN2 genes are strongly linked to early-onset AD (before age 65), while the APOE gene, particularly the APOE4 allele, is associated with increased risk in later-onset forms, with those carrying two copies at especially high risk, as demonstrated in the figure below, generally in the Northern Hemisphere as well as regions of Africa and South America, highlighting a difference in distribution of the APOE4 allele. Beyond genetic and familial risk, individuals already experiencing Mild Cognitive Impairment (MCI)—a well-documented precursor to AD—should also be targeted, as early intervention at this stage can help delay or reduce progression. Finally, populations with comorbid conditions such as diabetes, obesity, or hypertension should be screened early, as these health issues have been shown to elevate the risk of developing AD (Figure 5). By focusing first on elderly individuals, those with genetic markers or family history, and people with MCI or related comorbidities, early detection efforts can be directed where they are most likely to make a significant impact (Alzheimer's Association, 2025).

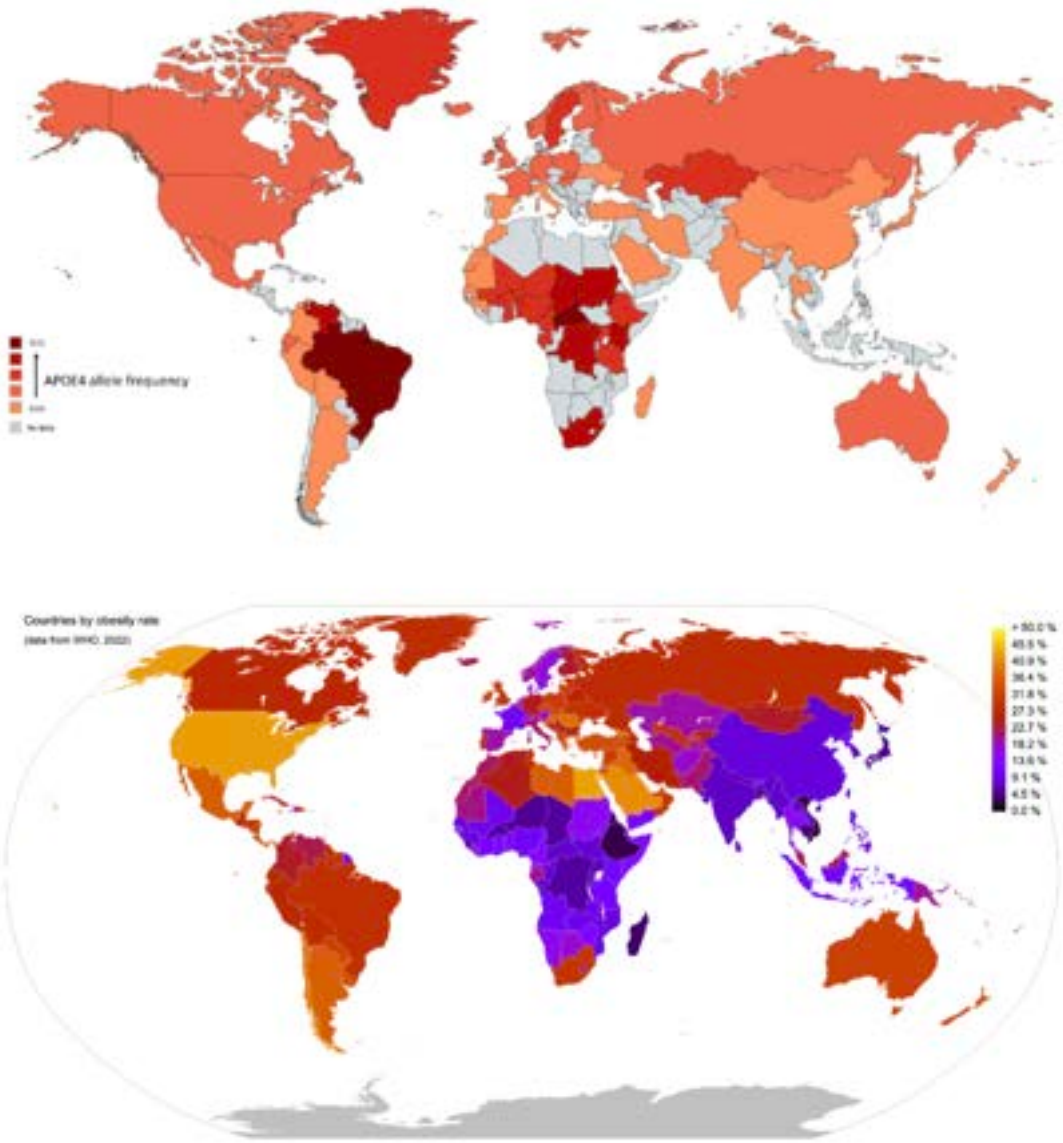

Figure 5: *Diversity maps.* The first map shows the genetic diversity of the APOE 4 allele, worldwide, with a deeper shade of red meaning that the allele frequency is much higher in those regions. The second map shows the global obesity rates, with the darker color (purple to dark red) meaning a smaller percentage of people in that region/country with obesity and a lighter color (light red to yellow) showing a larger percentage of obesity. Obesity itself, especially in the mid-life, has a clear link to developing AD (WHO, 2022).

AI in Neuroimaging

In recent years, the integration of artificial intelligence (AI) into neuroimaging has emerged as a powerful tool for enhancing diagnostic precision and efficiency in medical settings. Neuroimaging techniques such as magnetic resonance imaging (MRI),

computed tomography (CT), and positron emission tomography (PET) provide detailed ways of looking inside the brain (Figure 6). MRI uses strong magnets and radio waves to create high-resolution images of brain structures, allowing doctors to spot changes in brain tissue, shrinkage, or damage linked to diseases like AD. CT scans, which use X-rays to create cross-sectional images, are often used to quickly detect strokes, tumors, or bleeding in the brain. PET scans work differently by using a small amount of radioactive tracer to measure brain activity and metabolism, making it possible to detect abnormal patterns of energy use that may signal early stages of disease before structural changes appear. Machine learning (ML), a subset of AI, combines the power of these imaging methods with advanced computer algorithms to analyze vast datasets, identify patterns, make predictions, and support clinical decision-making. In healthcare, ML is commonly used to improve patient outcomes, from optimizing trauma-care responses to enabling more personalized treatment strategies (Coursera, 2025). However, challenges remain: neuroimaging alone cannot always capture dynamic brain changes over time, and the complexity of analyzing and interpreting such large datasets requires careful attention.

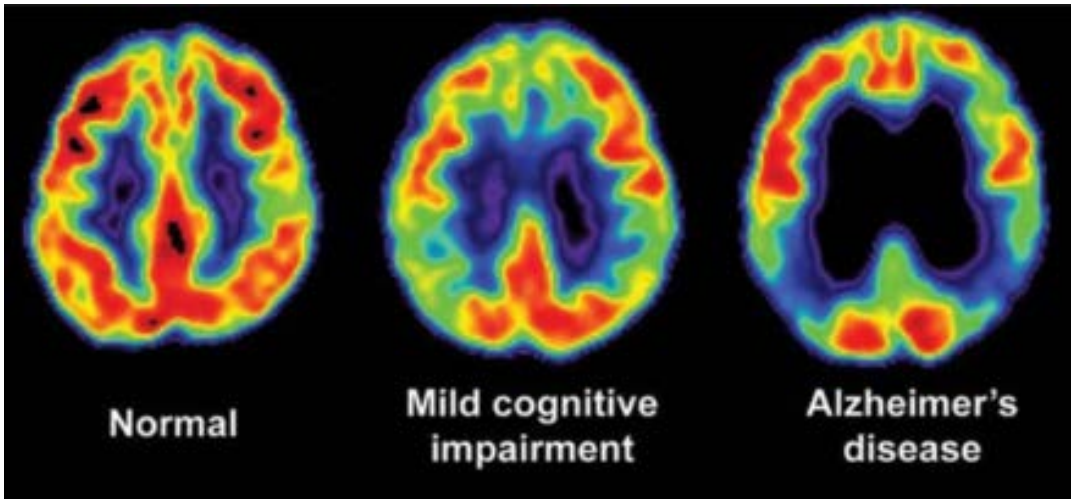

Figure 6: *Neuroimaging scans.* Neuroimaging taken from a normal “healthy” brain, a brain with mild cognitive impairment, and a brain diagnosed with Alzheimer’s disease. The black represents regions of neuron decay and red and blue represent normal, metabolic brain activity regions. This figure depicts a heatmap of an PET scan of three brain conditions: normal, MCI, and AD, and the progression/differences between each (MedReport Foundation, 2025).

Types of Machine Learning

Within machine learning, there are 2 subtypes commonly used in the medical setting: supervised learning techniques, which rely on labeled datasets, allow algorithms to classify abnormalities or predict disease progression, while unsupervised methods

uncover latent patterns in complex, unlabeled data. (Delua, 2021). Specifically, convolutional neural networks (CNNs), primarily supervised while incorporating some unsupervised aspects, have emerged as being significantly promising in image-based analysis. Preprocessing steps—noise reduction and data normalization—are crucial to improving model performance (Joseph et al, 2023). The outputs of AI-assisted neuroimaging often involve identifying diseases or disorders based on imaging inputs, which can facilitate early diagnosis and treatment planning (Joseph et al, 2023). (Figure 7). However, challenges such as high-dimensional data, computational demands, and bias in training datasets remain in CNN's. Despite this, AI has shown potential in streamlining imaging workflows by reducing scan times and the need for contrast supervision, and even in operational improvements such as predicting patient wait times and optimizing scheduling. As AI continues to evolve, it holds considerable promise in transforming both the technological and clinical techniques of diagnosing.

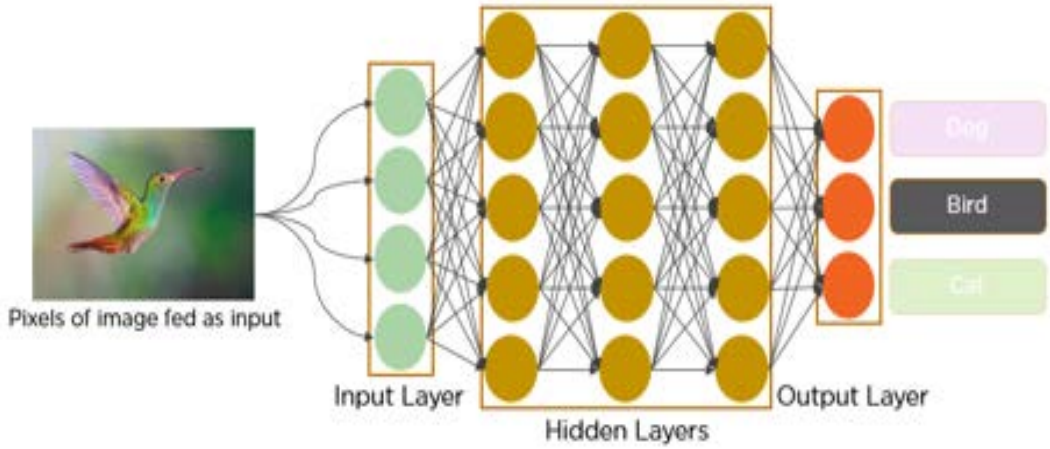

Figure 7: *CNN example.* The process shows the input as a clear picture of a bird being applied to a series of filters to the input image, detecting patterns and features at different levels of complexity. In relation to neuroimaging, the CNN can take multimodal, preprocessed images such as 3-D MRI/PET scans and distinguish the different subtle brain changes in the morphology to determine the type and level of AD development (Medium, 2024).

Current and FutureModels in AI-based Neuroimaging Field

Building on the current applications of AI in neuroimaging, where tools like CNNs already aid in detecting subtle brain changes and streamlining clinical workflows, researchers are now pushing toward more advanced models that can improve accuracy, interpretability, and multi-modal integration. This next section explores several emerging algorithms—called CAPCBAM, D3LM-LAN, and MLM-MCSVM—that build on the strengths and limitations of CNN-based systems. These models aim to address persistent challenges like loss of spatial information, limited interpretability, and reliance on single-modality data. All the models utilize data from the ADNI, a global research initiative whose purpose is to collect and analyze brain imaging, genetic, fluid biomarkers (like cerebrospinal fluid), and cognitive data from individuals at different stages of

cognitive aging and dementia to create tools for early diagnosis and to speed the development of treatments for AD. By evaluating their design and performance, we can see how the field is evolving toward earlier, more reliable, and clinically useful diagnoses of AD and related conditions. Ultimately, the goal of this section will be to evaluate the impact the following three algorithms can have on this field in the future, applying primarily to AD, potentially influencing further research into this field.

The CAPCBAM model is a new type of computer program designed to help doctors diagnose AD (Slimi et al, 2025). It builds on older image-recognition systems called Convolutional Neural Networks (CNNs), which are good at finding patterns in pictures but sometimes lose important details about how those patterns are arranged. To fix this, CAPCBAM uses Capsule Networks, which keep track of how features are connected in space (like how the nose relates to the eyes in a face). It also uses an attention system called CBAM that helps the model "focus" on the most important parts of brain scans and other data. By combining these two ideas, CAPCBAM can study brain images from MRI and PET scans, along with memory test scores, to detect whether a person is healthy, has mild memory problems, or has AD. In tests, the model was almost perfectly accurate (about 99–100%), meaning it rarely made mistakes. This level of accuracy suggests that CAPCBAM could become a powerful tool for diagnosing AD earlier and more reliably, which may lead to better treatment and care for patients (Slimi et al, 2025).

While the CAPCBAM model "focuses" on specific brain regions, the D3LM-LAN model works differently. It uses two types of brain scans at the same time: PET scans, which show how active different parts of the brain are (like measuring energy use), and MRI scans, which give very detailed pictures of brain structure (Mahmood et al, 2024). By combining both, the model can spot early signs of AD that might be missed when looking at just one scan. In testing, it was very accurate—about 97% in some cases. However, the model has some drawbacks: it needs very high-quality scans, it can be hard for doctors to understand exactly how it makes decisions, and it requires powerful computers to run (Mahmood et al, 2024).

Similar to D3LM-LAN, another model called MLM-MCSVM also analyzes brain data but adds an extra "optimization" step to improve its accuracy (Mahmood et al, 2024). It is especially strong at finding AD in its earliest stage, known as Mild Cognitive Impairment (MCI). In experiments, it correctly classified cases almost 99% of the time. One of its strengths is that it's easier to interpret than some deep learning models, so doctors can better understand why it made a certain prediction. On the downside, it can struggle when data from different hospitals or patient groups is inconsistent, and it is still expensive to run on a large scale. Like many AI models, it can sometimes act as a "black box," meaning its internal decision-making isn't always clear, which can make doctors hesitant to fully trust it (Mahmood et al, 2024).

Discussion

Among the three models, CAPCBAM emerges as the most effective for accurate AD diagnosis. Its near-perfect accuracy, coupled with the ability to integrate and prioritize multimodal data through attention mechanisms, allows it to produce highly individualized diagnostic predictions. The combined strengths of Capsule Networks and CBAM enable it to preserve complex spatial relationships in imaging data while focusing on clinically relevant features, enhancing both early-stage detection and overall classification performance. (Slimi et al, 2025). Unlike many deep learning models, CAPCBAM's attention layers offer a level of interpretability that can improve acceptance among healthcare professionals. In comparative benchmarks, it consistently outperforms both traditional deep models and alternative attention-based architectures, making it the most promising tool for reliable, precise, and clinically actionable AD detection. Clinically, its ability to highlight key areas of interest through attention maps not only improves diagnostic precision but also provides interpretability for healthcare professionals. Additionally, the model is trained using rich, multimodal data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) — a large research project that collects brain scans, genetic information, cerebrospinal fluid (CSF) biomarkers, and cognitive test scores from thousands of participants — including MRI, PET, CSF, genetics, and cognitive scores, enables the model to capture the heterogeneity of AD, supporting more personalized and biologically informed diagnoses.

Limitations in the Field

Despite the outstanding performance of the CAPCBAM model, the field itself (AI algorithms in neuroimaging diagnosis) faces significant limitations that could hinder clinical deployment. To begin, computational complexity is notably high for many models, requiring powerful hardware and substantial processing resources, which may not be feasible in all clinical settings, particularly those with limited infrastructure. Furthermore, many models depend on extensive data preprocessing—such as normalization, resizing, and augmentation—adds further time and resource costs (Slimi et al, 2025). Moreover, while ADNI provides rich multimodal data, its historical lack of diversity limits the generalizability of the model's predictions across broader, more varied populations. The dataset's overrepresentation of well-educated, White individuals and exclusion of participants with common comorbidities (e.g., cardiovascular disease, diabetes) means that the model may not fully capture the clinical variability of real-world AD cases (Ashford et al, 2022). While interpretability can be improved through improved heatmaps (representations of complex data), the time required to process and confirm outputs could delay clinical decision-making in urgent scenarios. Ultimately, future improvements in computational efficiency, dataset diversity, and multimodal integration will be necessary for this field to achieve full adaptability in clinical practice.

Future Directions

The future of AI in AD diagnosis in clinical detection lies in expanding the scope, improving efficiency, and integrating it seamlessly into healthcare workflows. To enhance early-stage detection, future iterations should be trained on larger, more diverse (ethnically, physiologically, and genetically), and longitudinal datasets, with ADNI 4 already attempting to accomplish this initiative with ethnically diverse populations of Black, Latinx, Asian, American Indian/Alaska Native, and Native Hawaiian/Other Pacific Islander individuals, that capture patients at preclinical or MCI stages, as well as those from underrepresented populations. This can be accomplished via younger representatives from these populations to represent these marginalized populations in various, homogenous regions. Incorporating additional modalities—such as CSF biomarkers, speech analysis, and genetic risk factors (such as the APOE 4 allele)—could allow the model to generate richer, more individualized risk profiles, improving both accuracy and generalizability. Computational optimization through pruning, quantization, or efficient routing algorithms will be essential to reduce hardware demands, making the model more accessible to clinics with limited resources.

Clinician Relationship

Clinically, these neuroimaging-based AI algorithms could function as an AI-driven screening layer, rapidly processing MRI, PET, and other multimodal data to flag high-risk individuals for neurologist review, serving as a decision-support system rather than a replacement for clinicians. As real-world validation progresses, the model's explainability—via attention-based heatmaps—will help build physician trust, allowing AI-human collaboration to enhance the performance of both (Figure 8). Long-term, integrating CAPCBAM into EHR systems, remote cognitive testing platforms, and population screening programs could make it a cornerstone tool for early AD detection, subtype classification, and personalized intervention planning. Ultimately, AI can serve as a second reader or decision-support system, flagging at-risk patients that a doctor might otherwise overlook, or providing confidence scores for ambiguous cases.

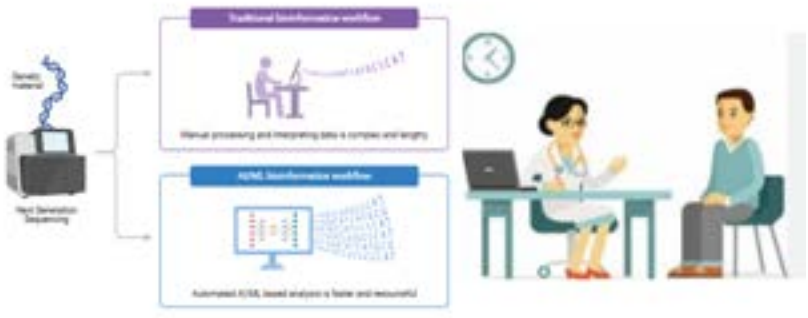

Figure 8: *AI-Doctor Relationship.* AI can analyze complex information in a much quicker and more efficient way, giving more time for doctors to interact with patients and provide more intimate and personal care/comfort. Image shows traditional manual analysis by doctors, contrasted by AI's more efficient way (BioRender, 2025).

Conclusion

This paper compared three advanced AI-based models for Alzheimer's disease (AD) diagnosis — CAPCBAM, D3LM-LAN, and MLM-MCSVM — with a focus on early detection accuracy, clinical utility, and interpretability. CAPCBAM, which integrates Capsule Networks with the Convolutional Block Attention Module, achieved the highest performance, with 99.95% accuracy, precision and recall above 99.8%, and an AUC of 0.99. Its ability to preserve spatial hierarchies and focus attention on clinically relevant regions makes it highly effective for MRI-based diagnosis. D3LM-LAN demonstrated strong multimodal classification capabilities using PET and MRI data, achieving accuracies up to 97.74%, while MLM-MCSVM leveraged optimized kernel selection to excel in early-stage detection, with accuracies near 98.6%. Despite these strengths, all models share limitations: high computational demands, dependence on large high-quality datasets, potential bias from underrepresentation in current datasets, and varying degrees of interpretability challenges in clinical practice. All of these models could eventually be utilized in the diagnostic process, demonstrated by their high accuracies and ROI regionalization of specific brain regions.

The field of AI-driven AD diagnosis is rapidly advancing, with emerging models outperforming many traditional neuroimaging methods and, in some cases, matching or exceeding the accuracy of radiologists for early detection. CAPCBAM, in particular, stands out for its ability to integrate multimodal data and provide attention-based interpretability, making it both powerful and clinically relevant. However, the lack of diversity in widely used datasets like ADNI limits generalizability, especially across populations with varying genetic, environmental, and socioeconomic risk profiles. Increasing representation of underrepresented populations, improving dataset standardization, and expanding longitudinal, multimodal data will be critical next steps. If these challenges are addressed, AI systems could serve as reliable triage tools in clinical workflows — identifying at-risk individuals early, improving trial recruitment, and enabling more personalized interventions — while complementing rather than replacing human expertise.

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