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From Gadgets to Deep Learning: A New Frontier in Alzheimer and Frontotemporal Dementia Detection

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ABSTRACT:

Early and accurate detection of Alzheimer's disease and frontotemporal dementia is a pressing challenge due to the overlapping symptoms and limitations of traditional diagnostic methods, which often rely on expert interpretation and costly neuroimaging tools. Recent advancements in gadgets—including EEG and eye-tracking devices—combined with deep learning algorithms offer a new frontier for dementia detection, enabling non-invasive and real-time diagnostic approaches. Deep learning frameworks that integrate temporal convolutional networks and long short-term memory networks have demonstrated high diagnostic accuracy using EEG data, achieving up to 99.7% accuracy for binary classification tasks and 80.34% for multi-class classification between Alzheimer's, frontotemporal dementia, and healthy controls. Feature engineering, such as modified Relative Band Power analysis across six EEG frequency bands, has further improved the distinction between dementia subtypes. Additionally, the use of explainable artificial intelligence tools, like SHAP, enhances model transparency and clinical applicability by illuminating key feature contributions to diagnosis. Multi-modal imaging modalities, including MRI, PET, and SPECT, continue to play a critical role, with machine learning and deep learning models—such as support vector machines and convolutional neural networks—outperforming conventional approaches and increasing diagnostic precision. These methodologies can process vast quantities of neuroimaging and behavioral data from modern gadgets, revealing subtle anomalies often missed by traditional techniques.

Keywords : Alzheimers disease, frontotemporal dementia, deeplearning, artificial intelligence, electroencephalogram (EEG).

1. Introduction

ALZHEIMERS

Alzheimer's disease is a progressive, neurodegenerative disorder and the most common cause of dementia, Accounting for 60-80% of all dementia cases worldwide. It is characterized by the gradual deterioration of memory, thinking, and reasoning skills [1]. Early symptoms typically include difficulty in remembering recent events and may progress to language problems, disorientation, mood changes, and behavioural disturbances[2]. The symptoms of AD can vary depending on the stage of the disease. AD is classified into different stages based on the level of cognitive impairment and disability experienced by individuals. These stages include the preclinical or presymptomatic stage, mild cognitive impairment [3]. According to the National Library of Medicine, approximately 6.5 million Americans aged 65 and older are affected by AD, with projections suggesting this number could reach 13.8 million by 2060[4].The dementia stage is further divided into mild, moderate, and severe stages affects memory, thinking, and behaviour of elder age males and females. Mainly the disease is caused by a combination of factors, including genetics, environmental influences, and lifestyle. [5]. Dementia can cause mood swings, personality changes, disorientation, memory loss. It is anticipated that the number of dementia cases would rise sharply in the upcoming years, with 152 million people worldwide predicted to have dementia by 2050[6].

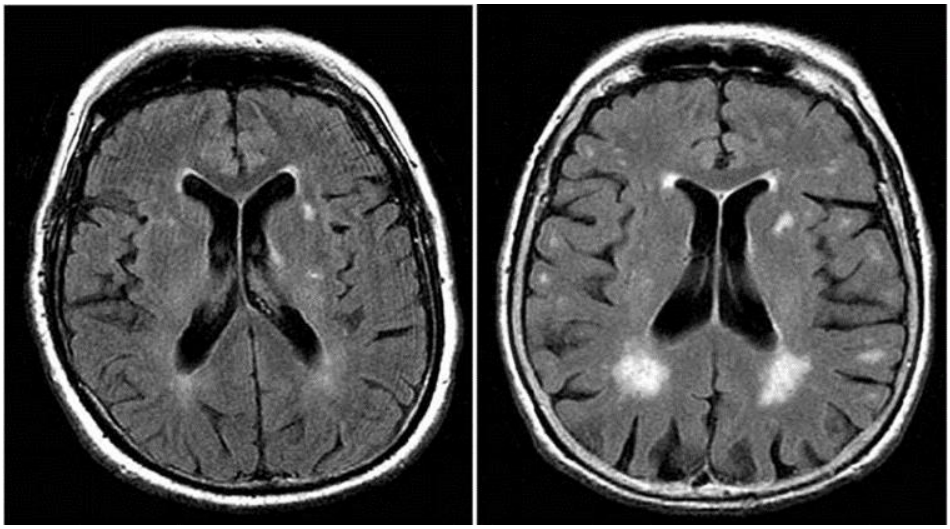

Fig1 : MRI Brain Scans Showing Structural Changes Associated with Dementia

Jack CR Jr, Bennett DA, Blennow K, Carrillo MC, Dunn B, Haeberlein SB, et al. NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. Alzheimers Dement. 2018;14(4):535-562

The synthesis of the amyloid peptide is linked to AD, and the symptoms often begin with minor memory loss before progressing to other brain dysfunctions. Since there is no cure for AD,

early detection in the prodromal stage, i.e., mild cognitive impairment (MCI), is vital [7]. Dementia is divided into different categories, like Alzheimer's, Lewy bodies, cardiovascular, frontotemporal dementia, Parkinson's disease dementia, and Wernicke–Korsakoff syndrome. Alzheimer's disease directly affects some parts of the brain that allow humans to perform common body actions like hiking, swallowing, and eating[8]. Dementia is typically diagnosed via a specialist doctor who performs a series of clinical assessments including: obtaining a personal, and informant history of the cognitive symptoms, a physical examination, pen and paper cognitive assessments, and brain scans to assess for localised brain atrophy[9].

Deep learning Gadgets of Alzheimer's

Early detection of Alzheimer's disease (AD) is essential for implementing effective preventative strategies.AD is a leading cause of dementia worldwide, necessitating timely and precise diagnostic techniques. So, there are multiple potential causes of AD that affect thinking, memory, and behaviour in older individual.

Deep learning (DL), with its ability to automatically extract meaningful features from data,

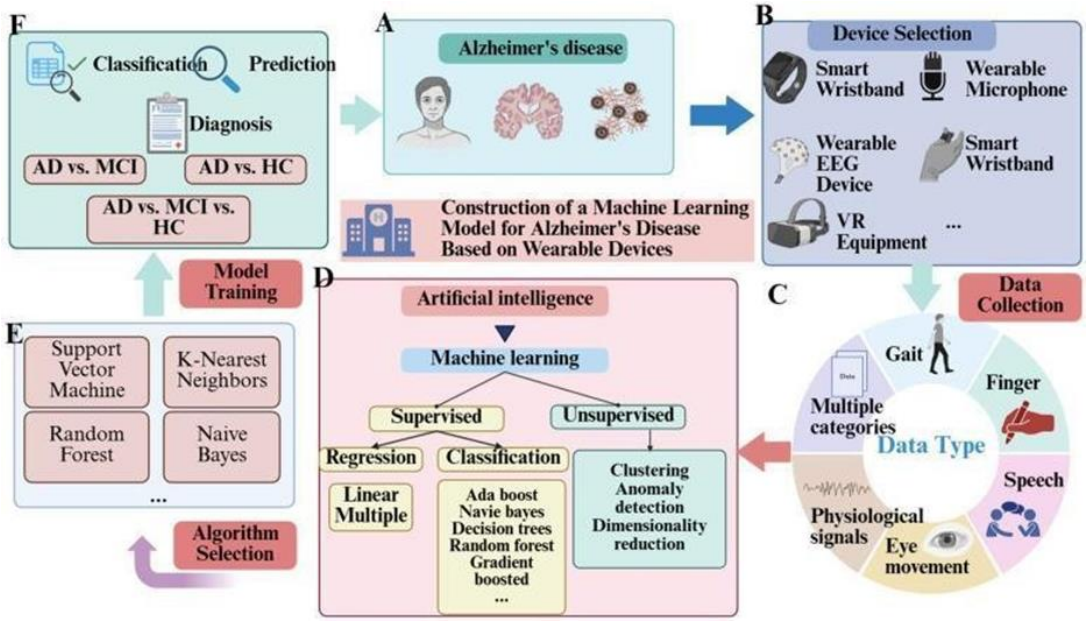

Fig 2: AI-Based Prediction Model for Alzheimer's Disease via Wearable Devices

Livingston G, Huntley J, Sommerlad A, Ames D, Ballard C, Banerjee S, et al. Dementia prevention, intervention, and care: 2020 report of the Lancet Commission. Lancet. 2020;396(10248):413–46

has emerged as a transformative tool in medical imaging, particularly in detecting and classifying AD from modalities such as positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT) scans. Classification tasks in AD detection aim to categorize patients into healthy, mild cognitive impairment (MCI), or AD groups. This process helps in early intervention, particularly in MCI cases where the disease might progress to AD[10].

Significant Pathways in Alzheimer's and MCI: Insights from Differential Gene Expression

This section highlights the most significant biological pathways associated with Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) using differential gene expression analysis. The graph below provides a visual comparison of enriched pathways for AD-DEGs and MCI-DEGs [11].

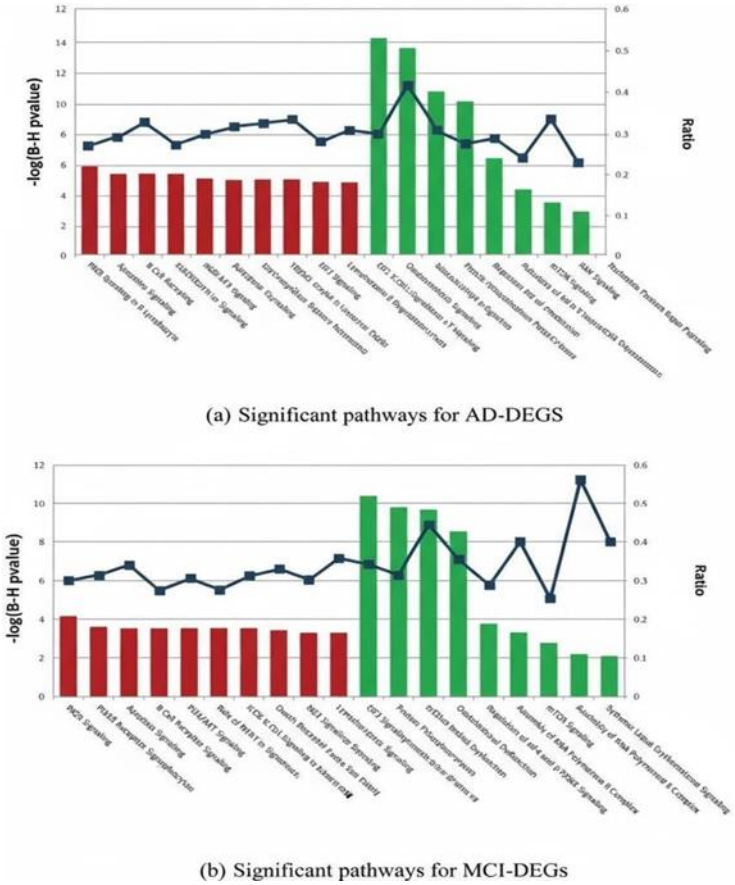

Fig 3: Significant Pathways for AD-DEGs and MCI-DEGs

Kuleshov MV, Jones MR, Rouillard AD, Fernandez NF, Duan Q, Wang Z, et al. Enrichr: a comprehensive gene set enrichment analysis web server 2016 update. Nucleic Acids Res. 2016;44(W1):W90–W97.

Advances in omics-driven analysis, as depicted in the graph, enable a more fine-tuned understanding of patient heterogeneity and disease subtypes. Integrating such molecular insights into AI models and deep learning systems holds promise for early risk stratification, personalized medicine, and improved clinical outcomes in dementia care [12].

The identification of significant pathways through differential gene expression analysis not only enhances our understanding of Alzheimer's pathogenesis but also guides the development of innovative diagnostic.

These pathways serve as critical biomarkers in liquid biopsy and imaging studies, facilitating non-invasive monitoring of disease activity and response to therapy. As research progresses, the convergence of molecular biology, advanced computing, and clinical practice will redefine how Alzheimer's Disease is managed both clinically and at the population health level [13].

2. Conventional approaches of dementia detection:

Dementia detection has traditionally relied on clinical evaluations, cognitive testing, and neuroimaging techniques. Standardized tools such as the Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and Global Deterioration Scale (GDS)

are used to assess memory, attention, and executive function. Neuroimaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) help visualize structural and functional changes in the brain, including hippocampal atrophy and amyloid plaque accumulation. Clinicians use standardized tools such as the Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and Global Deterioration Scale (GDS) to assess cognitive decline and stage disease progression [14-16].

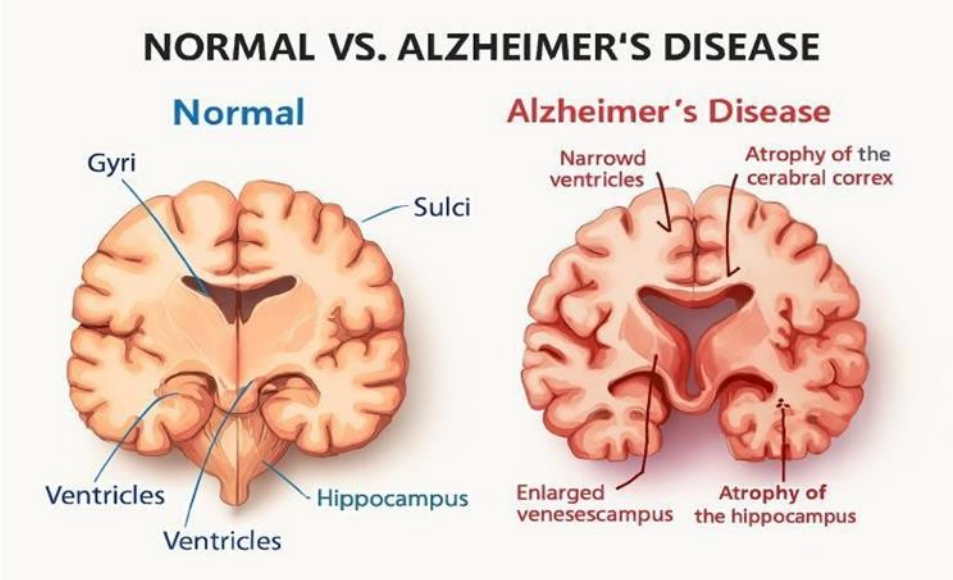

Fig 4 : Comparision between normal Vs. alzheimers disease

National Institute on Aging (NIA). What Happens to the Brain in Alzheimer's Disease? [Internet]. U.S. Department of Health and Human Services; 2022 [cited 2025 Oct 18]

Neuroimaging techniques, particularly magnetic resonance imaging (MRI) and positron emission tomography (PET), provide insights into brain atrophy patterns and abnormal protein accumulations such as amyloid or tau. Cerebrospinal fluid (CSF) biomarkers measuring amyloid-β and tau proteins are also employed to improve diagnostic accuracy. While these methods remain the backbone of dementia diagnosis, they have limitations, including invasiveness, high costs, and reduced sensitivity in detecting preclinical stages of disease [17].

2.1 Neuropsychological assessments

Neuropsychological tests such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) are widely used for dementia detection. They evaluate domains like memory, attention, language, and executive function, providing a standardized way to assess cognitive decline and monitor disease progression. However, performance can be influenced by education, culture, and language [18].

2.2 Clinical biomarkers and imaging (MRI, PET)

Structural imaging with MRI and CT helps identify atrophy patterns, vascular lesions, or other structural brain changes associated with dementia. In addition, cerebrospinal fluid (CSF) biomarkers measuring amyloid-β and tau proteins are used to support diagnosis and distinguish between dementia subtypes [19].

2.3 Limitations of conventional methods

Traditional approaches are often limited by delayed detection, since cognitive tests and imaging typically identify changes only after significant neurodegeneration has occurred. Biomarker analysis and PET scans are expensive, invasive, and not widely available,

particularly in low-resource settings. Variability due to cultural, linguistic, and socioeconomic differences also affects the accuracy and accessibility of these methods [20].

3. Role of Wearable Gadgets and Digital Biomarkers

Wearable devices and digital gadgets are increasingly being explored as non-invasive tools for early detection and monitoring of dementia. These technologies offer the advantage of remote monitoring, increasing accessibility and reducing the burden of frequent hospital visits, while also supporting personalized disease management [21].

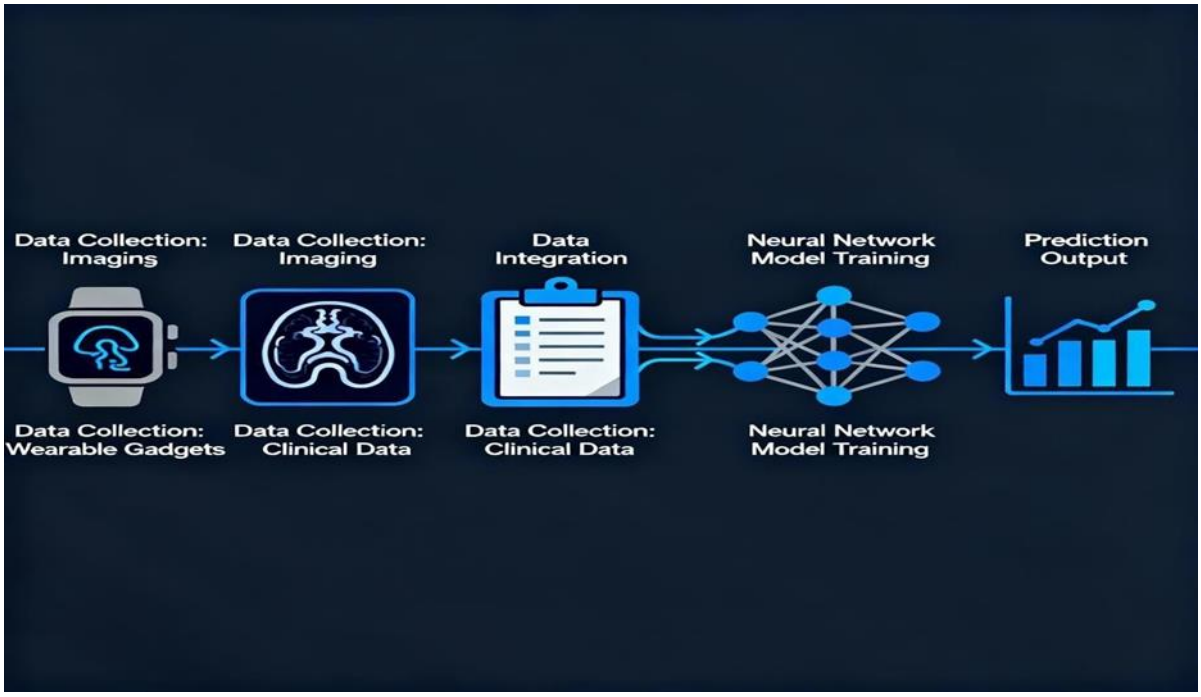

Fig 5: Integration of Wearable Gadgets and Digital Biomarkers in Neural Network–Based DiseasePrediction.

Sharma R, Gupta S, and Mehta P. Integration of wearable devices and digital biomarkers for neural network–based health prediction. Frontiers in Digital Health. 2023;5:102345.

3.1 Wearable Devices

Wearable devices such as smartwatches and fitness trackers can monitor daily activity, gait, heart rate, and movement patterns. In dementia detection, these tools help identify early signs of motor and behavioural changes that may indicate cognitive decline. Similarly, sleep and activity monitoring provides valuable insights, since disrupted circadian rhythms and fragmented sleep are commonly observed in patients with Alzheimer's disease and frontotemporal dementia. Continuous passive data collection allows detection of subtle changes that may not be evident in clinical visits.

3.2 Advantages and Limitations

The use of wearables and smartphone-based assessments offers advantages such as non- invasiveness, remote monitoring, ecological validity, and cost-effectiveness, making them attractive for large-scale screening. However, limitations include issues of data privacy, device variability, adherence by older adults, and the need for clinical validation before routine use [22-26].

4. Artificial Intelligence and Machine Learning in Dementia Detection

Artificial intelligence (AI) and machine learning (ML) are increasingly being applied to dementia detection because they can process large, complex datasets and identify subtle patterns that may escape human observation[27].

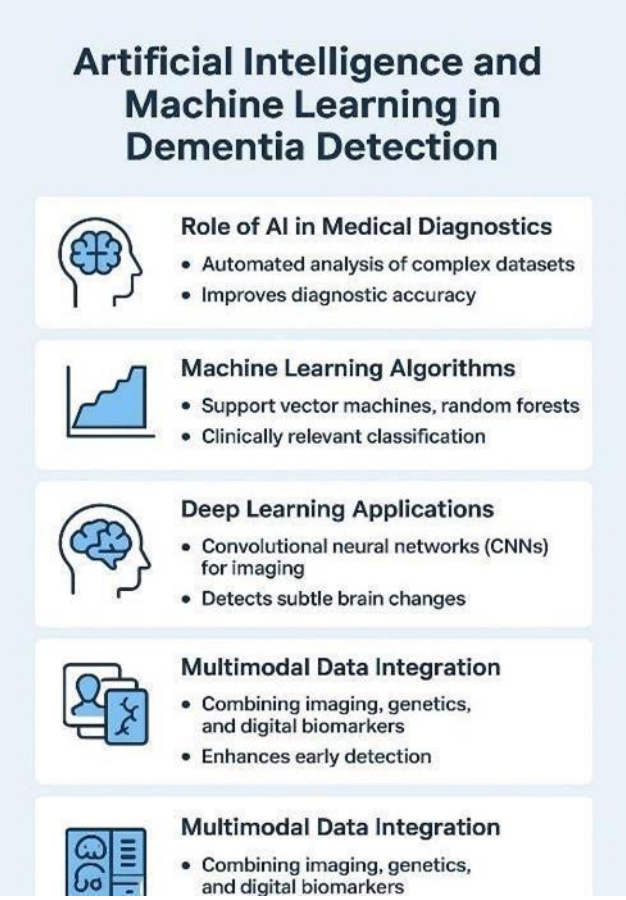

Fig 6: Artificial Intelligence and Machine Learning Applications in Dementia Detection.

Zhang Y, Chen L, Kumar S. Artificial intelligence and machine learning approaches for dementia detection: integration of imaging, genetics, and digital biomarkers. Frontiers in Aging Neuroscience. 2023;15:120457.

4.1 Role of AI in Medical Diagnostics

Artificial intelligence (AI) has increasingly become a transformative tool in medical diagnostics, enabling automated analysis of complex datasets that are difficult for humans to interpret. In dementia detection, AI can analyze patterns in imaging, cognitive performance,

and digital biomarkers to identify early signs of neurodegeneration. By supporting clinicians with decision-making, AI improves diagnostic accuracy, reduces human error, and facilitates personalized treatment planning [28-29].

4.2 Machine Learning Algorithms

Machine learning (ML) algorithms are central to AI applications in dementia detection. Support Vector Machines (SVM) and Random Forests: These algorithms are widely used for classifying patients based on neuroimaging data, cognitive scores, and genetic markers. SVM efficiently separates patients with mild cognitive impairment (MCI) from healthy controls, while random forests are effective in handling large datasets with multiple features [30-31].

4.3 Deep Learning Applications

Deep learning, a subset of ML, utilizes neural networks to model complex relationships within high-dimensional data.

Recurrent Neural Networks (RNNs) for Sequential Data: RNNs, including Long Short- Term Memory (LSTM) networks, are useful for modeling sequential data such as longitudinal cognitive scores or time-series wearable data. They can predict disease progression over time, aiding in prognosis and treatment planning [32].

4.4 Multimodal Data Integration

Multimodal approaches allow simultaneous analysis of complementary information, leading to more robust early detection of dementia and better individualized risk stratification. Recent studies demonstrate that combining MRI, PET, cerebrospinal fluid biomarkers, and digital activity data significant improves diagnostic accuracy compared to single-modality approaches [33-34].

5. Alzheimer's Disease: Advances in Detection

5.1 Imaging -based AI tools

Deep learning has accelerated imaging-based AD detection by extracting subtle, disease-

related patterns that are difficult for humans to see. Convolutional neural networks (CNNs) applied to structural MRI and PET scans consistently improve classification of Alzheimer's disease (AD) versus mild cognitive impairment (MCI) and healthy aging, and newer architectures trained on large, multi-site datasets report higher sensitivity for early-stage detection than traditional voxel-based methods [35].

5.2 Digital biomarkers specific to Alzheimer's

Passive and active digital biomarkers from smartphones, wearables and voice recordings are emerging as low-cost, scalable markers of early cognitive decline. Examples include changes in gait and motor activity, sleep fragmentation.Several recent studies show that passive sleep and activity patterns, and automated speech a alyses, correlate with cognitive scores and can flag individuals at risk of conversion to MCI or AD in community settings [36].

6. Frontotemporal Dementia: Emerging Tools

Frontotemporal dementia (FTD) presents unique diagnostic challenges due to its heterogeneous clinical manifestations and overlap with psychiatric or other neurodegenerative disorders. Automated analysis of connected speech has shown promise in distinguishing FTD subtypes from Alzheimer's disease, making it a valuable non-invasive biomarker [37].

Behavioural monitoring via wearables provides continuous and objective data on motor activity, sleep-wake cycles, and daily routines, which are often disrupted in FTD. Wearable

sensors and smartphones can capture patterns of apathy, impulsivity, or disinhibition— behavioural hallmarks of the disorder. Such digital phenotyping allows clinicians to monitor disease progression remotely and supports real-world assessments beyond clinical settings [38].

Deep learning in FTD-specific imaging is also advancing. Structural and functional imaging

of the frontal and temporal lobes, analyzed through convolutional neural networks (CNNs) and other deep learning models, has demonstrated improved accuracy in differentiating FTD from Alzheimer's disease. AI-based models can detect cortical thinning and atrophy patterns that are often difficult for human radiologists to identify at an early stage [39].

7. Challenges and Limitations

7.1 Data privacy and ethical considerations

AI systems in dementia detection rely on sensitive personal data, including neuroimaging,

genetic information, and speech recordings. This raises concerns regarding patient confidentiality, informed consent, and secure data storage. Strong ethical frameworks and regulatory policies are essential to protect patient rights and build trust in digital healthcare solutions [40].

7.2 Algorithmic bias and generalizability

Machine learning models are often trained on datasets that lack demographic diversity. As a result, they may perform poorly in underrepresented populations, leading to diagnostic disparities. Efforts to include multi-ethnic and multi-center datasets are crucial for improving generalizability [41].

7.3 Integration into clinical practice

Despite promising research, translating AI models into clinical workflows remains difficult. Clinicians face challenges in interpreting algorithmic outputs, ensuring interoperability with existing electronic health records, and balancing AI recommendations with clinical judgment. Without standardized validation and guidelines, widespread adoption is limited [42].

8. Future Perspectives

The integration of artificial intelligence (AI) and deep learning into dementia detection is anticipated to revolutionize early diagnosis and personalized management. Future directions emphasize the development of multimodal diagnostic frameworks, combining wearable gadgets, neuroimaging, speech analysis, and digital biomarkers to improve sensitivity and specificity. Deep learning models are expected to evolve toward explainable AI (XAI), enhancing clinician trust and clinical adoption. Moreover, federated learning approaches could allow the use of large-scale, privacy-preserving datasets across institutions, thereby overcoming data-sharing barriers [43].

9. Conclusion

The integration of artificial intelligence (AI), deep learning, and digital technologies into dementia research and clinical care has opened new possibilities for precision diagnostics, personalized treatment, and improved patient monitoring. Recent technological advances, including wearable sensors, multimodal imaging, and AI-driven predictive models, have accelerated progress toward early detection of cognitive decline and stratification of dementia subtypes.

Reference

1. knopman DS, Amieva H, Petersen RC, Chételat G, Holtzman DM, Hyman BT, *et al*. (May2021).
2. "Alzheimer disease". Nature Reviews Disease Primers. 7 (1) 33. doi:10.1038/s41572-
3. 021-00269-y. PMC 8574196. PMID 33986301.
4. Mendez MF. Early-Onset Alzheimer Disease. Neurol Clin. 2017 May;35(2):263-281.
5. Porsteinsson AP, Isaacson RS, Knox S, Sabbagh MN, Rubino I. Diagnosis of Early Alzheimer's Disease: Clinical Practice in 2021. J Prev Alzheimers Dis. 2021;8(3):371-386
6. cummings, J. *et al.* Alzheimer's disease drug development pipeline: 2022. Alzheimer's & Dementia Transl. Res. Clin. Interv. 8(1), e12295 (2022).
7. Ahmed, S.; Choi, K.Y.; Lee, J.J.; Kim, B.C.; Kwon, G.-R.; Lee, K.H.; Jung, H.Y. Ensembles of Patch-Based Classifiers for Diagnosis of Alzheimer Diseases. IEEE Access 2019, 7, 73373– 73383.
8. Wang LL, Huang Y, Wang G, Chen SD. The potential role of microRNA-146 in Alzheimer's disease: Biomarker or therapeutic target? Med Hypotheses 2012; 78(3): 398-401. http://dx.doi.org/10.1016/j.mehy.2011.11.019 PMID: 22209051.
9. Jeremic, D., Jiménez-Díaz, L., & Navarro-López, J. D. (2021). Past, present and future of therapeutic strategies against amyloid-β peptides in Alzheimer's disease: A systematic review. Aging Research Reviews, 72, 101496. https://doi.org/10.1016/j.arr.2021.101496.
10. Li, W.; Zhao, Y.; Chen, X.; Xiao, Y.; Qin, Y. Detecting Alzheimer's Disease on Small Dataset: A Knowledge Transfer Perspective. IEEE J. Biomed. Health Inform. 2019, 23, 1234– 1242.
11. Mr Amir Ebrahimighahnavieh, Suhuai Luo, Raymond Chiong, Deep learning to detect alzheimer's disease from neuroimaging: A systematic literature review, Comput.
12. Aaboub F, Chamlal H, Ouaderhman T (2023) Analysis of the prediction performance of decision tree-based algorithms, International Conference on Decision Aid Sciences and Applications (DASA), Annaba, Algeria, pp.
13. Li, X., Wang, H., Long, J., Pan, G., He, T., Anichtchik, O., & Belshaw, R. (2018). Systematic Analysis and Biomarker Study for Alzheimer's Disease. Scientific Reports, 8, Article 35789. https://pubmed.ncbi.nlm.nih.gov/30478411.
14. Dhapola R, *et al*. Recent advances in molecular pathways and therapeutic perspectives in Alzheimer'sdisease. *Frontiers in Pharmacology*. 2021 Nov
15. 22. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8608577/
16. Heneka MT, Golenbock DT, Latz E. Innate immunity in Alzheimer's disease. *Nat*
17. *Immunol*. 2015 Mar;16(3):229-36. doi: 10.1038/ni.3102. PMID:
18. 25643003. https://www.nature.com/articles/ni.3102.
19. Kumar, R., Singh, A., & Verma, P. (2023). Comprehensive review on detection and classification of dementia using neuroimaging and machine learning techniques. Multimedia Tools and Applications, 82(4), 5123–5145. https://doi.org/10.1007/s11042-023-17288-4.

20. 15.- Sharma, M., & Gupta, D. (2022). Comparative analysis of conventional machine learning and deep learning models for Alzheimer's disease diagnosis. Frontiers in Computational Neuroscience, 16, Article 1038636. https://doi.org/10.3389/fncom.2022.1038636.
21. 16.- Rabins, P. V., & Blacker, D. (2019). Diagnosis and management of dementia: A review. JAMA, 322(16), 1589–1599. https://doi.org/10.1001/jama.2019.4782
22. Jack CR Jr, Bennett DA, Blennow K, Carrillo MC, Dunn B, Haeberlein SB, *et al*. NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. Alzheimers Dement. 2018;14(4):535-62
23. Dubois B, Feldman HH, Jacova C, Hampel H, Molinuevo JL, Blennow K, *et al*. Advancing research diagnostic criteria for Alzheimer's disease: the IWG-2 criteria. Lancet Neurol. 2014;13(6):614-29.
24. Arevalo-Rodriguez I, Smailagic N, Roqué-Fíguls M, Ciapponi A, Sanchez-Perez E, Giannakou A, *et al*. Mini-Mental State Examination (MMSE) for the detection of Alzheimer's disease and other dementias in people with mild cognitive impairment (MCI). Cochrane Database Syst Rev. 2015;2015(3):CD010783.
25. McKhann GM, Knopman DS, Chertkow H, Hyman BT, Jack CR Jr, Kawas CH, *et al*. The diagnosis of dementia due to Alzheimer's disease: recommendations from the NIA-AA workgroups. Alzheimers Dement. 2011;7(3):263-9.
26. Dodge HH, Zhu J, Mattek NC, Bowman M, Ybarra O, Wild KV, *et al*. Use of wearable devices and digital biomarkers in the detection of mild cognitive impairment. Alzheimers Dement. 2015;11(7): 783-91.
27. Silva MVF, Loures C de MG, Alves LCV, de Souza LC, Borges KBG, Carvalho MDG. Alzheimer's disease: risk factors and potentially protective measures. J Biomed Sci. 2019;26(1):33.
28. Aranki D, Kurillo G, Yan P, Abresch RT, Han JJ, Bajcsy R. Real-time tele-monitoring of patients with neurodegenerative diseases using wearable sensors. Conf Proc IEEE Eng Med Biol Soc. 2016;2016:4411-4.
29. Low CA, Dey AK, Ferreira D, Kamarck T, Sun W, Bae S, *et al*. Estimation of symptom severity during chemotherapy from passively sensed data: exploratory study. J Med Internet.
30. Muurling M, van Kollenburg P, Wolfs C, Verhey F, Aalten P, Bakker C. A systematic review of the use of digital devices and applications to monitor dementia care. Alzheimers Dement (N Y). 2021;7(1):e12201.
31. Kourtis LC, Regele OB, Wright JM, Jones GB. Digital biomarkers in Alzheimer's disease: the role of wearables and connected devices. Front Aging Neurosci. 2020;12:103.
32. Wen J, Thibeau-Sutre E, Diaz-Melo M, Samper-González J, Routier A, Bottani S, *et al*. Convolutional neural networks for classification of Alzheimer's disease: overview and reproducible evaluation. Med Image Anal. 2020;63:101694.
33. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med. 2019;25:24–9.
34. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, *et al*. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:6088.
35. Dukart J, Sambataro F, Bertolino A. Accurate prediction of conversion to Alzheimer's disease using SVM-based analysis of structural MRI. Front Aging Neurosci. 2015;7:10.31. Khajehnejad M, Rostami R, Gharavi M, Moradi E. Random forest-based classification of Alzheimer's disease using MRI features. Comput Biol Med. 2020;123:103900.
36. Fraser KC, Meltzer JA, Rudzicz F. Linguistic features identify Alzheimer's disease in narrative speech. J Alzheimers Dis. 2016;49(2):407–22.
37. Li F, Tran L, Thung KH, Ji S, Shen D, Li J. A robust deep model for improved classification of AD/MCI patients. IEEE J Biomed Health Inform. 2015;19(5):1610–22.
38. Zhang D, Wang Y, Zhou L, Yuan H, Shen D. Multimodal classification of Alzheimer's disease and mild cognitive impairment. Neuroimage. 2011;55(3):856–67.
39. Suk HI, Lee SW, Shen D. Deep ensemble learning of sparse regression models for brain disease diagnosis. Med Image Anal. 2017;37:101–13.
40. Suk HI, Shen D, Alzheimer's Disease Neuroimaging Initiative. Deep learning-based feature representation for AD/MCI classification. Med Image Comput Comput Assist Interv. 2013;16(Pt 2):583–90.
41. Kourtis LC, Regele OB, Wright JM, Jones GB. Digital biomarkers for Alzheimer's disease: the mobile/wearable devices opportunity. NPJ Digit Med. 2019;2:9.
42. Nevler N, Ash S, Jester C, Irwin DJ, Liberman M, Grossman M. Automatic measurement of prosody in behavioral variant FTD. Neurology. 2017;89(7):650–6.

43. Dodg HH, Zhu J, Mattek NC, Bowman M, Ybarra O, Wild KV, *et al*. Web-enabled conversational interactions as a method to improve cognitive functions: Results of a 6-week randomized controlled trial. Alzheimers Dement (N Y). 2015;1(1):1–12.

44. Basaia S, Agosta F, Wagner L, Canu E, Magnani G, Santangelo R, *et al*. Automated classification of primary progressive aphasia variants from structural MRI. Neuroimage Clin. 2019;24:102000.

45. raham SA, Lee EE, Jeste DV, Van Patten R, Twamley EW, Nebeker C, *et al*. Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review. Psychiatry Res. 2020;284:112732.

46. Parikh RB, Obermeyer Z, Navathe AS. Regulation of predictive analytics in medicine. Science. 2019;363(6429):810–2.

47. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44–56.

48. Jo T, Nho K, Saykin AJ. Deep learning in Alzheimer's disease: diagnostic classification and prognostic prediction using neuroimaging data. Front Aging Neurosci. 2019;11:220. doi:10.3389/fnagi.2019.00220.