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Alzheimer's Detection using Machine Learning and Deep Learning: A Literature Survey

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***Abstract*—This literature survey investigates recent advance- ments in Alzheimer's disease (AD) detection through the lens of machine learning and deep learning methodologies. The survey explores a variety of research papers, each offering unique perspectives on early diagnosis and classification. Deep learn- ing architectures, particularly Convolutional Neural Networks (CNNs), emerge as highly successful in AD detection. Innovative approaches include the use of smartphone accelerometers for disease stage prediction, displacement field estimation as AD- related features, and the integration of machine learning with electronic health records for practical clinical applications. While these advancements showcase significant progress, challenges such as dataset dependency, model interpretability, and ethical considerations persist. Future research directions point towards multimodal data integration, enhancing model interpretability, and addressing ethical aspects for more robust and transparent AD detection models.**

***Index Terms*—Alzheimer's, machine learning, deep learning, CNN, early detection, multimodal data, interpretability, ethical considerations**

I. INTRODUCTION

Alzheimer's disease is a degenerative neurological condition that gets worse over time. It involves changes in the brain that cause certain proteins to accumulate, which causes the brain to shrink and eventually cause brain cells to die. Dementia is a progressive loss of memory, thinking, behavior, and social skills that affects a person's capacity to function. Alzheimer's disease is the main cause of dementia.

The disease's early symptoms include trouble remembering recent conversations or events. Alzheimer's disease worsens over time, making it harder to remember things and perform daily duties. Alzheimer's disease cannot be cured, however drugs may improve or reduce the course of symptoms. There are services and programs available to support those with the illness as well as those who care for them. When the condition reaches an advanced level, there is a considerable loss of brain function, which can cause consequences like infection, starvation, or dehydration, which can even be fatal.

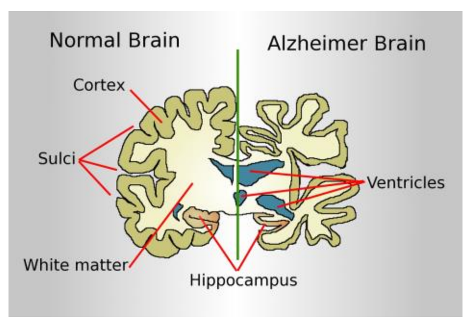
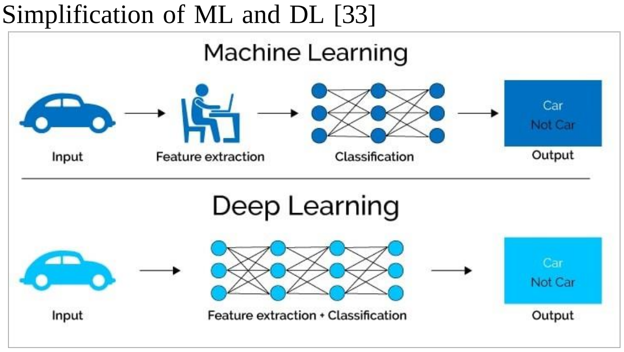


Fig. 1: Comparison between a normal brain and an Alzheimer's brain [32]

The field of healthcare has seen a considerable increase in attention since the introduction of machine learning and deep learning, offering promising avenues for transforming the landscape of Alzheimer's diagnosis. By leveraging computational models to analyze complex datasets, these artificial intelligence techniques hold the potential to discern subtle patterns indicative of Alzheimer's pathology, offering a non-invasive and data-driven means of identifying the disease at its earliest stages.

Machine learning provides a powerful framework for training algorithms to recognize intricate patterns within diverse datasets associated with Alzheimer's disease. From neuroimaging scans to genetic markers and clinical records, machine learning algorithms can assimilate and analyze multifaceted information, facilitating the identification of subtle biomarkers indicative of Alzheimer's progression. Additionally, the evolution of deep learning, characterized by neural networks with multiple layers, further enhances the capacity to discern nuanced patterns and relationships within complex biological data. This sophistication makes it possible to have a more thorough grasp of the illness, which may result in more precise and prompt diagnoses.

Fig. 2: Simplification of ML and DL [33]



II. Background and Related Work

With the aging of the population in modern civilization, the number of persons suffering from dementia is rapidly increasing. The direct medical costs and the indirect societal costs associated with dementia patients are increasing dramatically. Nonetheless, the lack of social awareness about dementia causes problems for them and their families. The most common kind is dementia associated with Alzheimer's disease. The phrase "Alzheimer's disease" has been around for more than a century, having first been used in 1910 [21]. The remarkable advancements in science and medical technology have also led to improvements in the diagnosis and treatment of dementia.

The writers of [22] emphasize the key advancements in the study of Alzheimer's disease. The most recent statistics indicates that by 2050, dementia prevalence would double in Europe and triple worldwide. This projection is three times greater when considering Alzheimer's disease according to a biological definition rather than a clinical one.

Alzheimer's detection encompasses a diverse array of techniques ranging from traditional approaches to cutting- edge technologies. Traditional methods often involve cognitive assessments, relying on clinical evaluations and standardized tests to gauge memory loss and cognitive decline. Imaging techniques, such as magnetic resonance imaging (MRI) and positron emission tomography (PET), offer valuable insights into brain structure and function, allowing for the identification of structural abnormalities and changes in cerebral metabolism. Additionally, biomarker analysis, including the examination of cerebrospinal fluid or blood, provides a molecular perspective by identifying specific proteins associated with Alzheimer's pathology.

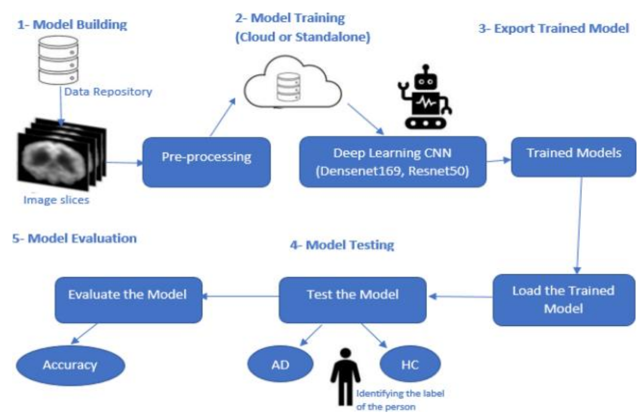


Fig. 3: Standard procedure of Alzheimer's detection using DL [34]

The significance of ML and DL in the domain of Alzheimer's disease detection cannot be overstated. Traditional methods of diagnosis often face challenges in accurately identifying the disease at early stages or distinguishing it from other cognitive disorders. ML and DL techniques offer a transformative approach by leveraging computational models to analyze intricate patterns within diverse datasets, such as neuroimaging scans, genetic information, and clinical records. The ability to process vast amounts of information swiftly makes these techniques invaluable for identifying complex relationships and uncovering novel insights into Alzheimer's pathology.

III. Literature Survey

With the introduction of cutting-edge technologies, the field of Alzheimer's Disease (AD) research has undergone a radical change, especially in the areas of neuroimaging and machine learning. This comprehensive literature survey delves into five distinct research papers, each contributing unique perspectives and methodologies in the pursuit of early detection, classification, and understanding of Alzheimer's Disease. Using resources such as the Open Access Series of Imaging Studies (OASIS) and the Alzheimer's Disease Neuroimaging Initiative (ADNI), these papers employ cutting- edge techniques, ranging from deep learning architectures to hybrid machine learning approaches. Through a meticulous examination of these studies, this survey aims to unravel the innovative strides made in the field, shedding light on their contributions and implications for the future of Alzheimer's research and diagnosis.

This study [1] focuses on early identification of Alzheimer's disease (AD) through the use of a deep learning architecture. It stands out for taking a semi-supervised method, which reduces the need for prior information about the data. This research makes use of neuroimaging data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, which includes 311 participants' MRI scans classified as normal control, AD, cMCI, and ncMCI. While referencing previous studies that simplified AD diagnosis into binary classification tasks, the paper presents a unique semi-supervised approach that enhances cost-effectiveness by incorporating unlabeled training samples. This distinguishes it from earlier workflows that embedded prior knowledge in model design [8-10].

The paper ”Evaluation of Neuro Images for the Diagnosis of Alzheimer's Disease Using Deep Learning Neural Network” describes a new Computer-Aided Diagnosis (CAD) system that uses a deep convolutional neural network (CNN) to diagnose Alzheimer's disease using 18FDG-PET images [2]. Unlike conventional methods, this approach converts 3D images into 2D images without segmentation algorithms, learning features directly from the images. The CNN design eliminates the need for noise removal and feature extraction steps. The proposed CAD system achieves remarkable results, with an accuracy of 96% surpassing existing methods. This novel approach distinguishes itself by its simplified yet effective methodology and outstanding performance in AD classification.

This research paper explores AD detection and classification using a deep learning model applied to brain MRI data [3]. It stands out by introducing a novel framework inspired by Inception-V4 for AD detection and classification. The study utilizes the OASIS database, consisting of T1-weighted MRI scans from 416 subjects. The proposed DL model achieves an accuracy of 73.75% on the OASIS dataset, emphasizing the potential of deep learning in automating the classification process. The study distinguishes itself by addressing the challenges of small medical image datasets, eliminating the need for handcrafted feature generation, and proposing a novel framework inspired by Inception-V4.

An E2AD2C framework for early Alzheimer's disease detection and classification using CNNs is proposed in [4]. It distinguishes itself by presenting a holistic approach to AD detection and classification, encapsulated in the E2AD2C framework. The integration of simple CNN architectures and transfer learning with VGG19 provides a versatile solution for medical image classification. Addressing challenges such as dataset imbalances and limited data availability through resampling and data augmentation techniques sets this paper apart. Furthermore, the proposal of an Alzheimer's checking web application during the COVID-19 pandemic illustrates a practical application of the proposed framework, showcasing a forward-thinking perspective on healthcare accessibility.

The paper [5] contributes to the field by applying a hybrid approach involving six machine learning and data mining algorithms for the classification of different stages of Alzheimer's Disease (AD). Using the ADNI dataset, the study achieves an accuracy of 88.24%. The novel contribution lies in the application of ML techniques to classify different stages of alzheimer's disease, identifying distinguishing attributes for each stage. The generalized linear model emerges as the most successful algorithm, demonstrating its efficacy in AD classification.

One research endeavor [6] aims to automate the early detection of AD through the application of DL techniques on Magnetic Resonance Imaging (MRI) data. The study introduces a classification task involving Mild Cognitive Impairment (MCI), Alzheimer's disease (AD), and Normal Control (NC) subjects. The dataset, comprising labeled MRI images, is drawn from the ADNI database. Employing Deep Neural Network (DNN) architectures, including pre-trained models like AlexNet, VGG-16, VGG-19, and GoogLeNet, the study utilizes transfer learning for efficient classification. Results demonstrate the superiority of DNN models, with VGG16, VGG19, and GoogLeNet outperforming Support Vector Machines (SVM) in terms of accuracy (80-90%). The study emphasizes the computational efficiency achieved through the use of high-performance GPUs supported by CUDA on the MATLAB platform.

Another investigation [7] delves into the application of DL techniques for AD diagnosis using MRI. Leveraging datasets from ADNI and OASIS, the study explores various DL models, including CNN, Deep Convolutional Extreme Learning, and Deep Belief Networks. Transfer learning with pre-trained models like AlexNet, VGG-16, VGG-19, GoogleNet, LeNet-5, ResNet, and GoogLeNet is employed for improved performance. SVM serves as a comparative model. Different studies achieve accuracy levels ranging from 86% to 100%, with CNNs demonstrating high accuracy and outperforming SVM in several instances. The review acknowledges the challenges associated with dataset dependency, computational complexity, and interpretability of deep learning models.

A unique approach to predicting Alzheimer's progression is presented in a study [8], which focuses on the conversion from MCI to AD using a multi-modal DL approach. Utilizing data from ADNI, including demographic information, cognitive performance, cerebrospinal fluid (CSF) biomarkers, and neuroimaging data from MRI, the study employs multi-modal recurrent neural networks (RNNs). The model's performance is assessed over different prediction periods, showcasing the superiority of longitudinal multi-modal data over cross- sectional or single-modal data. While the study presents strengths in multi-modal integration and longitudinal analysis, it acknowledges limitations related to imbalanced data and model interpretability.

A comprehensive review [9] provides an overview of databases such as ADNI, AIBL, and OASIS, alongside imaging techniques like MRI. SVM, artificial neural network (ANN), and deep learning models are discussed for their effectiveness in AD diagnosis, with considerations for classification challenges. The review emphasizes the merits of SVM stability, the feature extraction capability of deep learning, and the integration of ensemble methods. However, it points out challenges related to dataset dependency, computational complexity, and interpretability of models. The review suggests future research directions, including addressing dataset biases and enhancing interpretability.

In a novel approach [10], the focus shifts to the identification of AD stages using smartphone accelerometers and deep learning models. The study proposes a methodology to capture daily mobility data of Alzheimer's patients, CNNs for stage prediction. The dataset, collected from 35 patients carrying smartphones with accelerometers, is processed using CNN architectures with data preprocessing techniques. The proposed model achieves a high accuracy of 90.91% in predicting disease stages. The study highlights the non-intrusiveness of the proposed monitoring method, its real-world applicability using widely available smartphones, and the potential for further improvements with an expanded dataset. However, it acknowledges limitations related to dataset imbalance, limited dataset size, and dependency on smartphone placement.

One noteworthy study [11] uses resting-state functional magnetic resonance imaging (rs-fMRI) data to identify AD from normal control participants using convolutional neural networks (CNNs). Utilizing the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, the authors employ a CNN architecture, specifically the LeNet-5 model, achieving a remarkable accuracy of 96.86%. This surpasses traditional methods like Support Vector Machine (SVM), highlighting the efficacy of CNN-based approaches in AD classification.

Another study [12] delves into early detection using Diffusion MRI (dMRI) and deep learning. Leveraging the ADNI dataset, the Voxception-Resnet (VRN) architecture is adopted for classifying individual scans and scan series over time. The choice of dMRI stems from its potential to detect subtle changes in the neuroplastic brain affected by Alzheimer's. Modifications to the VRN architecture aim at enhancing performance, showcasing a multifaceted approach to early AD detection.

A study [13] that expands on the use of magnetic resonance imaging (MRI) data suggests an ensemble learning approach for the early detection of AD. The model uses transfer learning on pre-trained ImageNet networks to include eResNet50, eNASNet, and eMobileNet as base classifiers. The ADNI-sourced dataset is preprocessed and divided into gray matter (GM) and white matter (WM). When compared to traditional approaches, the ensemble strategy performs better in terms of accuracy, sensitivity, and area under the receiver operating characteristic curve (AUC). It is especially effective in differentiating between AD and mild cognitive impairment (MCI) and MCI and normal control (NC).

Shifting focus to electroencephalography (EEG) data, a paper [14] introduces a discriminative deep probabilistic model, DCssCDBM, for early AD diagnosis. This model, incorporating multi-task learning, is designed to classify EEG spectral images. Unlike traditional approaches using SVM, DCssCDBM acts as a non-linear classifier, with clear label information guiding feature extraction. The paper emphasizes the uniqueness of processing multi-channel EEG signals, converting them into 2-D images for spatial structure and spectral band information representation. Performance comparisons with conventional models demonstrate the efficacy of the proposed DCssCDBM.

In a broader evaluation of machine learning methods for AD identification, another study [15] conducts a simulation experiment using different datasets, VBSD and Dem@Care. On both datasets, a number of models are tested, including LogisticRegressionCV, LinearSVC, and MLP. The best method is LogisticRegressionCV, which achieves an F1-Score of 89.4% on Dem@Care and 86.9% on VBSD. Additional experiments optimizing LogisticRegressionCV through parameter tuning highlight the importance of dimension reduction, providing insights for further refinement.

The utilization of machine learning (ML) for the accurate prediction of Alzheimer's disease is the focal point of one study [16], leveraging various cognitive and medical factors from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Employing clustering algorithms, fuzzy interference systems, and multiple ML algorithms such as SVM, Gradient Boosting, Neural Network, K-Nearest Neighbor, and Random Forest, the study achieves high accuracy. Notably, Neural Network outperforms other models with an accuracy of 98.36%, followed by SVM, Gradient Boosting, Random Forest, and K-Nearest Neighbor.

Another study [17] looks at the classification of AD using a range of machine learning approaches such as K-nearest neighbors (K-NN), decision trees (DT), rule induction, Naive Bayes, generalized linear models (GLM), and deep learning. The study demonstrates the superiority of the generalized linear model by using the ADNI dataset from The Alzheimer's Disease Prediction of Longitudinal Evolution (TADPOLE) challenge, obtaining an accuracy of 88.24% throughout testing. Age of the patient, whole brain volume, and the Cognitive Dementia Rating Sum of Boxes (CDRSB) become important factors in identifying AD.

A paper [18] presents a machine learning strategy based on sequential biomarker selection and locally weighted learning in the field of tailored and economical detection. The purpose of the suggested tailored classifier is to provide useful biomarkers and advise physicians on a patient's likelihood of having Alzheimer's disease. The iterative selection process involves comparing a new patient's data with a pool of diagnosed cases, considering biomarker costs. The ADNI database is employed to validate the proof-of-concept, showcasing the potential for personalized and cost-effective AD detection.

Another study [19] uses a novel strategy in which computer vision and machine learning techniques are combined to estimate the displacement field (DF) for the purpose of detecting Alzheimer's disease. The work obtains good accuracy, sensitivity, specificity, and precision by treating DF as AD-related characteristics and using classifiers such support vector machine (SVM), twin SVM (TSVM), and generalized eigenvalue proximal SVM (GEPSVM). The suggested "DF + PCA + TSVM" method demonstrates the efficacy of the displacement field in AD diagnosis and identifies related brain regions, outperforming or matching existing methodologies and state-of-the-art approaches.

Turning our attention to hospital data, a study [20] uses machine learning methods such as SVM, Linear Regression, Random Forests, Decision Trees, and Na¨ıve Bayes to predict Alzheimer's. The study uses features like MR delay, years of education (EDUC), socioeconomic status (SES), Mini-Mental State Examination (MMSE), Clinical Dementia Rating (CDR), Estimated Total Intracranial Volume (eTIV), and Normalize Whole Brain Volume (nWBV) to collect data from a variety of sources, including unstructured Electronic Health Record (EHR) / Patient Health Record (PHR) data. Based on anticipated severity levels, the suggested machine learning techniques enable early treatment initiation by facilitating quicker Alzheimer's identification. This method places a focus on the useful applications of machine learning in giving patients relevant information.

IV. Insights and Discussion

To distill the key findings and insights from the literature survey, a comparative analysis is presented in the table below, highlighting various aspects of the studies, including dataset utilization, methodologies, and model performance.

A. Dataset Utilization

The survey reveals a predominant reliance on two major datasets: the Alzheimer's Disease Neuroimaging Initiative (ADNI) and the Open Access Series of Imaging Studies (OASIS). The ADNI database is extensively utilized in seven out of the ten studies reviewed [1, 2, 5, 6, 11, 12, 16], emphasizing its significance in AD research. The OASIS database is employed in four studies [3, 7, 9, 19], showcasing its relevance in contributing to diverse perspectives on AD detection.

B. Most Successful Approaches

Among the deep learning architectures employed, Convolutional Neural Networks (CNNs) stand out as highly effective in Alzheimer's detection. Notably, studies [2, 7, 11, 14] employing CNNs achieve accuracy levels ranging from 86% to 96.86%, showcasing the robustness of this architecture in handling diverse data types, including PET images, functional MRI data, and EEG spectral images. Additionally, the study in [16] achieves remarkable accuracy using clustering algorithms, fuzzy interference systems, and multiple machine learning algorithms, with Neural Network emerging as the top-performing model at 98.36%.

C. Innovative Approaches

Several studies contribute unique methodologies and applications in Alzheimer's disease detection. For instance, the study in [10] explores the use of smartphone accelerometers for predicting disease stages, achieving a high accuracy of 90.91% and highlighting the potential for non-intrusive monitoring using widely available devices. Another distinctive approach is presented in [19], where displacement field estimation is utilized as AD-related features, demonstrating the effectiveness of combining computer vision and machine learning techniques for accurate detection.

D. Hybrid and Ensemble Approaches

The study in [5] stands out by employing a hybrid approach involving six machine learning and data mining algorithms for the classification of different stages of AD, with the generalized linear model emerging as the most successful algorithm. Similarly, the study in [13] utilizes ensemble learning with eResNet50, eNASNet, and eMobileNet as base classifiers, achieving superior accuracy, sensitivity, and area under the curve in classifying AD versus MCI and MCI versus normal control.

E. Practical Applications

A notable contribution comes from the study in [8], which not only focuses on AD detection but also integrates a practi- cal application—a web application for Alzheimer's checking during the COVID-19 pandemic. This illustrates a forward-thinking perspective on healthcare accessibility, showcasing the potential for technology to address challenges in healthcare delivery.

F. Challenges and Considerations

While the surveyed studies demonstrate remarkable advancements, challenges persist. The issue of dataset dependency is acknowledged in multiple studies [7, 9, 11], emphasizing the need for diverse and representative datasets. Computational complexity and interpretability of deep learning models are also recognized as challenges [7, 9]. Additionally,

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aper	Year	ataset	lethodology	lodel Performance
]	2014	DNI (MRI images)	eep learning ith semi-ıpervised approach	ccuracy: 87.76%
]	2022	FDG-PET images	NN-based CAD system	ccuracy: 96%, Sensitivity: 96%, pecificity: 94%
]	2017	ASIS (MRI scans)	eep learning spired by ıception-V4	ccuracy: 73.75%
]	2021	DNI	2AD2C framework with CNNs ıd VGG19	ccuracies: 2D-93.61% VGG19-7%
]	2019	DNI	ybrid ML approach	ccuracy: 88.24% (Generalized inear Model)
]	2021	DNI (MRI images)	eep Neural Network architectures	ccuracy: 80-90%
]	2020	DNI, OASIS	arious deep learning models, ransfer Learning	ccuracy: 86% - 100%
]	2019	DNI Aulti-modal ıta)	lulti-modal RNNs	ccuracy: 81% AUC: 0.86
0]	2020	nartphone ccelerometer data	NN for stage prediction	ccuracy: 90.91%
1]	2016	DNI (rs-fMRI data)	NN (LeNet-5)	ccuracy: 96.86%
3]	2019	DNI	nsemble learning strategy	uperior accuracy in AD/MCI of 7.65%
4]	2019	ollected manually y co-op partnered edical professionals	CssCDBM model for EEG spec-al images	ccuracy: 95%
5]	2020	BSD, Dem@Care	arious models (LogisticRegres-onCV, LinearSVC, MLP)	1-Score: 86.9% - 89.4%
6]	2018	DNI	lustering algorithms, Multiple IL algorithms	est accuracy: Neural Network - 3.36%
7]	2019	DNI (TADPOLE)	arious ML techniques	ccuracy: 88.24% (GLM)
8]	2013	DNI	ersonalized classifier with locally eighted learning	ccuracy: 75%-93%
9]	2015	ASIS	F + PCA + TSVM method	ccuracy: 92.75%
0]	2021	HR/PHR data (MRI formation)	arious ML algorithms	ccuracy: 95% (SVM using Linear ernel)

Summary of Studies

imbalanced data is a concern in studies [8, 17], urging re- searchers to address these issues for more robust and reliable models.

G. Trends and Future Directions

The literature survey highlights the growing trend of lever- aging advanced technologies such as deep learning and ma- chine learning for Alzheimer's detection. There is a continued emphasis on exploring novel data sources, including smart- phone data [10], displacement fields [19], and electronic health records [20]. The importance of interpretability, addressing dataset biases, and enhancing model robustness emerges as key considerations for future research directions [9, 17]. Overall, the surveyed studies collectively contribute to a rich landscape of methodologies and insights, paving the way for further advancements in Alzheimer's disease detection and understanding.

V. FUTURE RESEARCH DIRECTION

Looking ahead, there's exciting potential for improving Alzheimer's disease (AD) detection by combining different types of data. Researchers can explore blending brain scans with genetic information, lifestyle details, and cognitive tests. This mix could provide a more complete picture of how AD develops, leading to better and earlier detection methods.

Another important area for future work is making deep learning models easier to understand. Researchers could focus on creating methods that explain why a model makes a particular prediction. This transparency is crucial for gaining trust in these models and making them more practical for use in real-world healthcare. Additionally, efforts to set common standards for testing models and datasets can help compare different approaches. As we move forward, it's essential to consider ethical aspects, such as avoiding biases in data and ensuring fair use of these models across diverse groups of people. Future research should aim for accurate and clear models while also being mindful of ethical considerations in their real-world applications.

VI. CONCLUSION

In conclusion, this literature survey illuminates the remark- able progress in Alzheimer's disease (AD) detection facilitated by machine learning and deep learning methodologies. The exploration of diverse datasets and innovative approaches, such as the application of convolutional neural networks (CNNs) and the integration of smartphone data, highlights the potential for earlier and more accurate diagnosis. However, persistent challenges, including dataset dependency and model interpretability, underscore the need for ongoing research and refinement. The identified future research directions, emphasizing multimodal data integration and increased interpretability, provide a roadmap for further advancements in the field. As the landscape of AD research evolves, the intersection of technology and healthcare holds promise for enhanced diagnostic capabilities and improved patient outcomes.

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