**Literature Survey**

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that has garnered significant attention in recent years due to its increasing prevalence and the lack of effective treatments. Early diagnosis and accurate classification of AD are critical for managing the disease and improving patient outcomes. Over the past decade, researchers have explored various machine learning (ML) and deep learning (DL) techniques to address these challenges, leveraging neuroimaging data, cerebrospinal fluid (CSF) biomarkers, and clinical datasets.

**Machine Learning Approaches**

Traditional machine learning algorithms have been widely used for AD classification and prediction. For instance, Taeho Jo [7] employed a multi-kernel Support Vector Machine (SVM) to classify AD and Mild Cognitive Impairment (MCI), achieving prediction accuracies of 95.9% and 75.8%, respectively. Similarly, C. Kavitha [10] compared several ML algorithms, including SVM, Random Forest, and Decision Tree, on the OASIS Longitudinal CSV Dataset, with Random Forest achieving the highest accuracy of 86.92%. Roobaea Alroobaea [11] further demonstrated the effectiveness of ML techniques, with Logistic Regression and Random Forest yielding accuracies of 84.33% and 83.92%, respectively, on the ADNI and OASIS datasets.

**Deep Learning Breakthroughs**

Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in AD diagnosis. Hadeer A. [8] fine-tuned the VGG-19 model, achieving a 97% accuracy rate for AD classification. Maysam Orouskhani [9] reported even higher accuracy (99.41%) using the VGG-G16 model on the OASIS dataset, outperforming other architectures like SCNN and ResNet-CNN. Deep learning’s ability to automatically extract features from raw data has made it a preferred choice for neuroimaging analysis. For example, Manan Binth Taj Noor [12] highlighted the use of CNNs on the ADNI dataset, achieving an impressive 99.9% accuracy for rs-fMRI classification.

**Hybrid and Ensemble Models**

Researchers have also explored hybrid and ensemble models to improve classification performance. A study by Sharma et al. [25] utilized a fuzzy hyperplane-based least square twin support vector machine (FLS-TWSVM) for feature classification, achieving accuracies of 97.15%, 97.29%, and 95% for distinguishing between cognitively normal (CN), AD, and MCI cases. Similarly, Stamate et al. [22] combined deep learning, extreme gradient boosting (XGBoost), and Random Forest to analyze plasma metabolites, achieving AUC values of 0.85, 0.88, and 0.85, respectively. These hybrid approaches demonstrate the potential of combining multiple techniques to enhance diagnostic accuracy.

**Biomarker-Based Approaches**

Beyond neuroimaging, researchers have explored the use of biomarkers for AD diagnosis. Aljović et al. [23] developed an artificial neural network (ANN) framework using CSF biomarkers, achieving 95.5% sensitivity for AD and 91.43% specificity for healthy subjects. Hassan et al. [24] further advanced this approach, using machine learning algorithms like Sequential Minimal Optimization, Naïve Bayes, and J48 to achieve 98.82% accuracy with CSF biomarkers. Ryzhikova et al. [27] introduced a novel approach using near-infrared (NIR) Raman spectroscopy on CSF samples, achieving 84% sensitivity and specificity, highlighting the potential of integrating spectroscopy with ML for AD diagnosis.

**Challenges and Future Directions**

Despite these advancements, several challenges remain. Many studies rely on limited datasets, such as ADNI and OASIS, which may not fully capture the diversity of AD cases. Additionally, the interpretability of deep learning models remains a concern, as highlighted by the need for explainable AI (XAI) techniques. Future research should focus on integrating multimodal data (e.g., MRI, PET, CSF biomarkers) and leveraging federated learning to address data privacy and decentralization issues. Generative adversarial networks (GANs) and reinforcement learning also offer promising avenues for improving model generalization and diagnostic accuracy.

In conclusion, the integration of machine learning and deep learning techniques has significantly advanced the field of AD diagnosis. By combining neuroimaging, biomarkers, and clinical data, researchers are moving closer to developing robust, real-time diagnostic tools that can improve patient outcomes and reduce the global burden of Alzheimer’s disease.