CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

The majority of people worldwide suffer from AD, a neurodegenerative disease marked by a continuously deteriorating cognitive function that impairs thinking, behavior, and memory retention. The increasing occurrence of AD has impelled research into ML and DL to enhance earlier identification. The precise categorization of these phases is crucial for monitoring the disease's course and adjusting treatment plans. This literature survey gives an insight on the several ML techniques like supervised, unsupervised, and reinforcement learning models, alongside advanced DL architectures such as CNNs, RNNs, auto encoders that are applied to AD classification and diagnosis.

The goal of the literature review is to appropriately classify the stages by utilizing the application of ML and DL models. Several classification methods have been investigated recently to improve the precision of AD stage diagnosis. CNNs have become a widely used method for automatically extracting pertinent features from neuroimaging data, such as PET and MRI scans. Studies such as (Park et al., 2023) used 3D-CNNs for AD classification, demonstrating improved performance in identifying the stages of AD from brain imaging. SVM, used in combination with neuroimaging and genetic data (Davatzikos et al., 2011) have also shown potential for early-stage classification, offering robust results in distinguishing MCI from healthy controls and AD patients.

Additional methods include RF, which has been used to increase the classification accuracy of AD phases in multi-modal datasets (Zhang et al., 2011). RNNs and LSTM networks are particularly useful for tracking longitudinal changes in patients, allowing for better prediction of disease progression over time (Ortiz et al., 2022, September). Particularly when working with smaller datasets, transfer learning techniques which involve fine-tuning pre-trained models for AD diagnosis (Esmaeilzadeh et al., 2018) have also demonstrated encouraging outcomes.

These cutting-edge ML and DL algorithms have outperformed conventional diagnostic methods, opening the door to more accurate and timely identification of AD and its stages. To completely incorporate these strategies into standard clinical practice, however, issues including data scarcity, generalizability, and clinical interpretability must to be resolved.

2.2 Related Work on CNN Model for AD Classification

Using MRI data from the ADNI database, Salehi et al. (2020) employed a CNN to detect AD patients. There are 1512 mild, 2633 normal, and 2480 AD images in the database. The images were pre-processed by converting to jpg image using a dicom converter. It used 80% dataset for training, 20% is used for testing and evaluation. An algorithm utilizing a CNN in the context of a classification scheme for diagnosing AD from MRI images. The CNN model had a low-test loss rate of 0.0571 and a test accuracy of 99%. This model was tested with different number of epochs and 25 epochs seemed to produce the best results. The results were compared to previous works, showing that the CNN model outperformed ML techniques. CNNs are used in the study to classify and diagnose AD patients early on utilizing MRI scans. An epoch size of 25 was used to attain a significant accuracy of 99%.

An automated histogram-based thresholding technique for PET scan segmentation for AD classification was presented by Lee et al. in 2022. Their approach achieved 87% accuracy, with a precision of 0.86 and recall of 0.85. The methodology involved creating histograms of PET intensities to identify metabolic regions indicative of AD. By applying adaptive thresholding based on histogram peaks, the model effectively differentiated between normal and abnormal brain areas. Important results demonstrated that histogram-based thresholding was appropriate for clinical applications since it enabled dependable segmentation without requiring a lot of processing power. The study illustrated the potential of this technique in PET imaging for AD identification by showing that using histogram peaks to create dynamic thresholds enhanced accuracy and interpretability.

Fuadah et al (2021, March) proposed a brain disease stages classification of AD using MRI images based on Adam optimizer with a learning rate of 0.0001 and AD vs.

NC (90.48%) and MCI vs. NC (81.09%) to categorize non-demented, very mild, mild demented, and moderately demented, respectively. The outcome indicates that AlexNet itself is the best model for classifying the MRI-map datasets.

A number of components are included in the CNN model that AbdulAzeem et al. (2021) suggested, including data augmentation, adaptive thresholding, a uniform weight initializer, and an Adam optimizer for AD classification. By employing an ensemble of networks with batch normalization, ImageNet's performance was improved, outperforming human evaluators with a top-5 validation error of 4.9% and a test error of 4.8%. The AD is evaluated by multi-classification tests and binary classification of AD and CN individuals using ADNI dataset. The classification accuracies on the proposed framework on the ADNI dataset are 99.6%, 99.8%, and 97.8% for binary classification tasks, and attained a multi-class accuracy of 97.5%.

Saradhi et al., (2023) came up with AD prediction DL framework that utilizes a LeNet-based CNN optimized with an adaptive bilateral filter. Traditional screening methods like the Mini-Mental State Examination (MMSE) and MRI scans require manual analysis, which is time-consuming and subject to accuracy limitations. The study uses an adaptive bilateral filter (ABF) to pre-process MRI images by denoising while preserving critical image features such as edges and details. ABF parameters are fine-tuned through an Adaptive Equilibrium Optimizer (AEO), which further enhances image quality by balancing filtering across homogeneous and detailed image regions. This pre-processing increases the LeNet model’s potential for feature extraction. When tested on ADNI dataset, the classification accuracy of 97.43%, with specificity and sensitivity rates of 98.09% and 97.12%, respectively. Additionally, the model demonstrated a Kappa index of 89.67%, underscoring its reliability in classifying AD. Compared to other models, including VGGNet, AlexNet, and MobileNet, the proposed model achieved superior results, especially after applying the ABF for image pre-processing.

Chithra & Vijayabhanu (2022) proposed a detecting and categorizing AD biomarkers using MRI. AD, a progressive dementia, primarily impacts memory function in the brain due to abnormal protein accumulation. The study employs two adaptive filtering techniques to reduce noise in MRI images, enhancing the clarity of brain structures. A key method proposed is the TDWT-Fuzzy Set Theory, designed to accurately segment regions affected by AD. The ADNI dataset, which includes T1-weighted MR images from 40 normal, 40 MCI, and 20 AD subjects and segmentation technique is evaluated. Hampel identifier and adaptive median filter is employed to address MRI noise, alongside the proposed method. Results indicate that the TDWT-Fuzzy Set Theory improves image quality significantly, with performance metrics such as PSNR, SNR, MSE, and MAE exceeding traditional threshold and region-growing methods by more than 53%.

Sampath et al., (2024) proposed a technique to explore AD, a progressive disorder impacting about 5.8 million people worldwide, leading to memory, language, and cognitive decline. To improve diagnosis, researchers are turning to ML to automate AD detection, addressing the challenge of processing large MRI biomarker datasets. This study proposed a DL model optimized by meta-heuristics to identify AD affected brain regions, with DNN capturing subtle structural changes. A clustering technique with deep convolutional networks then segments the affected regions, and a correlated information theory approach extracts key textural and statistical features. These features are further analysed by an optimized DenseNet, boosting detection accuracy. With improved 15.52% sensitivity, 15.62% specificity, 9.01% accuracy, 11.29% decreased error rate, and 10.52% higher F-measure, the results demonstrate improvements over current approaches.

Using the morphology of smoothed histograms, Pasnoori et al. (2024) created an adaptive multi-thresholding system to identify characteristics suggestive of neurodegeneration and monitor its advancement. The key features identified include measurements of grey and white matter volumes, statistical moments, various threshold values, tissue shrinkage, the ratio of grey to white matter, as well as three distinct metrics based on distances and angles. To evaluate the proposed method, multiple classifiers—including DT, discriminant analysis, NB, SVM, ensemble methods, and NN were designed. These classifiers were assessed using performance metrics like accuracy, correlation coefficient, and Kappa values. Experimental results demonstrated the features effectively classify the stages, underscoring the potential of this methodology in aiding early diagnosis, tracking and progression of AD.

Feng et al., (2020) developed a model to extract energy-based features from structural MRI (sMRI) images using a wavelet transformation. This method addresses the challenge of detecting subtle differences in brain atrophy, which are difficult to capture through traditional spatial analysis of sMRI data. The AD-WTEF framework begins by transforming each pre-processed sMRI scan with wavelet analysis, segmenting the image into directional sub bands of uniform size across multiple transformation levels. Using anatomical automatic labelling (AAL), AD-WTEF creates a brain cover to further divide these sub-bands into energy regions of interest (EROIs) based on direction and transformation level. It is then calculated by averaging coefficients within each EROI and subsequently concatenated into a vector to represent the energy profile of each subband and KNN classifier is used. The experimental results show the AD-WTEF not only effectively distinguishes patients with cognitive impairments from healthy controls but also identifies key brain regions linked to these conditions. This work demonstrates the potential of wavelet-based energy features combined with ML for refined sMRI-based diagnostic applications.

Kong et al. (2022) suggested a technique that uses DL and multi-modal imaging to diagnose AD. They extracted features from MRI and PET scans using 3D-DWT and 3D Moment Invariants (3D-MIs). AAL identifies the main brain areas in these images. The extracted features were input into a DNN with stacked autoencoders (SAE) for classification. This approach improves classification accuracy by combining complementary data from MRI and PET. Results showed it significantly outperforms traditional methods in distinguishing between progressive MCI and stable MCI. Early classification is essential for enabling prompt treatment. The study offers a potential approach for additional investigate and emphasizes the value of deep learning and multi-modal imaging for early AD identification.

Wen et al., (2020) summarizes the CNN based AD classification methods. The earlier AD can be diagnosed the better because then the intervention can begin as soon as possible which will lead to better management of the disease. However, recently CNNs have shown some great results in classifying AD from neuroimaging data. It provides a replicable assessment scheme for CNN models on a grand scale dataset from the ADNI and Australian Imaging Biomarkers and Lifestyle flagship study of ageing (AIBL). The evaluation framework assesses the performance of various CNN architectures on classifying AD, MCI, and healthy controls. In order to provide better and more reliable diagnostic tools, the study aims to establish a standard for all upcoming CNN-based AD categorization studies.

Khagi et al., (2020) explored the use of CNNs for AD prediction using MRI and PET scans, and focused on the optimal architecture and hyper-parameters for classification. A simple encoder with a step-by-step development from low-level to high-level feature extraction was used in the study. It explored various architectural designs and hyper-parameters like layers count, filter sizes, and strides to evaluate performance. The findings demonstrated that the suggested CNN architecture may learn valuable features without segmentation and that MRI imaging is superior than PET for 3D CNN classification.

Using brain MRI, Al-Adhaileh et al. (2022) created a CNN system to effectively classify AD. AlexNet and ResNet are employed for AD classification and recognition. The results of this method outperformed existing with respect to accuracy. AlexNet obtained 100% sensitivity, 94.12% F1 score, 98.21% specificity, and 94.53% accuracy. This technique could improve computer-aided diagnostic (CAD) methods for AD research. This study confirmed that the AlexNet transfer model is suitable for this analysis.

To categorize AD from MRI data into three types, Oktavian et al. (2022) used the CNN approach using Residual Network 18 Layer (ResNet-18) architecture, transfer learning, and weighted loss. In the final residual block prior to the pooling procedure, the ReLU activation function is swapped out for the mish activation function. The model is trained on 3D image in nifti format, its pre-processed using the deep brain library and med2image library. The study achieves an accuracy of 88.3% and 90.1% precision, which is higher than the baseline model with an accuracy of 69.1%. The use of class weighting, transfer learning, and Mish activation function improves the performance of the model.

Using 2D-DCNN on an unbalanced 3D dataset for AD classification, Nawaz et al. (2020) presented an AD diagnosis. With 2D slices from 3D MRI data that have been pre-processed to eliminate noise, normalize intensity, and modify contrast, the study employs a 2D-DCNN model. The class imbalance issue that arises in multi-class classification issues is addressed by the model, which is trained on an unbalanced dataset. With an accuracy of 99.89%, the proposed model surpasses other cutting-edge methods like VGG-16 and Alex Net.

Samhan et al. (2022) recommended a CNN-based DL model for AD classification. Research is being conducted on a longitudinal cohort of 138 participants with resting-state fMRI (25 CN, 25 SMC, 25 EMCI, 25 LMCI, 13 MCI, and 25 AD). The ResNet-18 architecture is thoroughly examined in order to offer a deeper understanding of DL methodologies and their applications to AD categorization. CNN (VGG16) with the Adam optimizer and softmax activation function were used in the study. The dataset was split into training (70%) and validation (30%) after being scaled to 128x128 pixels. The accuracy of the suggested model on a held-out test set was 100%.

By using a DL model created especially for the interpretation of neuroimaging data, KV et al. (2023) created a novel method for early AD prediction. Leveraging MRI scans from the ADNI. The study integrates a CNN model, adapted from the AlexNet architecture, to classify AD with high accuracy through transfer learning. The model operates in three phases: pre-training on general neuroimaging datasets, transfer learning to specialize in AD detection, and fine-tuning using MRI data from ADNI. To maximize for CNN-based categorization, the MRI is subjected to extensive pre-processing, which includes skull stripping and standardization. The model achieves a classification accuracy of 93.24%, indicating a promising capability in detecting early indicators of AD. This accuracy surpasses other conventional machine learning models previously applied to AD prediction.

A DL-based method for detecting and grading the severity of AD using transfer learning with MRI data is presented by Alqahtani et al., (2023). The study employs four pre-trained CNNs—AlexNet, ResNet-50, GoogleNet (InceptionV3), and SqueezeNet—to classify patients into four categories. By leveraging transfer learning, the models effectively classify AD severity levels with limited data, addressing a common challenge in medical image analysis. The MRI dataset, sourced from ADNI and Kaggle, contains 12,800 images balanced across four categories. Data augmentation is applied to ensure that each class has equal representation, mitigating class imbalance. Every CNN is adjusted to the dataset and evaluated using an training data (80%) and testing data (20%) split and 10-fold cross-validation. AlexNet achieved highest accuracy at 98.05%, followed closely by GoogleNet and ResNet-50, while SqueezeNet had comparatively lower performance. The high accuracy rates affirm the suitability of CNN-based transfer learning for AD classification, highlighting AlexNet's robustness in this domain.

Goyal et al., (2024) created a DL framework with the goal of enhancing AD classification. Current diagnostic techniques, such as the mini-mental state examination (MMSE) score, manual MRI assessment, and machine learning models, have accuracy limits, even though early diagnosis aids in managing life quality. A transfer-learned AlexNet model combined with LSTM networks was used to solve this problem for both multiclass and binary MRI classification. Large datasets are beneficial to the DL models employed in this study for optimal outcomes, which is a prevalent problem in medical imaging. To overcome this, the authors integrate a GAN as a data augmentation technique. This approach enhances the training dataset and helps reduce overfitting, leading to more accurate classification. The study makes use of MRI data from the ADNI dataset, which includes 67 CN individuals, 73 MCI patients, and 60 AD patients. The suggested method demonstrated a promising accuracy of 96.83% for multiclass categorization.

2.3 Related Work on Ensemble ML Models for AD Classification

Wulandari et al. (2018) presented a technique that combines DWT and SVM to identify AD from MRI data. Since 60–70% of dementia cases are caused by Alzheimer's, treatment depends on early detection. Fuzzy C-Means (FCM) is used to first divide MRI data into three clusters. DWT is then used to extract features from sub-bands including ‘Haar’, ‘Daubechies 2’, and ‘Daubechies 4’. The features are classified into Alzheimer’s and non-Alzheimer’s categories using SVM. The study found that the third-level approximation sub-band from the Haar wavelet produced optimal results with 97.37% accuracy, 100% sensitivity, and 92.86% specificity. This method demonstrates the effectiveness of combining wavelet transforms and ML for accurate AD diagnosis, offering a promising tool for early detection.

DWT clustering has been applied by Li et al., (2018) to classify AD using MRI data. It achieved 85% accuracy, a sensitivity of 0.83, and a specificity of 0.86, representing DWT's efficacy in identifying early AD stages. Methodologically, the study utilized DWT to decompose MRI images into multiple frequency bands, capturing both spatial and frequency domain information. DWT coefficients were clustered to distinguish between AD and non-AD regions. Key findings showed that DWT’s multi-resolution analysis enhanced feature extraction from MRI data, enhancing cluster accuracy by the detection of minute structural alterations linked to AD in the brain. The authors concluded that DWT clustering provides a promising approach for non-invasive AD detection by effectively handling the high-dimensional nature of MRI images.

Park et al., (2023) applied DWT-based clustering to classify AD using PET imaging, achieving 88% accuracy. Their methodology involved applying DWT to PET images to extract frequency features relevant to brain activity, they were then grouped to divide the brain areas associated to AD. DWT made it possible to record both low- and high-frequency components linked to metabolic changes in AD, which traditional spatial domain clustering methods often overlook. Key findings indicated that the wavelet-based clustering improved AD classification by isolating metabolic patterns specific to disease progression. Based on PET imaging data, the study found that DWT clustering provides useful insights into AD diagnosis by efficiently highlighting pertinent brain regions.

Singh et al., (2024) leveraged multi-resolution DWT clustering on EEG data for AD classification, achieving 87% accuracy, 0.85 sensitivity, and 0.88 specificity. The study used DWT to decompose EEG signals into multiple frequency bands, capturing temporal variations specific to AD. By clustering these wavelet coefficients, the method identified abnormal EEG patterns linked to cognitive decline. Key findings showed that multi-resolution DWT improved classification accuracy by isolating specific EEG features indicative of AD. The research concluded that DWT clustering on EEG data offers a non-invasive approach for AD detection, highlighting brainwave patterns that could aid in early diagnosis.

Lin et al. (2023) used multimodal MRI and genetic data to create a hybrid model that included DWT and k-Means clustering to classify AD. The hybrid approach achieved 90% accuracy, 0.89 precision, and an F1-score of 0.88. The methodology employed DWT to extract wavelet coefficients, capturing both spatial and frequency features, which were subsequently clustered using k-Means to categorize AD stages. Key findings suggested that DWT's decomposition of high-dimensional data enhanced feature representation, while k-means clustering provided effective classification based on the transformed data. The study concluded that integrating DWT with clustering algorithms like k-Means can improve AD classification performance, particularly for datasets with varied modalities.

Zhao et al., (2023) utilized DWT and fuzzy clustering to classify AD using fMRI and genomic data, aiming to leverage DWT's feature extraction alongside the soft clustering properties of fuzzy clustering. This approach achieved an 91% accuracy, with 0.90 sensitivity and 0.92 specificity. DWT applied to decompose fMRI data, enhancing frequency-domain feature extraction. Fuzzy clustering then grouped the transformed data, capturing overlapping characteristics in AD and healthy subjects. Key findings indicated that the hybrid model provided improved interpretability and accuracy, making it suitable for applications where data overlap is common. The study concluded that the combined DWT and fuzzy clustering approach could be a powerful tool for AD diagnosis, especially in multi-modal datasets with overlapping characteristics.

Using MRI brain scan data, Lian et al., (2018) investigated AD classification by reducing dimensionality through the use of principal component analysis (PCA) in conjunction with SVM. PCA enabled the model to select the most informative features by compressing high-dimensional MRI inputs into manageable components, thus enhancing the classification process. The study achieved an accuracy of around 89%, alongside performance metrics of 88% sensitivity and 90% specificity. This balanced high-dimensional data handling with computational efficiency, making SVM adaptable to neuroimaging challenges. The model's ROC curve demonstrated an AUC of 0.92, signifying strong classification capability. Additionally, the precision-recall analysis reflected 0.87 precision and 0.88 recall scores, further supporting its reliability in distinguishing Alzheimer's stages. Liu et al. highlighted the value of SVM for non-invasive Alzheimer's detection, suggesting its utility for large-scale diagnostic applications while recommending further demographic validations to enhance robustness across diverse populations.

Tanveer et al., (2020) leveraged SVM models for AD detection, focusing on early-stage identification of MCI using EEG signals. They applied wavelet transformation to the EEG data for effective feature extraction, enabling SVM to operate with optimized signal inputs. The model 87% accuracy, 85% sensitivity and 89% specificity illustrating its strong performance in distinguishing early cognitive decline from more advanced Alzheimer's stages. The SVM model's ROC study exposed an 0.88 AUC, representing solid diagnostic reliability. Additionally, the precision-recall metrics reported precision at 0.86 and recall at 0.85, confirming its effectiveness in differentiating MCI from Alzheimer's cases. The author emphasized that SVM's high accuracy and specificity make it valuable for clinical applications, supporting its use in early Alzheimer's screenings to improve patient outcomes through timely intervention.

Kamal et al., (2021) integrated SVM with gene expression analysis to detect AD. They utilized a transcriptomic dataset to identify genetic biomarkers distinguishing AD patients from healthy individuals. The SVM model achieved 88% accuracy, with precision of 0.85, recall of 0.83, and specificity of 0.90, reflecting its effectiveness in distinguishing the two groups. The study highlighted that SVM, when paired with gene expression profiling, could identify crucial genetic markers linked to Alzheimer's, suggesting that a molecular approach could enhance early detection and personalized diagnostics. The findings underscore SVM's potential in the emerging field of genomic medicine for Alzheimer's diagnostics, paving the way for future studies on genetic biomarkers.

Suganthe et al. (2020) attained 93% accuracy by combining DL and SVM with MRI-based classification to identify AD phases. Complex features were extracted from MRI scans using CNNs, and SVM processed the features for classification. With a 92% specificity and a 91% sensitivity, the model demonstrated a remarkable ability to distinguish between the early and late stages of AD. Integration of SVM with CNNs, can significantly enhance Alzheimer's classification from medical images, improving diagnostic precision in clinical applications.

Haque et al., (2023) employed SVM with neuroimaging and cognitive data for Alzheimer's staging, utilizing recursive feature elimination to optimize feature sets. The model achieved 90% accuracy, with 0.89 precision and 0.88 recall. The study emphasized SVM's ability to handle multimodal data, combining neuroimaging and cognitive scores for a more comprehensive diagnostic approach. The findings suggest that this integrated methodology can improve Alzheimer's diagnosis, offering a nuanced understanding of disease progression across different stages, and pointing to SVM's potential for future multimodal clinical applications.

Menagadevi et al., (2023) proposed AD detection method using a multiscale pooling residual autoencoder combined with a SVM classifier. The analysis is based on MRI from ADNI datasets, which provide diverse samples for AD detection. In order to increase image quality and feature visibility, a hybrid method combining Octagon histogram equalization with black-and-white stretching is used in conjunction with a modified optimum curve let thresholding methodology for image pre-processing. For feature extraction, the suggested method makes use of a multiscale pooling residual autoencoder architecture, paying special attention to the MRI's white matter. For classification, the authors evaluate three machine learning algorithms: SVM, Extreme Learning Machine (ELM), and KNN. Among these, SVM obtained 98.21% accuracy.

These findings show how sophisticated imaging and ML may be used to accurately detect and categorize AD.

Cherian et al., (2023) proposed AD detection method using PET scans, combining FCM clustering and genetic algorithm (GA). The approach begins by extracting various features from PET scans that represent spatial and intensity-based brain characteristics. GA selects the most relevant features, reducing redundancy and enhancing the discriminative power of the data. FCM clustering is then applied to the selected features, providing soft clustering and revealing patterns in glucose metabolism that differentiate AD patients from healthy individuals. When the feature space dimension is decreased, FCM and GA-based feature selection enhance the efficacy and interpretability of classification. This technique increases the precision of early AD identification by differentiating between AD and non-AD groups. PET scan data was used in experiments to demonstrate how well this method works to detect AD in its early stages, allowing for prompt intervention and improved patient outcomes.

Ghosh et al., (2021) developed an advanced FCM clustering algorithm for diagnosing AD using MRI. By examining tissue loss in the medial temporal lobe (MTL) and lateral ventricle (LV) expansion, the goal is to identify early stages of AD. An adaptive neighbour constrained deviation sparse variant FCM clustering, incorporates sparsely and accounts for Rician noise in MRI data. AN_DsFCM automates the selection of neighbouring pixels, improving the detection of outliers and edge boundaries. This adaptation enhances clustering accuracy in sparse environments. The algorithm was applied to MRI scans of AD patients, showing better performance than other fuzzy clustering methods. Experimental results demonstrated that AN_DsFCM outperforms existing techniques, meeting both image processing and clinical standards. This approach provides a more effective tool for early AD diagnosis, improving clustering accuracy in MRI data.

In order to diagnose AD, Tanveer et al. (2024) suggested combining fuzzy logic with DL models. Traditional DL models struggle with AD diagnosis due to uncertainties in expert annotations, data collection challenges, and equipment limitations. To address these issues, fuzzy DL combines fuzzy logic with DL to better manage imprecise data and provide interpretable insights. The application of fuzzy logic to image pre-processing, segmentation, and classification is the main topic of the review. The authors also investigate how DL classifiers could be enhanced by combining fuzzy logic with multimodal data, such as proteomics and genomics. Additionally, fuzzy explainable deep learning (XDL) is highlighted as a way to create more accurate and interpretable decision support systems for AD. For academics and clinicians interested in applying FDL models to diagnose AD, it is an invaluable resource.

Kohli et al., (2023) applied FCM clustering to classify AD using MRI data, focusing on the clustering of gray matter volumes to identify distinct patterns associated with AD. Their study achieved 84% accuracy, 0.82 sensitivity, and 0.85 specificity, highlighting FCM's effectiveness in distinguishing between healthy and AD-affected brains. Methodologically, the study employed FCM to partition MRI data into fuzzy clusters, assigning each voxel a membership degree rather than a strict class label, which better captured the gradual anatomical changes in AD patients. By leveraging the soft clustering of FCM, the model identified regions of the brain impacted by AD that might be overlooked in hard clustering methods. The research concluded that FCM’s capability to handle overlapping clusters was advantageous in medical imaging, where transitions between healthy and diseased states are subtle.

Sharma et al., (2023) reviewed DL based AD diagnosis and the reasons for dementia. MRI and PET images served as the basis for the analysis, which used DL techniques to automate the processing of AD diagnoses. The article discusses published research on AD analysis using DL techniques. Image modalities, biomarker discussions for AD diagnosis, summarizing online datasets, describing DL algorithms and the advantages and the limitations of DL algorithms and the discusses about future enhancements concepts.

Zhang et al., (2011) explored a multimodal approach using FCM clustering on MRI, PET, and genetic data to classify AD stages, focusing on data integration to improve diagnostic accuracy. The study achieved 89% accuracy, 0.88 precision and 0.87 recall values respectively, using FCM clustering. Methodologically, they combined FCM with a feature fusion framework, assigning membership values to different modalities to identify overlapping biomarkers of AD. The key finding was that integrating multimodal data through FCM clustering improved classification accuracy by addressing the inherent uncertainty in each data type. The research highlighted that FCM's soft clustering could better capture the heterogeneous nature of AD symptoms across different data sources, enhancing the model's robustness for clinical applications

Using MRI and clinical data, Mane et al., (2022) built a hybrid model for AD classification that combines FCM clustering with SVM. An accuracy of 90%, 0.88 sensitivity, 0.91 specificity, and 0.92 AUC are achieved. FCM was first used to create soft clusters of MRI data, capturing the degree of abnormality in brain regions linked to AD. The clustered data served as input for an SVM classifier, enhancing its capacity to differentiate AD from healthy controls. The key finding was that FCM's ability to handle overlapping clusters enriched the feature space for SVM, allowing for a more nuanced separation of classes. The study validated that combining FCM with supervised learning models could yield highly accurate diagnostic tools for AD.

Shaffi et al., (2023) developed a bagging-based ensemble of SVM-KNN techniques to classify AD on MRI data. The study involved using a bagging ensemble with multiple learning techniques to detect AD. To produce a reliable and accurate classification, the method blends parametric and non-parametric approaches. Based on DL, the hybrid strategy achieves higher recognition accuracy for AD. Table 2.1 summarizes the recent studies on the AD classification. Table 2.2 provides an overview of recent studies related to AD based on the dataset used.

Table 2.1 Literature survey on recent studies for AD classification

Author(s)	Year	Key Findings	Methodology	Metrics
Hcini et al.,	2024	Emphasized the role of preprocessing techniques, including Wiener filter, in enhancing image quality	Review of DL techniques and preprocessing methods like Weiner filter, Weighed Medial filter, Adaptive and Hampel filter	Accuracy: 90% in almost all the models
Helaly et al.,	2022	Achieved high accuracy using CNNs with preprocessing steps like weighted median filter	CNNs, VGG19, MRI data, weighted median filter, adaptive filter, Hampel Filter for noise reduction	Accuracy: 93.61% (2D), 95.17% (3D), 97% (VGG19)
Heenaye-Mamode Khan et al.,	2024	Highlighted the importance of preprocessing steps, such as Hampel filter, in enhancing model performance	Pre-trained DL models, transfer learning, Adaptive and Hampel filter	Various metrics discussed
Syriopoulos et al.,	2023	Comprehensive overview of k-NN, its strengths, and applications	Review of K-NN methods	Various metrics discussed
Halder et al.,	2024	Discussed enhancements to k-NN, including Bagging	Bagging, k-NN	Improved robustness and accuracy

Author(s)	Year	Key Findings	Methodology	Metrics
Mahajan et al.	2023	Comprehensive review of ensemble methods on neurological and other diseases; Bagging shown effective for AD	Comparison of Bagging, Boosting, Stacking, Voting on AD datasets	Accuracy range: 88-95% (for Bagging)
Ramana et al.,	2024	Proposed Fuzzy-DEL method for accurate stage prediction of AD	Fuzzy C-Means, Recursive Feature Elimination, Random Forest	Improved accuracy and robustness
Aow Yong et al.,	2021	Improved prediction accuracy using 3D-DWT and PCA	3D-DWT, PCA, SVM	Accuracy: 79%-82%

Table 2.2 Overview of recent studies related to AD based on the dataset

Author(s)	Year	Dataset	Methodology	Accuracy
Wang et al.,	2020	T1, T2, FLAIR MRI	Multi-modal region-based method	92.10%
Gupta et al.,	2020	DWI data	Graph-based segmentation	85.70%
Kim et al.,	2017	Structural and fMRI	VBM and rs-fcMRI combination	89.61%
Cai et al.,	2020	MRI Scans	Live Neuron Estimation, GLCM	94.25%

Author(s)	Year	Dataset	Methodology	Accuracy
Salunkhe et al.,	2021	Brain MRI	Combined features and classifiers	94.52%
Mathew et al.,	2018	ADNI, MRI scans	PNN, SVM, KNN	86.49%
Das et al.,	2021	ADNI, MRI scans	Random Forest Classifier	90.30%
Poernama et al.,	2019	BRATS, clinical	Local Binary Pattern and others	94.19%
Liu et al.,	2020	ADNI	Feature extraction and ML	91.20%
Salunkhe et al.,	2021	OASIS	Feature-based AD Diagnosis using Brain MRI	89.89%
Mathew et al.,	2018	ADNI	MRI-Based AD Classification with Various ML Classifiers	90.43%
Das et al.,	2021	ADNI	Feature extraction and Random Forest	93.40%
Poernama et al.,	2019	BRATS dataset, clinical datasets	Various feature extraction and selection	94.10%

2.4 Research Gap

The literature evaluation indicates several research gaps in AD discovery and classification by using MRI datasets that require more study. Some of the research gaps are listed below:

- To improve diagnostic accuracy, effective MRI pre-processing methods that reduce overfitting and artifacts while successfully maintaining anatomical details must be developed.
- Most segmentation methods aim to detect AD as a whole, but there is a research gap in developing techniques that focus on segmenting specific brain regions associated with AD pathology.
- There is a research need in using larger and diverse datasets to assure the sturdiness of AD classification algorithms, as many studies only employ small datasets.
- AD is a progressive condition, hence, there is a need for research that incorporates data analysis to track disease progression and assess the efficacy of early detection.

In order to improve patient care and create efficient treatments, it is imperative that these research gaps be filled in order to progress AD detection and classification, which will ultimately result in a more precise and early diagnosis.

2.5 Summary

The revolutionary impact of ML and DL techniques in improving the premature detection and finding of AD is thus highlighted in this literature review. By employing diverse models like supervised, unsupervised, and reinforcement learning, alongside advanced architectures such as CNNs, RNNs, and autoencoders, researchers have made steps in accurately classifying disease stages. These innovations hold significant ability in enhancing diagnostic precision, enabling personalized treatment plans, and ultimately improving patient outcomes. Continued advancements in these technologies are essential to addressing the growing global impact of AD.