CHAPTER 3

RESEARCH METHODOLOGY

This chapter briefs the research framework of all the proposed methods in this study. This chapter discusses the research methodology in detail, the pre-trained AlexNet architecture, experimental setup and dataset description.

3.1 Research Framework

The comprehensive process of this research is portrayed below. The outline of the AD detection study methodology is displayed in Figure 3.1. It provides a thorough graphic depiction of every step involved in this research.

3.1.1 Data Acquisition

The process starts with the procurement of image. Two distinct datasets ADNI and OASIS from Kaggle are used in this study. The ADNI dataset compiles a vast array of brain imaging data, which is vital for studying the progression of AD. It includes MRI, PET, and clinical data across various stages of the disease. The OASIS dataset also focuses on neuroimaging data, specifically targeted at understanding aging and its effects, making it suitable for AD research as well. These datasets acts as a foundational resource for applying subsequent image processing techniques.

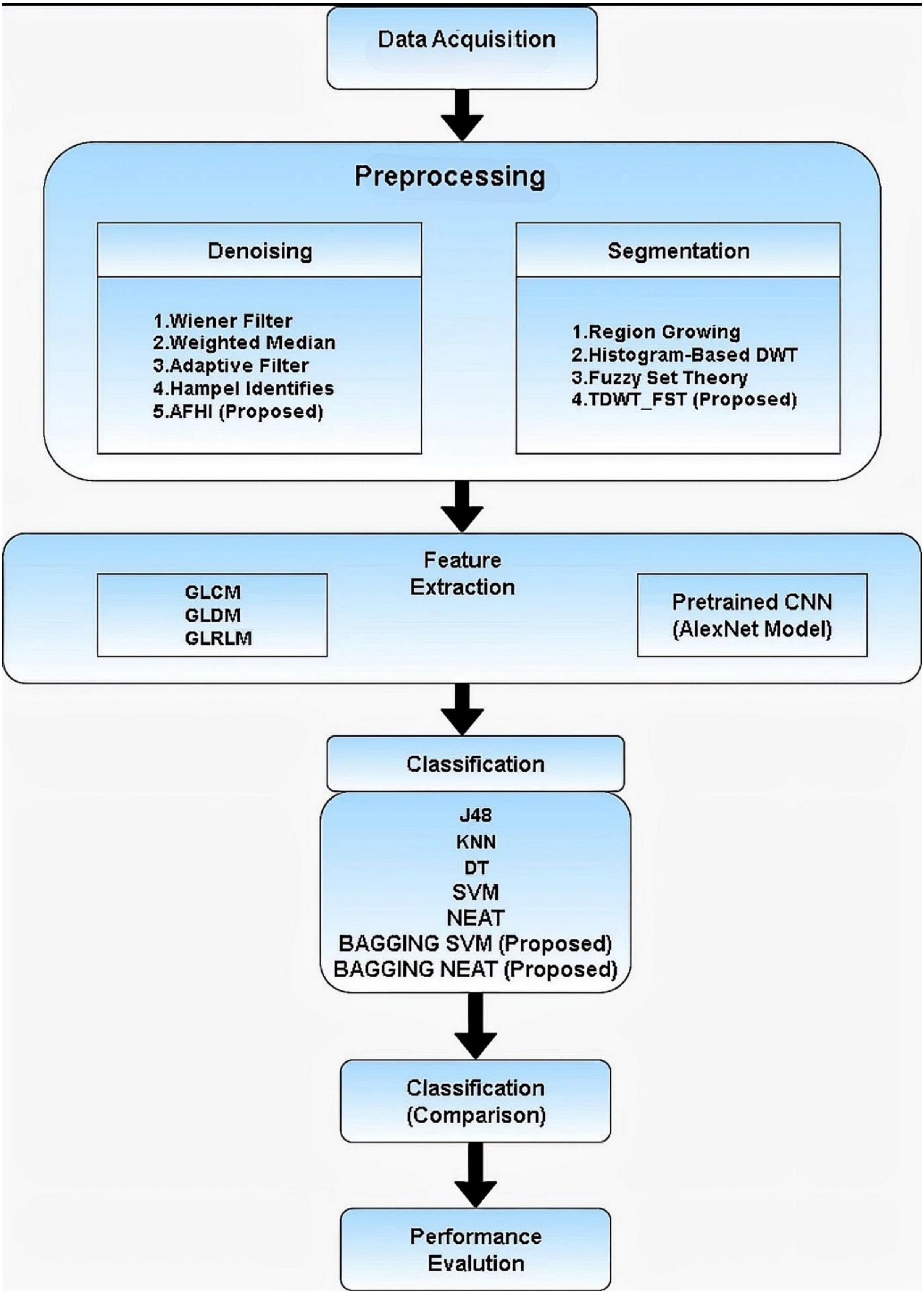

Figure 3.1 Overview of the Research Methodology for AD Classification

3.1.2 Pre-Processing

To improve the image quality before they are analyzed, pre-processing is required. Pre-processing is achieved in two stages:

i) De-noising methods aim to remove the noise from images, which can be detrimental to accurate analysis. During image de-noising, the wiener filter reduces noise based on the statistical characteristics of the signal. It especially excels in scenarios with known noise profiles, adjusting the filter according to local image variance. The weighted median filter, unlike simple median filters, this method assigns weights to neighboring pixel values. It focuses on preserving edges while effectively reducing impulse noise by considering how much each pixel contributes to the median calculation. An adaptive filter modifies its parameters dynamically according to local image conditions, which allows it to better suit varying noise types throughout different image regions. The hampel filter is a robust outlier filter that identifies and corrects outliers based on absolute deviation from local median values. It is particularly useful in scenarios where the image contains sporadic noise. The AFHI (proposed technique) novel de-noising method likely addresses specific challenges such as preserving critical features while removing noise, and enhancing overall image clarity. The objective of executing pre-processing is to exclude Gaussian and salt & pepper noises and highlight AD features for better diagnosis. The Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are the three-performance measures used to assess the proposed hybrid AFHI method.

ii) Segmentation involves partitioning processed images into meaningful segments to facilitate targeted analysis. It includes region growing, histogram-based DWT, FCM and TDWT-FST (proposed technique). The region growing starts with seed points and iteratively merges pixels based on predefined criteria such as color or intensity similarity, effectively identifying regions of interest. The histogram based discrete wavelet transform analyzes the frequency components of an image to facilitate segmentation based on the statistical distribution of pixel values across different regions. The FCM is a clustering-based approach that allows overlapping membership of pixels in multiple clusters, this algorithm is adept at handling ambiguous boundaries between different segments, making it highly suitable for medical imaging where clarity might be compromised. The TDWT-FST (proposed technique) indicates an integration of Transform Domain techniques with Fuzzy Set Theory to improve segmentation accuracy by considering texture information together with statistical data. The PSNR, SNR and SSIM are the three-performance metrics used in this study to assess region growing, histogram based discrete wavelet transform, fuzzy set theory FCM and TDWT-FST methods.

3.1.3 Feature Extraction

A pivotal phase where vital attributes from pre-processed images are identified for classification purposes. By examining brain images, conventional feature extraction methods such as the Gray Level Dependence Matrix (GLDM), Gray Level Run Length Matrix (GLRLM), and Gray Level Co-occurrence Matrix (GLCM) are essential for AD identification. The GLDM captures gray level distribution, revealing subtle changes in brain tissue. The GLRLM analyzes consecutive pixel patterns, helping detect texture irregularities. The GLCM examines spatial relationships between pixels to identify affected brain areas.

The research employs these three conventional methods GLDM, GLRLM and GLCM. Also, a pre-trained AlexNet model, a powerful CNN known for its ability to learn hierarchical representations of images are also applied. The basics of pre-trained AlexNet Architecture is described as follows. Five convolution layers, three max-pooling layers, two Normalized layers, two FCL, and one SoftMax layer in this architecture. Each convolution layer contains a convolution filter and a non-linear activation function called "ReLU." The pooling layers are utilized to carry out the max-pooling operation. The presence of fully connected layers results in a static input size. The AlexNet architecture and the given input size are displayed in Figure 3.2. In general, the input size is

224x224x3 however because of padding the input size happens to be 227x227x3. Over 60 million parameters are present in this AlexNet.

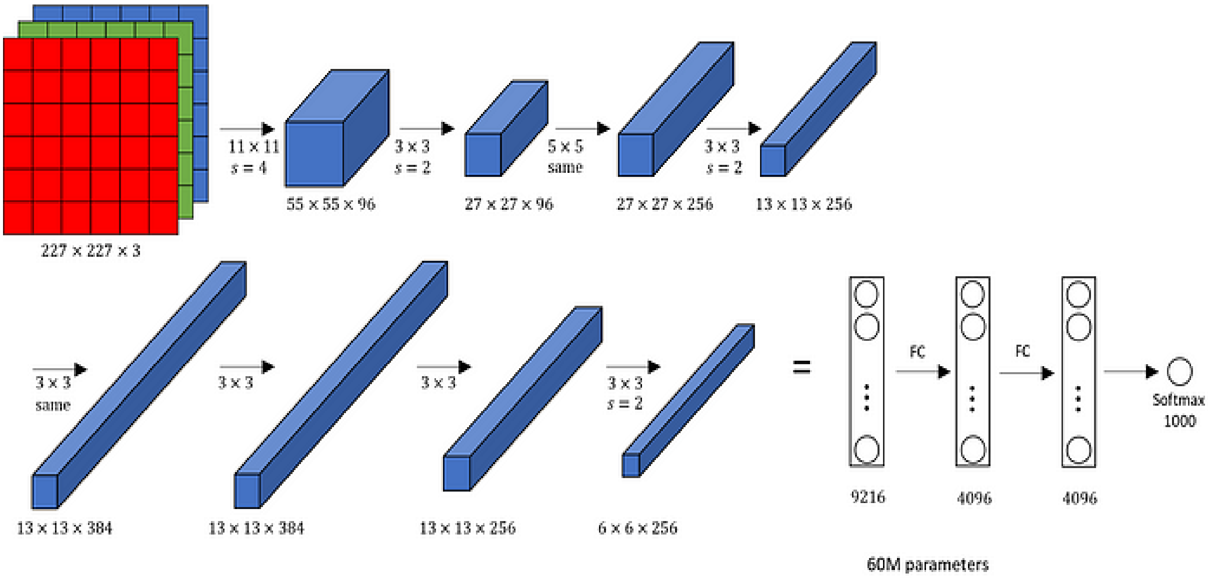

Figure 3.2 AlexNet Architecture

Among the features of AlexNet are With a batch size of 128 and a learning technique, ReLU is the activation function called "tanh." Max pooling is the most used pooling form. By applying a convolution filter to an image, the CNN architecture's max pooling gathers the map features. By decreasing the number of parameters and network computations, the image's spatial dimension is progressively decreased. A CNN AlexNet model that has been pre-trained and has FCL to extract features.

3.1.4 Classification Techniques

This phase involves the applying the proposed hybrid methods for classifying the extracted features into meaningful categories relating to AD. The two different kinds of hybrid methods are proposed for classification: BAGGING_SVM and BAGGING_ NEAT.

The first method, namely the BAGGING_SVM method, enhances the performance of AD classification by hybridizing the BAGGING and SVM algorithms. By averaging the predictions of several models trained on various subsets of data, bagging helps to reduce SVM overfitting. The BAGGING_SVM method is assessed using performance criteria such as accuracy, precision, recall, and F1-score.

The second method, namely BAGGING_NEAT, improves the performance of AD classification by hybridizing the BAGGING and NEAT algorithms. The BAGGING_NEAT method is assessed using performance criteria. Lastly, specific criteria are used to evaluate and compare the effectiveness of the two classification techniques.

3.1.5 Performance Evaluation

Evaluating the classification techniques is the goal of the research's last phase. Researchers can determine the better approach for identifying AD using neuroimaging data by comparing the BAGGING_SVM and BAGGING_NEAT approaches using performance measures. With the ultimate goal of more precise and prompt diagnoses in clinical settings, each of these stages makes a substantial contribution to improving the detection and diagnosis of AD using cutting-edge image processing and ML approaches.

3.2 Experimental Setup and Dataset Description

This section contains the dataset description and system configuration details. Intel Core Windows 10 and an Intel Core i7 7th generation processor with 2.7 GHz, 8 GB of RAM, and a 2TB SSD are used for the research. The proposed method is evaluated using Matlab 2020b tool. The Graphics Processing Unit (GPU) used is NVIDIA GeForce RTX 2080.

The datasets utilized in this investigation are described in the part that follows. These include the number of subjects and sample photos that were contained in the AD database. The specifics of acquiring brain neuron images for analysis and justification are covered. The suggested approaches were evaluated using the ADNI and OASIS image databases from https://adni.loni.usc.edu/ and KAGGLE.

3.2.1 Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset

In this research, brain neuron images from ADNI dataset were used. The ADNI was established in 2003 as a collaborative effort involving the National Institute on Aging (NIA), National Institute of Biomedical Imaging and Bioengineering (NIBIB), the Food and Drug Administration (FDA). It aimed to investigate the potential of combining serial MRI, PET, various biological markers, and clinical and neuropsychological assessments to monitor MCI and AD stages progression.

ADNI dataset utilized for this research comprises 570 subjects, classified into different groups: 211 Healthy Controls (HC), 188 diagnosed with MCI, and 171 diagnosed with AD. To ensure diagnostic consistency across various subsets within ADNI (ADNI, ADNI2, ADNIGO, and ADNI3), subjects had to meet specific additional criteria, aside from diagnoses made by clinicians based on clinical interviews and examination results.

Specifically, Healthy Controls (HC) were required to have a Mini-Mental State Exam (MMSE) score of at least 24 and a Clinical Dementia Rating (CDR) of 0. For individuals diagnosed with MCI, the criteria included an MMSE score of 24, a CDR of 0.5, and a Memory Box score of 0.5. Subjects diagnosed with AD needed to exhibit an MMSE score less than 27 and a CDR of 0.5. Here's a tabular representation summarizing the composition of subjects within the ADNI dataset.

Table.3.1 ADNI dataset description

CDR	Image Count	Corresponding Mental state
0	1676	Non Dementia(Normal)
0.5	896	Very Mild Dementia(stage 1)
1	65	Mild Dementia(Stage 2)
2	1158	Moderate Dementia(stage 3)

Table 3.1 outlines the distribution of subjects categorized by diagnosis within the ADNI dataset, showcasing the individuals count included in each diagnostic category.

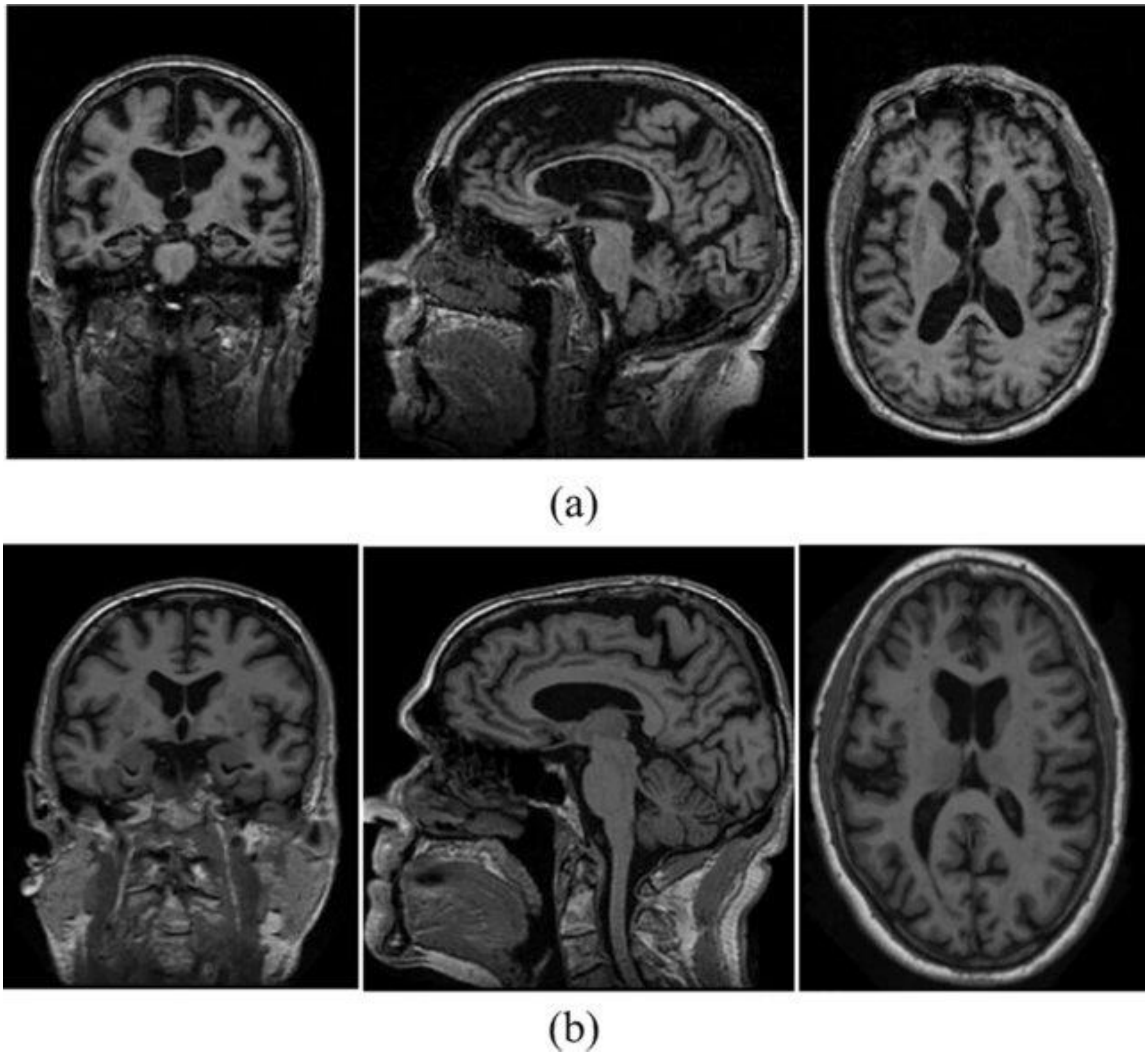

Figure 3.3 ADNI dataset samples

Brain MRIs from the ADNI database are displayed in the figure above, exhibiting coronal, sagittal, and axial views from left to right. Figure 3.3 panel (a) showcases MRI images from individuals diagnosed with Alzheimer’s disease, while panel (b) displays images from healthy controls. Figure 3.3 (a) & (b) shows the three different planes such as coronal (left), sagittal(middle) and axial(right).

3.2.2 Organization for the Advancement of Structured Information Standards (OASIS) dataset

From the OASIS dataset, a total of 3795 images were included, comprising 1200 Non – Demented, 1200 Very Mild Dementia, 1200 Mild Dementia, and 195 Moderate Dementia with AD. Similar to ADNI subjects, individuals in the OASIS dataset had to meet specific criteria for MMSE and CDR scores. Additionally, diagnoses were made by clinicians based on thorough clinical interviews and examination results. Here's an updated breakdown of subjects within the OASIS dataset:

Table.3.2 OASIS-3 Dataset description

CDR	Image Count	Corresponding Mental State
0	1200	Non-Dementia (Normal)
0.5	1200	Very Mild Dementia (stage 1)
1	1200	Mild Dementia (Stage 2)
2	195	Moderate Dementia (stage 3)

Table 3.2 provides an overview of the distribution of subjects categorized by diagnosis within the OASIS-3 dataset, demonstrating the number of individuals included in each diagnostic category - Healthy Controls and AD.

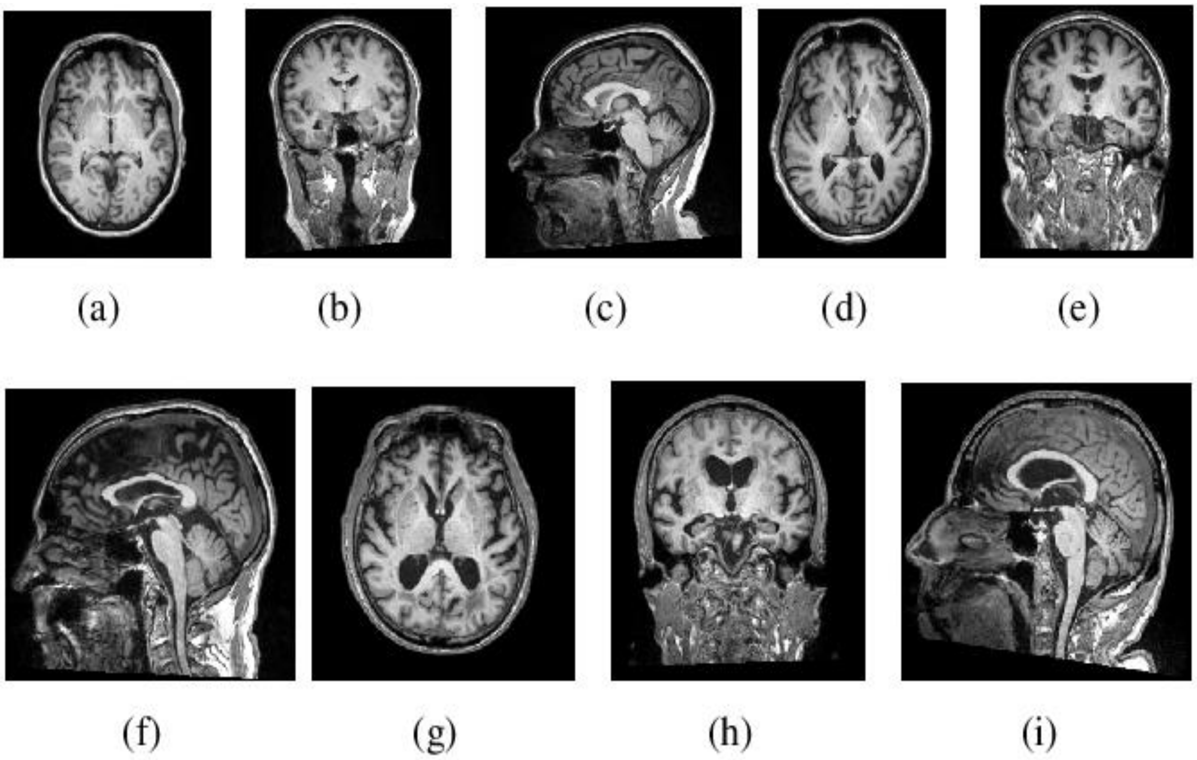

Figure 3.4 OASIS dataset samples

Above figure presents sample images sourced from OASIS dataset. Figure 3.4 panels (a), (b), and (c) showcase images in axial, coronal, and sagittal planes, respectively, depicting a patient categorized as CN. In contrast, figure 3.4 panels (d), (e), and (f) display images from a patient diagnosed with MCI across axial, coronal, and sagittal views. Finally, figure 3.4 panels (g), (h), and (i) exhibit images from a patient diagnosed with AD across axial, coronal, and sagittal planes.

3.3 Summary

In this chapter, the outline of the research procedure of all the proposed methods, which contains data acquisition, pre-processing techniques like de-noising and segmentation, then the feature extraction techniques like GLDM, GLRLM and GLCM also, a pre-trained AlexNet model. The classification methods such as BAGGING_SVM and BAGGING_NEAT are explained in brief. This chapter discusses about the experimental setup and the dataset description in detail. ADNI and OASIS datasets used to evaluate the proposed methods that is suitable for the training are discussed.