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Enhancing insights: unravelling the potential of preprocessing MRI for artificial intelligence based Alzheimer's disease classification

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6.1 Introduction

Neurodegenerative Disorders (ND) are a group of conditions characterized by the gradual degeneration and dysfunction of neurons in the central nervous system, and sometimes in the peripheral nervous system. These diseases primarily affect the structure and functioning of the brain, leading to a progressive decline in cognitive abilities, motor skills, and overall neurological function (Amor et al., 2010). These diseases have complex causes that involve genetic mutations, environmental factors, abnormal protein accumulation, oxidative stress, and inflammation. They occur with varied symptoms such as memory loss, cognitive impairment, movement difficulties, muscle weakness, and changes in behavior and mood. If not early detected, the symptoms worsen over time and can impact daily functioning and independence (Liu et al., 2017).

Alzheimer's Disease (AD), Parkinson's Disease (PD), Huntington's Disease (HD), and Amyotrophic Lateral Sclerosis (ALS) are prominent ND (Ahmad et al., 2017). Although these diseases have

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distinct characteristics, they demonstrate commonalities regarding underlying mechanisms and their impact on the nervous system. Individuals with ND experience various physical, cognitive, and emotional effects. Cognitive decline typically involves memory, problem-solving, and attention difficulties, while motor symptoms such as tremors, muscle stiffness, and coordination issues can worsen over time and lead to mobility problems (Sun & Wang, 2018). Daily activities like bathing, dressing, and eating may become challenging without assistance, and communication difficulties may arise, with speech becoming slurred or difficult to understand. Individuals may also experience mood swings, irritability, and other behavioral and emotional changes. Providing support to those with ND can be challenging for caregivers, with physical, emotional, and financial burdens to consider. Different factors, such as age, healthcare access, and location, affect the mortality rates of ND (Schulte et al., 1996). AD is the most common among the ND, causing 1.5 million global deaths in 2019 (Liu et al., 2019). PD may lead to higher mortality rates due to complications, while HD has higher mortality rates due to pneumonia, choking, or falls. ALS reduces life expectancy to two to five years postdiagnosis, but medical care and research advancements can influence mortality rates over time. Medical practitioners can detect ND through clinical evaluation, medical history assessment, and diagnostic tests. These tests include cognitive testing, imaging techniques, biomarker analysis, genetic testing, and electrophysiological tests. It is imperative to consult with a healthcare professional for an accurate diagnosis and appropriate management. This chapter concentrates on AD, the different biomarkers, especially Magnetic Resonance Imaging (MRI), and its preprocessing pipeline.

The neurodegeneration in AD affects cognition and is caused by structural changes in the brain (Scheltens et al., 2016). Typically, patients don't exhibit diagnostic signs until after irreversible neural damage has already taken place. AD is an untreatable disease using conventional medication, a life changing neurological sickness affecting the elderly, leading to several patient hardships. The World Alzheimer's Report (Gauthier et al., 2022)warns of an immense rise in AD cases by 2050. The neurological disease is found to affect elderly people succumbing to several hardships. AD-inflicted patients must endure many difficulties like memory loss, behavioral changes, and vision and mobility impairment, which affect their lives in day-to-day activities (McDade, 2022). Therefore initiating treatments as soon as AD is discovered is essential to slow the disease's progression and improve patients' quality of life.

Early AD detection using computer-assisted systems using neuroimaging data may be feasible, given the rapid development of machine learning and scanning. In recent years artificial intelligence (AI), in particular machine learning (ML), has attracted many researchers to contribute in diverse fields and challenging research assignments such as: anomaly detection (Lalotra et al., 2022; Yahaya et al., 2021; Yahaya et al., 2020), brain signal analysis (Fabietti, 2020a; Fabietti, 2020b; Fabietti et al., 2022; Fabietti, Averna et al., 2020; Fabietti et al., Mahmud & Lotfi, 2020, 2022; Rahman et al., 2020; Tahura et al., 2021; Wadhera & Mahmud, 2022a), neurodevelopmental disorder assessment and classification focusing on autism (Ahmed, 2022; Al Banna et al., 2020; Biswas, Kaiser, et al., 2021; Ghosh, Banna, et al., 2021; Mahmud et al., 2022; Sumi et al., 2018; Tania et al., 2021; Wadhera & Mahmud, 2022b), neurological disorder detection and management (Al Mamun et al., 2021; Biswas et al., 2021; Jesmin et al., 2020b; Shaffi et al., 2022; Ullah et al., 2018), supporting the detection and management of the COVID19 pandemic (Bhapkar et al., 2021; Jesmin et al., 2020a; Kumar et al., 2021; Mahmud & Kaiser, 2021; Paul et al., 2022; Prakash et al., 2021; Satu, 2021), elderly monitoring and care (Nahiduzzaman et al., 2020), cyber security and trust management (Ahmed et al., 2021; Esha et al., 2021; Farhin et al., 2020b, 2020a; Islam et al., 2021; Zaman et al., 2021), ultrasound image (Singh et al., 2021), various disease diagnosis (Chen, 2022; Deepa et al., 2021; Kumar, 2022; Mammoottil, 2022; Mukherjee, Bhattacharyya, et al., 2021; 2021; Zohora et al., 2020), smart healthcare service delivery (Biswas, 2021; Farhin et al., 2021; Kaiser et al., 2020), text and social media mining (Adiba et al., 2020; Ghosh, 2021; Rabby, 2018), understanding student engagement (Ahuja, 2021; Rahman et al., 2022), and so on. Developments in AI techniques have augmented the diagnosis of AD with accurate results in an efficient manner using medical data that includes images from Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Computerized Tomography (CT). Deep learning with MRI has become a powerful technique because of its ability to extract high-level characteristics through a local connection, weight sharing, and spatial invariance (Li et al., 2021).

Additionally, MRI is an imperative non-invasive imaging technique that can effectively detect structural and functional changes in the brain. It is the ultimate tool to identify significant indicators of AD and reliably track its progression (Brier et al., 2016). However, the MRI images can be distorted or contain noise, irregularities, and motion and intensity inhomogeneity, which might prove fatal for accurate AD decision-making (Krupa & Bekiesińska-Figatowska, 2015). Therefore it necessitates the need to develop tools to preprocess the MRI before it is fed to AI models.

This research aims to discover the different artifacts or anomalies present in an MRI scan and to evade the irregularities at each step by preprocessing the images. The dataset is taken from widely used databases like the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. Preprocessing MRI scan images is essential for accurately detecting and analyzing AD. Preprocessing steps aim to minimize these artifacts, making it easier for researchers and clinicians to identify and measure alterations in brain structures associated with AD. We found some preprocessing steps from the literature, including motion correction, image registration or normalization, bias field correction, mitigating noise, skull stripping, and segmentation (Manjón, 2017).

The distortions seen in MRI scans can be due to the patient's movements during the scan process. The distortions due to patient motion can be corrected using algorithms that will realign the images. MRI scans of a patient are taken at different time intervals and are commonly represented as 3D images. A point in the 3D volume is called a voxel. Due to the difference in time points of the image slices, the voxel points of all the slices in a volume may not be aligned to a common space. The image registration preprocessing step helps to register the voxel obtained from different time points to a common anatomical space and subsequently helps in accurate comparisons. Nonuniformities in the magnetic field can affect the intensity of the MRI scans. These image intensity values can be normalized using bias field correction algorithms (Perumal & Velmurugan, 2018). Eliminating irregularities is another preprocessing step where problems such as image noise are corrected which can adversely affect the accuracy and subsequent analyses in the AD detection process.

For AD detection, it would be ideal for medical practitioners to obtain accurate and exclusive MRI scans without structures of the head such as the skull, scalp, and eyes. Skull stripping algorithms can be used as a preprocessing step to eliminate the non-brain structures. All these non-exhaustive preprocessing steps result in obtaining MRI scans suitable for accurate AD diagnosis by medical practitioners and early detection using AI techniques (see Fig. 6.1).

In each preprocessing level, a quality assessment must be carried out. Several methods identified from the literature include Signal-to-Noise Ratio (SNR), Contrast-to-Noise Ratio (CNR), Image Similarity Metrics (ISM), Fractional Anisotropy Analysis (FAA), Chi-squared Analysis (CA), and Mask Quality Analysis (MQA) (Cai et al., 2021). The SNR measures the ratio

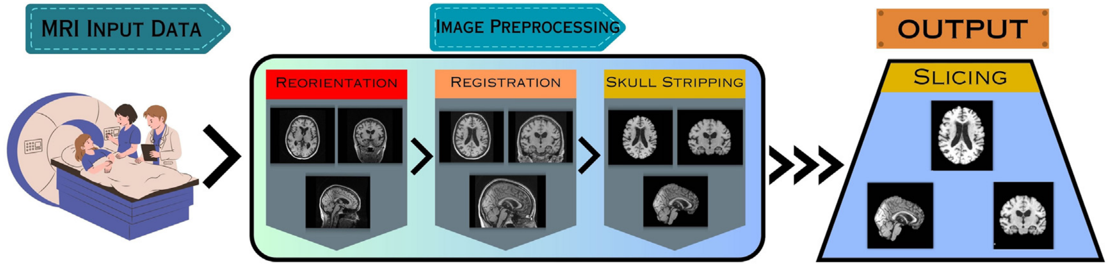

Figure 6.1 Pipeline. Preprocessing pipeline for MRI scans.

between the strength of the MRI signal to the background noise (Johnson, 2006). Therefore a high SNR means better image quality. CNR measures the ratio between the contrast of the MRI signal to the background noise (Rodriguez-Molares et al., 2018). A high CNR indicates better contrast enabling one to differentiate between tissues. ISM compares the preprocessed image with that of a good quality reference image and measures the degree of similarities like the intensity of the image, texture, or shape (Kokare et al., 2003).

We found several commonly used preprocessing tools from the literature, including the FSL (FMRIB Software Library) (Smith et al., 2004), Free Surfer (Sarica et al., 2014), Statistical Parametric Mapping (Kiebel et al., 1997), Advanced Normalization tools (Cieslak et al., 2021), and AFNI software (Cox, 2019). This chapter discusses the use of the FSL software for each preprocessing step and quality assessment.

The rest of the chapter is organized as follows: Section 6.2 presents a brief literature review of AD detection with MRI and the preprocessing pipeline, Section 6.3 presents a detailed description of the preprocessing pipeline considering MRI, and Section 6.4 presents a discussion on the quality assessment methods prevalently used with MRI data. Conclusions are drawn in Section 6.5.

6.2 Literature review

This literature review examines the existing anomalies of MRI scans and evades the irregularities at each step by preprocessing the images. We explore the different preprocessing steps, including reorientation, image registration, skull stripping, and slicing. This review also identifies quality assessment techniques like SNR, CNR, ISM, FAA, CA, and MQA. It also covers software tools concurrently used for the preprocessing steps.

This literature thus gives a thorough overview of the current approaches for preprocessing MRI scans and suggests critical topics for further study. By integrating the available research on preprocessing MRI, the aim is to develop a robust and user-friendly application for MRI preprocessing that will produce accurate and noise-free images for further analysis with AI tools and prediction subsequently.

6.2.1 Key findings, theories, and trends

MRI is a medical imaging technique that uses a powerful magnetic field, radio waves, and a computer to create detailed images of the inside of the body. MRI images are used to diagnose neurodegenerative illness for example AD, Glioma, and different types of cancers. MRI processing methods often use preprocessing methods to develop accurate models of diagnosed diseases. All studies used different preprocessing methods to improve and enhance MRI scans for easy diagnosis of disease.

A study (Perumal & Velmurugan, 2018) used MRI as the initial way to more accurately diagnose disorders by looking for lung cancer. There are a lot of irrelevant items that reduce accuracy, so the objective is to enhance MRI images of the lung using filtering techniques, removing noise, enhancing contrast, and increasing pixel intensity as part of preprocessing (Maitra et al., 2011). This process makes the image of the scan more suitable than the original image because of the preprocessing methods. The original image was converted to a grayscale image and resized images into different sizes, and noises were removed by using the filtering technique from the gray image and applying the Adaptive Histogram Equalization to enhance the contrast of the image (Solomon & Breckon, 2011). The difference between maximum and minimum pixel intensity was considered to be the contrast. Another technique Salt and Pepper was used for noise removal. Salt and pepper noise distorts images during quick transients, such as faulty switching places (Mythili & Kavitha, 2011). In Gaussian noise, the original value of each pixel in the image changes by a small amount. Gaussian noise indicates the probability density function of the normal distribution which plays the most important role in both theory and applications (Bar-Shalom et al., 2001). Speckle noise is a granular noise that inherently exists in and degrades the quality of the active radar and synthetic aperture radar images. Ultrasonic medical devices are usually characterized by this type of noise (Mansourpour et al., 2006). The report discusses filters that are used for enhancing an image, in which the high frequencies are suppressed, for example smoothing the image, or the low frequencies are enhanced or detected, detecting edges (Lysaker et al., 2003). Inverse filtering and noise smoothing are optimally balanced by the Wiener filtering approach. The blurring is simultaneously inverted, and the additive noise is removed (Diniz, 2008). Another filtering technique, the Median filter, depends on certain conditions, such as changing the size of images (Leavline & Singh, 2013).

In the article by Srivaramangai et al. (2017), the authors focus on preprocessing methods including noise removal and image enhancement while processing MRI images for colorectal cancer. Using statistical methods that produce noise free edges that are sharpened and intensified, performance is measured. The process involves low level operations such as picture improvement, noise reduction, and sharpening. Any imaging modality, including CT, PET, and MRI, typically produces pictures with artifacts for one of the following reasons: Metal artifacts and hardening of motion beams can create patient specific artifacts, while processing techniques and equipment-based abnormalities are typically brought on by the partial volume, ring, and staircase effect (Jabbar, 2014). The preprocessing method used is similar to (Perumal & Velmurugan, 2018) and enhances the clarity, brightness, and contrast, eliminating the noise, and adjusting the color, hue, and intensity levels. The authors begin the preprocessing with scaling as the first step, Noise removal is based on filtering and multi-fractal wavelet followed by general contrast enhancement and adaptive histogram equalization (Kamboj & Rani, 2013). Mean, median, and adaptive median filters are three types of filtering algorithms used for preprocessing. The authors prove that the techniques used in their work are beneficial as they produce a high quality image without losing any information and offer a crisp image free of any artifacts. Additionally, the techniques aid in the accurate detection of the disease or determining the stage of colorectal cancer.

Dang et al., 2022 address the treatment of Glioma grading by using MRI-based classifications to create a reliable model for Glioma diagnosis with three key steps. First, UNet architecture and preprocessing methods are used to segment the MRI images. In the second step, the brain tumor regions are extracted using segmentation (Decuyper et al., 2021). Finally, the Glioma is classified as high and low grade with the help of VGG and GoogleNet implementations. These input categories are used in conjunction with the VGG and GoogleNet classification algorithms. Performance has been improved by optimizing each hyperparameter (Ahammed Muneer et al., 2019). The proposed models were then assessed using the Dice coefficient, Precision, Recall, and Accuracy performance criteria to choose the most efficient segmentation and classification method. Significant visualization maps are also produced with Grad-CAM. Except for FLAIR images, which are sufficiently clear to identify the edema with the hyper-intense regions, each of the MRI modalities would be altered by the various values. The authors claim that the main benefit of their work is when using the Gamma distortion tool. Using the exponent "Gamma," this technique can be used to enhance photos or movies, producing high-quality visuals that can be utilized for precise prediction.

The work by Mathew and Christy (2022) prepares the MRI scans for segmentation and classification, reviews the different preprocessing techniques used in brain MRI images, and emphasizes how important it is that the image be free of extraneous elements and noise. The image preprocessing stage includes a variety of changes that will be made to the initial image to improve quality before segmentation and classification operations are carried out. Image registration, bias field correction, normalization, histogram equalization, skull stripping, and filters were the preprocessing techniques used in this research article. The work proves beneficial when compared with concurrent research in that the histogram equalization method produces more accurate results. The article sheds light on future work in experimenting with more automated preprocessing tools for MRI scans with minimal noise.

Cervical cancer is the fourth most prevalent gynecological malignant cancer worldwide, according to Bnouni et al. (2021). This disease is one of the main reasons why women die from cancer. In the article, the author discusses MRI being used to determine the cancer stage (tumor size, nodal status, and local extension), which affects treatment planning. The research work, as part of preprocessing, uses an automated cervical tumor segmentation technique that will reduce the burden of manual segmentation and is essential for accurate cancer diagnosis and prognosis. However, due to intensity inhomogeneity, poor contrast, and noise present in medical images, conventional automatic segmentation methods, including DL methods, may not succeed. The research article recommends the use of an ensemble preprocessing method to enhance the segmentation performance of a DL method for cervical cancer. The preprocessing steps discussed in this work are sharpening and smoothing, morphological, and histogram-based image processing methods. The experiments produced segmentation maps of high precision and significance and an accuracy of 76.8% is an encouraging result. The authors claim that the preprocessed segmentation maps have helped AI techniques to produce predictions with high-performance measures. The authors are working on integrating the present model with random field models to create quality images with higher accuracy.

Diffuse is a dedicated toolbox written in Python language for preprocessing MRI images and is publicly available on GitHub (Brun et al., 2019; Brainvisa-Diffuse, 2023) used numerous preprocessing techniques with MRI scans using the diffuse pipeline. The capacity of each technique to recover the correct geometry of the brain, the estimation and derivation of tensor model indices in the white matter, and ultimately the spatial dispersion of six well known connection routes are all compared by the authors. The research proves that eddy current correction improves the performance of obtaining better scan images. However, for susceptibility distortions, the experiments justify the need for further smoothening of images. The article highlights their attempts to obtain a measure of the strong dependence of diffusion metrics in the preprocessing settings. According to Rajeshwari and Sharmila (2013) the main objective of the research is to improve resolution and de-noise images to improve their quality. There also exists a need to enhance the image to maintain the edges and contour information in medical images after they have been effectively de-noised. The effectiveness of these methods is evaluated in this paper using the Peak Signal-to-Noise Ratio (PSNR). The preprocessor also includes filtration and resolution enhancement. According to this study, the resolution enhancement technique proved to show a higher PSNR than the denoised image.

The goal of Borole et al. (2015) was to learn about image processing methods for detecting brain tumors using MRI scans. The research paper discusses the various preprocessing methods—filtering, contrast enhancement, and edge detection using the MATLAB tool for the detection of brain tumor MRI images. The preprocessed images are further processed for Histogram threshold, Segmentation, and Morphological operation for precise and accurate prediction from the AI engine. This work has proved helpful for doctors in determining the early stages of brain tumors. In numerous research with MRI brain scans, nonbiological variations were found due to the effects of scanning and acquisition settings. Li et al. (2021) assess the preprocessing methods, including bias field correction and image resampling, to help remove the scanner anomalies and improve the radiomic features in brain MRI. The study further proves that the intensity normalization methods, though ineffective in removing scanner effects, improve the robustness of brain images. Suhas and Venugopal (2017) discuss in their article MRI image preprocessing using linear and nonlinear filters. The author experiments with the Linear smoothing or Mean filter, Midpoint filter, and the Nonlinear median filter (Goossens et al., 2009; Lysaker et al., 2003). The authors propose a new technique which is a combination of both the median and mean filters. The proposed, when compared with existing linear and nonlinear filters using statistical parameters like PSNR, SNR, and root-mean-square-error, shows improvement in denoising, and structural details are retained. The author proves the method to be beneficial for early detection and accuracy with AI engines.

Virtual phantoms are useful tools to assess the variability in MRI imaging to evaluate the impact of the different acquisition parameters (Bologna et al., 2019; Collins et al., 1998) use virtual phantom tools to identify the radiomic features of MRI images and evaluate the scanning parameters. The effect of these parameters is subsequently measured to understand the effect of MRI image preprocessing and the stability of radiomic features. The authors show that the preprocessing has significantly increased the robustness of the radiomic features.

6.2.2 Gaps and limitations

According to the literature review presented above, the difficult task encountered is the removal of images during the AI classification process with the preprocessing method segmentation. This is due to the segmented areas of these photos that are not part of the ground truth (Dang et al., 2022). This anomaly also affects the bias in the classification results.

Another performance issue occurs due to image distortions, besides the motion of patients, and the temper of the patient, like anxiety, confusion, anger, etc. Such emotions were difficult to mitigate (Bnouni et al., 2021). In the case of identifying the central white matter for the ROI based analysis, the difficulty in quantifying the differences between the pipeline performance considerably affects denoising the MRI image (Brun et al., 2019).

Need to address the problem by using MRI based classification to create a precise model for Glioma diagnosis (Dang et al., 2022). Removing some images during classification and segmentation is one of the trickiest. Because the segmented portions of these images are not based on ground truths, it would be useless to incorporate the non-tumor regions into classification models as input. However, while removing records of poor performance, this issue also introduces bias into classification results. Also, it is highly necessary to recognize the complex structure of the brain's structure and image processing techniques for brain tumor detection (Borole et al., 2015).

The preprocessing and harmonization techniques affect the elimination of the scanner effect in the radiomic features of brain MRI (Li et al., 2021). However, it is unable to eliminate radiomic feature-level scanner effects, and the radionics studies' reproducibility continues to be problematic.

This literature review discusses the different studies that have used MRI scans to diagnose various diseases, including AD, and implement numerous preprocessing techniques, including ensemble methods, to help de-noise the images for doctors, which is one of the most important steps for treatment. Studies have proven benefits in showcasing preprocessing techniques with good performance measures. The preprocessing techniques will help give robust, accurate, precise, and feature rich images suitable for early detection and accurate prediction using AI-based machine learning and deep learning techniques. According to these research articles reviewed here, current and future research aims to better solve all the limitations and gaps found in the literature review.

6.3 MRI preprocessing pipeline

In this section, we provide a comprehensive pipeline for preprocessing MRI scans. The process involves reorientation, registration, skull stripping, and slicing. The preprocessing tasks were conducted on an Apple macOS machine having an Apple M2 CPU, 8 GB of RAM, and a 10-core GPU. We obtained the data used for the preparation from the ADNI (https://adni.loni.usc.ed.u/) (Jack et al., 2008). ADNI has been consistently developing clinical, imaging, genetic, and biochemical biomarkers since its establishment in 2004. These biomarkers are essential in the early detection and tracking of Alzheimer's disease. We downloaded T1-weighted MRI images with Magnetization Prepared Rapid Gradient Echo (MPRAGE) of individuals aged between 50 and 65 years and of either gender from ADNI. MPRAGE is a technique used in MRI machines to produce high quality anatomical brain tissue images, highlighting the contrast between gray and white matter (Mugler &

Brookeman, 1990). We acquired all datasets in NIfTI format from ADNI-1, ADNI-2, and ADNI-GO cohorts.

We used FSL (FMRIB Software Library) which is a popular software package created by the FMRIB Center at the University of Oxford. It provides various tools and techniques for processing and analyzing neuroimaging data, specifically functional MRI (fMRI) (Smith et al., 2004). In this study, we used FSL to perform tasks like image reorientation, registration, skull stripping, and slicing. This helps to better understand brain function and study neurological and psychiatric disorders. FSL incorporates important methods for neuroimaging analysis, which include, FSL reorientation, brain extraction tool (BET), and FLIRT (https://fsl.fmrib.ox.ac.uk/fsl/fslwiki). Fig. 6.2 shows the FSL IDE containing tasks that include preprocessing. However, in this study, we used command line tools of FSL to accomplish

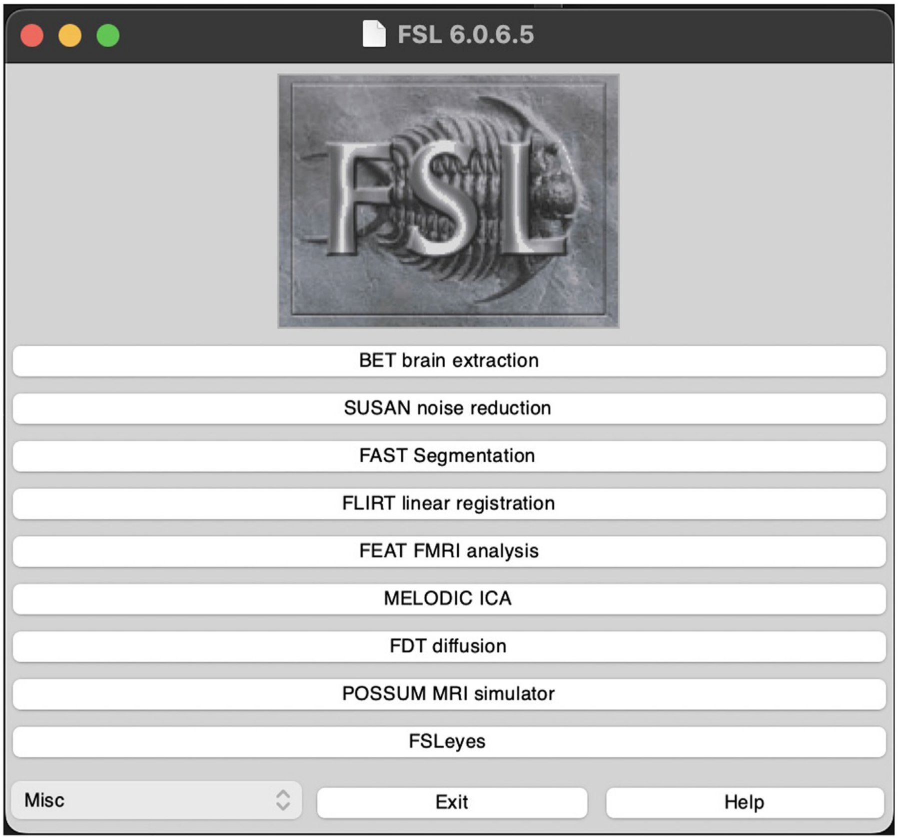

Figure 6.2 FSL IDE. The FSL (FMRIB) IDE for preprocessing

the preprocessing tasks that were run from the terminal window of macOS. We also used the "*fsleyes*" tool (refer Fig. 6.2) which is a powerful neuroimaging tool for exploring and analyzing MRI data processed with FSL. The tool allows for easy visualization of 2D and 3D data, with options for adjusting intensity, changing color maps, and applying overlays. "*fsleyes*" is an essential resource for researchers, clinicians, and educators in the field of neuroimaging. The following sections show the details of each preprocessing step using the FSL command line tool.

6.3.1 Reorientation of magnetic resonance imaging

Reorientation is a process of modifying the orientation of MRI images by applying transformations to align them with a standardized reference space (Mongerson et al., 2017). We used the command line tool "fslreorient2std" within FSL which is designed to standardize and reorient neuroimaging data. This ensures that the images are consistently oriented, enabling easier comparison and integration of data from different subjects or studies. The command line syntax for reorientation is given in the following statement:

```
fslreorient2std infname outfname
```

The "*infname*" parameter represents the input file name, which is the original MRI image that needs to be reoriented. The "*outfname*" parameter represents the output file name, specifying where the reoriented image will be saved. "*fsleyes*" is used to visualize the image obtained after reorientation as seen in Fig. 6.3. By using this command, we were able to align the image with a standardized orientation, facilitating comparison and compatibility across different analyses and software packages. This helps ensure consistency and improves the reliability of subsequent analyses and data integration.

6.3.2 Image registration

Image registration is the process of aligning different images to a common coordinate space. The command line tool FLIRT is used as a linear transformation tool such as translation, rotation, and scaling (Glasser et al., 2013). The tool aligns one image to another. It is commonly used for aligning different modalities

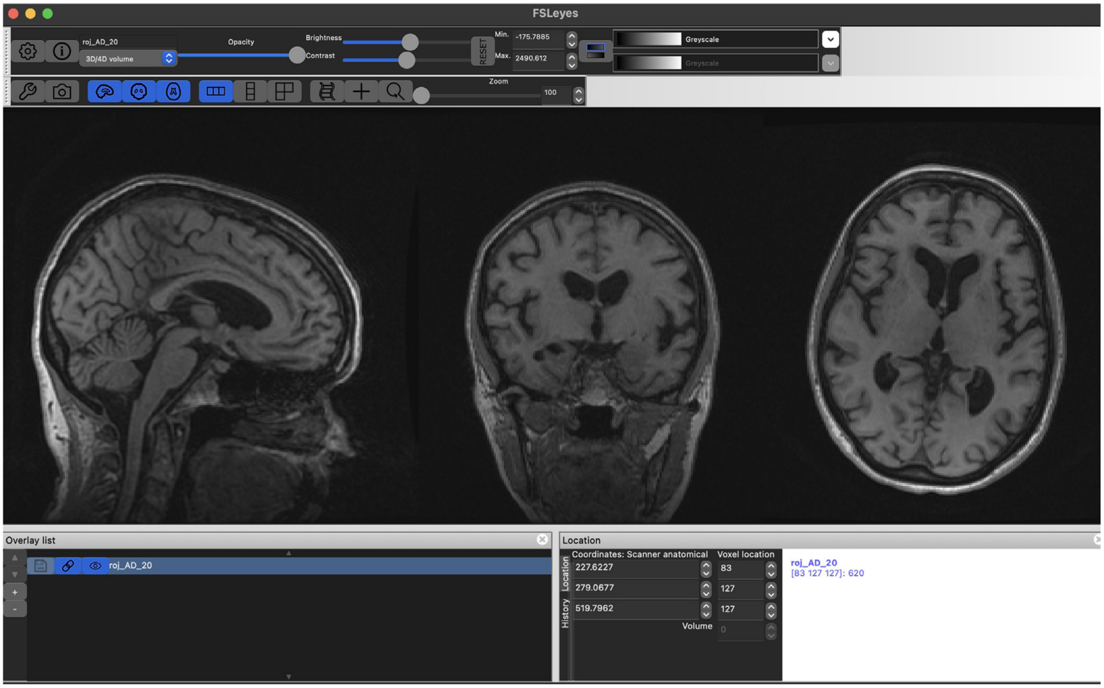

Figure 6.3 MRI after reorientation

of imaging data or aligning an individual's data to a template or standard space. The command line syntax for registration using the FSL tool is shown in the statement:

```
flirt -in rofname -ref referencefname -out outfname -omat
fname.mat -bins 256 -cost corratio -searchrx 0 0 -searchry 0 0 -
searchrz 0 0 -dof 12 -interp spline
```

Table 6.1 shows the "*flirt*" command with specific parameters for image registration, the breakdown of the commands, and their options, and Fig. 6.4 shows MRI images after registration.

6.3.3 Use brain extraction tool for skull stripping

The MRI image obtained after the process of registration contains non-brain tissues that need to be removed. Skull stripping is the process of isolating the brain region from non-brain tissues, like the skull, scalp, and nonbrain structures (Smith et al., 2004). This separation helps with focusing on analyzing and visualizing brain

Table 6.1 Parameters and their descriptions for the flirt command line tool.

Command	Options
flirt	This is the command to execute FLIRT
-in rofname	Specifies the input image file name to be registered
-ref referencefname	Specifies the reference image file name to which the input image will be aligned
-out outfname	Specifies the output image file name after registration
-omat fname.mat	Specifies the output matrix file name that stores the transformation matrix
-bins 256	Sets the number of histogram bins used for image intensity matching
-cost corration	Specifies the cost function to be used for registration, and in this case, the correlation ratio
-searchrx 0 0	Sets the search range for registration in the x direction which is set to 0 indicating no search
-searchry 0 0	Sets the search range for registration in the y direction which is set to 0 indicating no search
-searchrz 0 0	Sets the search range for registration in the z direction which is set to 0 indicating no search
-dof 12	Sets the degrees of freedom for the transformation model and 12 indicates a full affine transformation
-interp spline	Specifies the interpolation method to be used during resampling

structures. Skull stripping is a crucial preprocessing step for different neuroimaging analyses, including brain morphometry, functional connectivity, and diffusion tensor imaging. BET produced skull-stripped images are visually appealing and easier to interpret, making them useful for educational, research, or clinical purposes. The command line syntax for skull stripping is shown in the statement:

```
bet infname outfname -R -f 0.5 -g 0
```

To perform skull stripping on an MRI image, you must specify the input file name as "*infname*" and the output file name as "*outfname*." BET (Brain Extraction Tool) is a widely used tool in FSL for skull stripping and uses a fractional intensity threshold (*f* parameter) to segment the brain based on intensity values. This threshold determines the sensitivity of the algorithm and can be adjusted to include more or less brain tissue. Therefore a "*f 0.5*" is used to control the sensitivity of the algorithm. Additionally, there are two other options to consider: "*R*" for robust brain center estimation, and "*g 0*" to refine the skull stripping using local intensity gradients. A higher fractional intensity threshold includes more

Figure 6.4 MRI after registration

brain tissue, while a lower value removes more non-brain structures. Fig. 6.5 visualizes a skull stripped MRI scan.

6.3.4 The slicer tool to extract planes

The reoriented, registered, and skull-stripped MRI now exists in a 3D format consisting of three planes, namely axial, coronal, and sagittal. With the help of the Slicer software, it is possible to generate a 2D view of any plane from an input volume (Pieper et al., 2004). Slicer is an open source tool that allows for medical image analysis, research, and visualization. It offers various features to process and explore medical imaging data including MRI, CT, and PET. The command line syntax for slicing is shown in the statement:

```
slicer infname -z -90 outfname
```

The breakdown of the above statement includes the following components: "*slicer*" which is used to invoke the software,

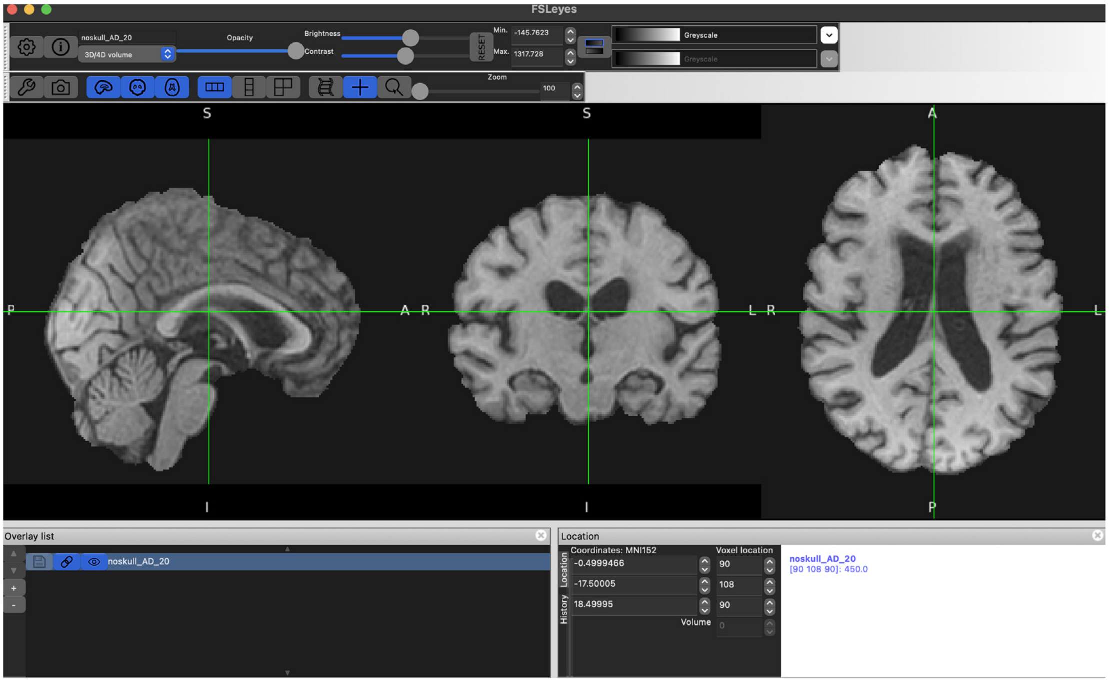

Figure 6.5 MRI after skull stripping

"*infname*" which stands for the input volume file name containing the MRI data, "$z - 90$" which specifies the desired orientation and slice position for the generated image (in this case, it indicates an axial or transverse view and selects the slice located at 90 mm along the *z-axis)*, and "*outfname*" which is the output file name or path where the image will be saved. The orientation x and y represent the sagittal and coronal planes respectively. By executing this command, the *Slicer* software will load the input volume and extract the desired slice at the specified position. The resulting 2D axial view image will be saved under the specified file name or path, allowing for visualization, analysis, or further processing of the specific slice of interest.

6.4 Conclusion and future work

This study aims to use various preprocessing techniques to enhance the accuracy of predicting AD before its symptoms appear. By utilizing AI techniques, the project seeks to identify any irregularities in MRI scans that could pose a threat to accurate AD prediction if left unaddressed.

The importance of preprocessing lies in its potential to reduce healthcare costs, improve the accuracy of predictions, and ultimately save lives by mitigating any irregularities in MRI scans. This proposed research work has numerous academic and scientific significance. The research investigates into the details of MRI scan images, identifying any anomalies that may exist, and the potential harm they could cause if not dealt with properly. By utilizing the FSL tool, the study created preprocessed models that will ensure better performance measures when predicting AD with AI techniques. The results of this research will contribute to the development of more effective tools, ultimately improving the accuracy and effectiveness of AD prediction.

Currently, most of the studies use preprocessed data from public databases without considering its quality, which is crucial in medicine. This research focuses on enhancing MRI images through preprocessing techniques. The results of the preprocessing are evaluated for quality and reviewed for further improvement. The findings of this research will aid various AI techniques in providing more accurate and precise disease predictions, increasing trust in the medical field. Additionally, this project has the potential to benefit the human community by addressing local healthcare challenges, advancing scientific knowledge in various fields, and promoting innovation, research expertise, and career growth. The study also has the potential to improve the accuracy of AI-generated results by identifying and eliminating irregularities in medical biomarkers. This study can potentially facilitate the development of more accurate and transparent predictive models and decision-support tools for healthcare providers. Ultimately, this research can help healthcare professionals obtain clean and improved data suitable for AI technologies in predicting AD. In summary, this project contributes to advancing AI and preprocessing steps of MRI scans. The FSL encompasses other tools for noise reduction, segmentation, and diffusion which can be explored in the future. In addition, the study can further explore bias correction and enhancement besides quality assessments at each phase of preprocessing.

6.5 AI disclosure

During the preparation of this work, the author(s) used Grammarly to rephrase sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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