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Optimizing MRI Preprocessing Techniques for Enhanced Alzheimer's Disease Detection

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Abstract

Alzheimer's disease (AD) presents an acute global health challenge, with a sharp rise in cases prompting urgent action from the healthcare community. Recognizing the potential of Artificial Intelligence (AI) in early detection and treatment planning, researchers are focusing on optimizing MRI scans, a key diagnostic tool. However, MRI images often suffer from distortions like motion artifact and intensity fluctuations, compromising AI predictions. This study investigates MRI artifacts and proposes preprocessing solutions such as reorientation, registration, skull stripping, and slicing to enhance image quality. Integration into a user-friendly GUI aims to streamline healthcare operations, empowering medical professionals with accurate AD predictions. This research advances early detection efforts, improving patient outcomes and fostering innovation in medical imaging.

Keywords: *Artificial intelligence (AI); Preprocessing; Registration; Reorientation; Skull Stripping; Slicing*

1. Introduction

Alzheimer's disease (AD) is a prevalent neurodegenerative ailment that affects cognition and is brought on by structural changes in the brain [1]. Typically, patients don't exhibit diagnostic signs until after irreversible neural damage has already taken place. AD is an untreatable, life-changing neurological sickness affecting the elderly, leading to several patient hardships. The World Alzheimer Report [2] warns of an immense rise in AD cases by 2050. AD-inflicted patients must endure many difficulties like memory loss, behavioral changes, and vision and mobility impairment, which affect their life in day-to-day activities. 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 life in day-to-day activities [3]. Therefore, initiating treatments as

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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. Developments in Artificial Intelligence (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 magnetic resonance imaging (MRI) has become a powerful technique because of its ability to extract high level characteristics through local connection, weight sharing, and spatial invariance [4]. 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 [5]. Therefore, it necessitates the need to develop tools to preprocess the anomalies of MRI before it is fed to AI networks.

This research aims to discover the different artifacts of anomalies of an MRI scan image 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 dataset (ADNI). 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 brain structure changes associated with AD. We found some preprocessing steps from the literature review, including image registration or normalization, reorientation, skull stripping, and slicing [6].

An MRI image can get distorted 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 scan of a patient are taken at different time intervals and are usually in three-dimensional format. 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 preprocessing step, image registration, helps to register the voxel obtained from different time points to a common anatomical space and subsequently helps in accurate comparisons. Non-uniformities in the magnetic field can affect the intensity of the MRI scan images. These image intensity values can be normalized using bias field correction algorithms [7]. Another preprocessing step is eliminating irregularities, such as image noise, that can adversely affect the accuracy and subsequent analyses in AD detection.

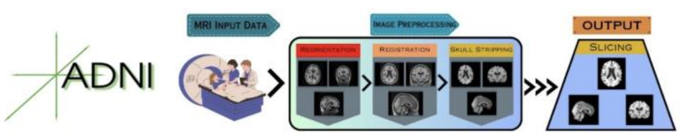

Fig. 1. Preprocessing Pipeline for MRI Image

For AD detection, it would be ideal for medical practitioners to obtain an accurate and exclusive MRI brain image without brain tissues such as the skull, scalp, and eyes. Skull stripping algorithms can be used as a preprocessing step to eliminate the non-brain tissues. All these non-exhaustive preprocessing steps result in obtaining MRI scan images suitable for accurate AD diagnosis by medical practitioners and early detection using artificial techniques. Figure 1 depicts the different stages in the preprocessing pipeline.

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, fractional anisotropy analysis, chi-squared analysis, and mask quality analysis [8]. The SNR measures the ratio between the strength of the MRI signal to the background noise [9]. Therefore a high SNR means better image quality. CNR measures the ratio between the contrast of the MRI signal to the background noise [10]. A high CNR indicates better contrast enabling one to differentiate between tissues clearly. Image similarity metrics compare the preprocessed image with that of a good-quality reference image and measure the degree of similarities like the intensity of the image, texture, or shape [11].

We found several commonly used preprocessing tools from the literature, including the FSL (FMRIB) software library [12], Free Surfer [13], Statistical Parametric mapping [14], Advanced Normalization tools [15], and AFNI software [16]. This research work also undertakes a comprehensive study of all available software tools and proposes an indigenous development of software methods for each preprocessing step and quality assessment software. Additionally, all the developed tools are proposed to be integrated into an interactive computer application that can ease the preprocessing operations of a healthcare professional.

The subsequent section of the article is structured in the following manner: Section 2 provides a concise overview of the existing literature using MRI preprocessing, Section 3 comprehensively explains the methodology of using the raw MRI and preprocessing techniques for AD diagnosis. The section also discusses the software design and integrating the preprocessing steps to ultimately produce a sliced image suitable for diagnosis. Section 4 discusses the results of the working of the application, and in section 5, conclusions are derived.

II. Review of Existing Literature

A. Overview: An introduction to the literature review section, outlining its purpose and scope.

A rising number of people die each year from Alzheimer's disease (AD), making it one of the significant causes of suffering and mortality globally. Numerous research works have examined AD's risk factors, diagnosis, and treatment for several years. AD-inflicted patients must endure many difficulties like memory loss, behavioral changes, and vision and mobility impairment, which affect their life in day-to-day activities. Therefore, initiating treatments as soon as AD is discovered is essential to slow the disease's progression and improve patients' quality of life. Developments in Artificial Intelligence (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). Due to its capacity to extract high-level features through local connectivity, weight sharing, and spatial invariance, deep learning using magnetic resonance imaging (MRI) has emerged as an effective tool. 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.

This literature review will examine the existing anomalies of an MRI scan image and evade the irregularities at each step by preprocessing the images. We will explore the different preprocessing steps, including motion correction, image registration or normalization, bias field correction, mitigating noise, skull stripping, and segmentation. This review will also identify the quality assessment techniques like signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), image similarity metrics, fractional anisotropy analysis, chi-squared analysis, and mask quality analysis. The review also covers software tools concurrently used for the preprocessing steps.

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

B. Summary of existing literature: A synthesis of the key findings, theories, and trends from the existing literature on the topic.

MRI scan 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 algorithms will use preprocessing methods to develop accurate models of diagnose diseases. All studies used different preprocessing methods to improve and enhance MRI images for easy diagnose disease.

In their study, Perumal et al. [7] 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 enhancing MRI images of lung using filtering techniques, removing noise, enhancing contrast and increasing pixel intensity as part of preprocessing [17]. This process makes the makes the image of the scan more suitable than the original image because of the preprocessing methods. The original image will be converted to Gray scale image, resize images into different sizes, noises removed by using filtering technique from gray image and applying the Adaptive Histogram Equalization to enhance contrast of the image [18]. The difference between maximum and minimum pixel intensity is considered to be the contrast. Another technique Salt and pepper is used for noise removal. Salt and pepper noise distorts images during quick transients, such as faulty switching places [19]. In Gaussian noise the original value of each pixel in the image will change 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 [20]. 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 [21]. The article discuss about 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 [22]. Inverse filtering and noise smoothing are optimally balanced by the Wiener filtering approach. The blurring is simultaneously inverted and the additive noise is removed [23]. Another filtering technique, Median filter, depending on certain conditions, such as, it will change the size of images [24].

In the article by Srivaramangai et al. [25] 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 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 patientspecific artifacts, while processing techniques and equipmentbased abnormalities are typically brought on by the partial volume, ring and staircase effect [26]. The preprocessing method used is similar to [7] 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 multifractal wavelet followed by general contrast enhancement and adaptive histogram equalization [27].

Mean, median, and adaptive median filters are three types of filtering algorithms used for preprocessing. The authors proves that the techniques used their work beneficial as it produces a high-quality image without losing any information and offers a crisp image free of any artifacts. Additionally the techniques aids in the accurate detection of the disease or determining the stage of colorectal cancer.

Khiet et al. [28] addresses 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 [29]. 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 [30]. The proposed models are then assessed using the Dice coefficient, Precision, Recall, and Accuracy performance criteria in order to choose the most efficient segmentation and classification method. Significant visualization maps are also produced with Grad-CAM. With the exception of 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 that the main benefit in 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 Ashly et al. [31] prepares the MRI scans for segmentation and classification, review the different preprocessing techniques used in brain MRI images, and emphasize 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 researches is that the histogram equalization method produces results that are more accurate. The article sheds light to 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 Nesrine et al. [32]. This disease is one of the main reasons why women die from cancer. In the article the author discuss about MRI beign used to determine the cancer stage (tumor size, nodal status, and local extension), which affects treatment planning. The research work, as part of preprocessing, use 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 deep learning 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 paper are sharpening and smoothing, morphological, and histogram-based image processing methods. The experiments produced segmentation maps of high precise and significance and 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 measure. The authors are working on integrating the present model with random field models to create quality imges with higher accuracy.

Diffuse is a dedicated toolbox written in Python language for preprocessing MRI images and is publicly available in Github [33]. Lucile et al. [34] used numerous preprocessing techniques with MRI scan images 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 tends to improve 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 et al. [35] the main objective of the research is to improve resolution and denoise images in order to improve their quality. There also exist a need to better enhance the image to maintain the edges and contour information in medical images after they have been effectively denoised. The effectiveness of these methods is evaluated in this paper using the peak signal to noise ratio (PSNR). The preprocesser 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 Vipin et al. [36] is to learn about image processing methods for detecting brain tumors using MRI scans. The research paper discusses about the various preprocessing methods - Filtering, contrast enhancement, 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 in order for precise and accurate prediction from the AI engine. This research work have proved helpful for doctors in determining the early stages of brain tumour. In numerous research with MRI brain images non-biological variations were found due to effects of scanning and acquisition settings. Yingping et al. [4] assesses the preprocessing methods including Bias field correction and image resampling to help remove the scanner anamolies and improve the radiomic features in brain MRI. The study further proves that the intensity normalization methods, though not effective in removing scanner effects, improve the robustness of brain image. Suhas et al. [37] discuss in their article about MRI image preprocessing using linear and nonlinear filters. The author experiments with the Linear smoothing or Mean filter, Midpoint filter and the Nonliner Median filter [38] [22]. The authors proposes a new technique which is combination of both the median and mean filters. The proposed when compared with existing linear and nonlinear filters using statistical parameters like Peak signalto-noise ratio, signal-to-noise ration and root-mean-squareerror shows improvement in denoising and structural details are retained. The author proves the method to be beneficial early detection and accuracy with AI engines.

Brain age, estimated from T1-weighted magnetic resonance images (T1w MRI), serves as a straightforward diagnostic biomarker for brain aging and associated diseases. Current predictions for brain age in healthy individuals exhibit an accuracy range of two to three years. However, comparing results across studies is difficult due to variations in datasets, preprocessing pipelines, and evaluation protocols. Lara et al. [39] examine the impact of T1w image preprocessing on the performance of four recent deep-learning brain age models. Four distinct preprocessing pipelines, differing in registration transform, grayscale correction, and software implementation, were evaluated. The findings revealed that the choice of software and preprocessing steps could significantly affect prediction accuracy, with a maximum increase of 0.75 years in mean absolute error (MAE) for the same model and dataset. While grayscale correction showed no significant impact on MAE, using affine rather than rigid registration to a brain atlas significantly improved MAE. Models trained on 3D images with isotropic 1 mm^3 resolution were less sensitive to preprocessing variations compared to 2D models or those trained on downsampled 3D images. Extensive T1w preprocessing improved MAE, especially when predicting on new datasets, contrary to prevailing literature that suggests minimally preprocessed T1w scans are better for age predictions on MRIs from unseen scanners. The study demonstrates that applying some form of offset correction is essential for generalizing model performance across datasets from unseen sites, regardless of the preprocessing used during training. Virtual phantoms are useful tools to assess the variability in MRI imaging and allow us to evaluate the impact of the different acquisition parameters [40]. Marco et al. [41] uses virtual phantom tools to identify the radiomic features of MRI image and evaluate the scanning parameters. The effect of these parameters are 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.

C. Gaps and Limitations

According to the literature review the difficult tasks 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 [28]. This anomaly also affects the bias in the classification results.

Another performance issue occurs due to image distortions, besides motion of patients, the temper of the patient like anxiety, confusion, anger, etc. Such emotions were found to be difficult to mitigate [32]. In the case of identifying the central white-matter for the ROI-based analysis, the difficulty to quantify the differences between the pipeline performance affect considerably in denoising the MRI image [34].

Need to address the problem by using MRI-based classification to create a precise model for glioma diagnosis [28]. The removal of some images during classification and segmentation is one of the trickiest ones. Due to the fact that the segmented portions of these images are not based on the ground truths, it would be useless if incorporating the nontumor 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 [36].

The preprocessing and harmonization techniques affect the elimination of scanner effect in radiomic features of brain MRI [4]. However it is unable to eliminate radiomic featurelevel scanner effects and the radionics studies' reproducibility continues to be problematic.

III. Proposed Methodology

The proposed methodology for processing raw data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) involves a comprehensive approach using the FMRIB Software Library (FSL) and a graphical user interface (GUI) pipeline. Initially, raw MRI and PET images, along with clinical and demographic data, are collected from the ADNI database. These data undergo preprocessing steps, including conversion to NIfTI format, skull stripping, intensity correction, and spatial normalization. Clinical data is also cleaned and normalized, with missing values handled appropriately. Feature extraction is then performed to extract relevant features from both images and clinical data. These features are integrated into a unified dataset for further analysis. Machine learning or deep learning models are chosen for AD diagnosis or prediction, with the dataset split into training, validation, and test sets. The model is trained, and hyperparameters are optimized using the validation set. The performance of the model is evaluated using the test set and external datasets, if available, to assess its generalizability. Ethical considerations are paramount throughout the process to ensure compliance with guidelines for research involving human subjects. The results are documented and reported, with future research directions discussed for potential enhancements to the methodology.

A. MRI Preprocessing Pipeline

In this section, we outline a detailed process for preparing MRI scans using the FMRIB Software Library (FSL) on a Windows OS system. The machine is equipped with an Intel CPU, 8 GB of RAM, and a 10-core GPU, providing sufficient computational power for the tasks. Data were sourced from the ADNI, a vital repository for Alzheimer's biomarker research [42]. The dataset includes T1-weighted MRI scans using Magnetization Prepared - Rapid Gradient Echo (MPRAGE) from individuals aged 50 to 65 from ADNI-1, ADNI-2, and ADNI-GO cohorts. MPRAGE is renowned for its ability to produce high-quality brain tissue images with clear grey and white matter contrast. FSL, developed by the FMRIB Center at the University of Oxford, was utilized for preprocessing steps such as image reorientation, registration, skull stripping, and slicing. These steps are crucial for understanding brain function and studying neurological and psychiatric conditions. While FSL provides a graphical interface, this study employed its command-line tools for efficiency, executed from the Ubuntu 18.04.6 LTC terminal. Additionally, *fsleyes*, a powerful neuroimaging tool, was used for visualizing and analyzing the processed MRI data, making it valuable for researchers, clinicians, and educators in neuroimaging.

B. Reorientation of Magnetic Resonance Image

Reorientation is a crucial step in adjusting the orientation of MRI images to align them with a standardized reference space [43]. In our methodology, we utilized the *fslreorient2std* command line tool provided by FSL, specifically designed for standardizing and reorienting neuroimaging data. This process ensures that all images are consistently oriented, essential for easier comparison and integration of data from various subjects or studies. The command line syntax for reorientation is as follows: *fslreorient2std infname outfname*. Here, *infname* corresponds to the input file name, representing the original MRI image requiring reorientation, while *outfname* indicates the output file name, specifying where the reoriented image will be saved. Visualizing the reoriented image using *fsleyes* allows us to confirm the alignment with a standardized orientation, thereby facilitating comparison and compatibility across different analyses and software packages. This meticulous approach ensures data consistency and enhances the reliability of subsequent analyses and data integration.

C. Image Registration

Matching various photographs to a single coordinate system is called image registration. For linear transformations, including translation, rotation, and scaling, the command-line utility FLIRT is utilized [44]. One image is aligned with another via the tool. It is frequently used to align imaging data from several modalities or a person's data to a template or standard space. The statement displays the command line syntax for registering with the FSL tool: *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 I displays the 'flirt' command, its specific image registration settings, a breakdown of commands and their alternatives, and the MRI images after registration.

D. Skull Stripping

The MRI image obtained after registration must be cleaned up of non-brain tissues. The *skull stripping* procedure involves separating the brain region from non-brain tissues such as the scalp, skull, and non-brain structures [45]. This division facilitates concentration on the examination and illustration of brain anatomy. A vital preliminary step for various neuroimaging investigations, such as brain morphometry, functional connectivity, and imaging with diffusion tensor. Skull-stripped images created using BET are valuable for research, teaching, and therapeutic applications because they are more aesthetically pleasing and simpler to understand. The following statement displays the command line syntax for skull stripping: *bet infname outfname –R –f 0.5 –g 0.bet infname outfname –R –f 0.5 –g 0*

TABLE I
PARAMETERS AND ITS DESCRIPTION FOR THE FLIRT COMMAND LINE TOOL.

Command	Options
flirt	This is the command to execute FLIRT
-in rofname	Specifies the input image filename to be registered
-ref referencefname	Specifies the reference image filename to which the input image will be aligned
-out outfname	Specifies the output image filename after registration
-omat fname.mat	Specifies the output matrix filename 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 this case, 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.

To perform skull stripping on an MRI image, you must specify the input file name as *infname* and the output file name as *outfname*. The Brain Extraction Tool (BET) is a commonly used tool in FSL for skull stripping, which segments the brain based on intensity values using a fractional intensity threshold (*-f* parameter). This threshold controls the algorithm's sensitivity and can be adjusted to include brain tissue. For instance, a *-f 0.5* threshold is used to moderate the algorithm's sensitivity. Additionally, two other options can be considered: *-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 brain tissue, whereas a lower value removes more non-brain structures.

E. Image Slicing

After reorientation, registration, and skull stripping, the MRI data is in a 3D format, representing axial, coronal, and sagittal planes. Using Slicer software, it is possible to generate a 2D view of any plane from the 3D volume [46]. Slicer is an open-source tool for medical image analysis, research, and visualization, supporting various imaging modalities such as MRI, CT, and PET. The command line syntax for slicing is as follows: *slicer infname -z -90 outfname*. Here, *slicer* is the command to invoke the software, *infname* is the input volume file name containing the MRI data, *-z -90* specifies the desired orientation and slice position for the generated image (indicating an axial or transverse view and selecting the slice at -90mm along the z-axis), and *outfname* is the output file name or path where the image will be saved. The orientation options *-x* and *-y* represent the sagittal and coronal planes, respectively. Executing this command will load the input volume into Slicer, extract the desired slice at the specified position, and save the resulting 2D axial view image, allowing for visualization, analysis, or further processing of the specific slice. Here, *slicer* is the command to invoke the software, *infname* is the input volume file name containing the MRI data, *-z -90* specifies the desired orientation and slice position for the generated image (indicating an axial or transverse view and selecting the slice at -90mm along the z-axis), and *outfname* is the output file name or path where the image will be saved. The orientation options *-x* and *-y* represent the sagittal and coronal planes, respectively. This command will load the input volume into Slicer, extract the desired slice at the specified position, and save the resulting 2D axial view image, allowing for visualization, analysis, or further processing of the specific slice. Table II provides a summary of the key characteristics, strengths, and weaknesses of the steps envisaged in the MRI preprocessing pipeline.

F. Graphical User Interface [GUI] design

Designing a GUI for mobile devices to input MRI images, undergo preprocessing, and store results involves several key considerations to ensure usability, functionality, and efficiency. The GUI has been designed to be intuitive and user-friendly and seamlessly guide users through the image processing workflow. The GUI design should feature an interface for users to upload MRI images from their mobile devices easily. This can be achieved through a file upload button that uploads the images from storage. Once the image is uploaded, the GUI provides options for preprocessing, such as registration, reorientation, skull stripping, and slicing, to optimize the quality of the MRI data. The GUI incorporates responsive design principles to ensure smooth user interaction and adapts to different screen sizes and orientations. Clear and concise instructions are provided to guide users through each step of the preprocessing process. Visual feedback, such as progress indicators or status updates, helps users track the processing status and anticipate the next steps. Implementing a GUI for an application that integrates with Android Studio and HTML involves several steps. In Android Studio, we created activities for the login for users who already have an account (Refer Fig 2(a)) and a registration page for new users (Refer Fig. 2(b)).

The GUI is integrated with a backend system to manage data storage and retrieve results efficiently. This backend system can utilize cloud or local storage services based on user preferences and security considerations. Figure 3 shows the main activity page that includes four buttons for MRI upload, preprocessing, and storing results adequate for subsequent AI training and classification. The *Upload Image* is used to upload images to the back-end storage in respective folders based on the categories of MRI raw scans obtained. The *Preprocess* will load the MRI scans individually and pass through reorientation, registration, skull stripping, and slicing.

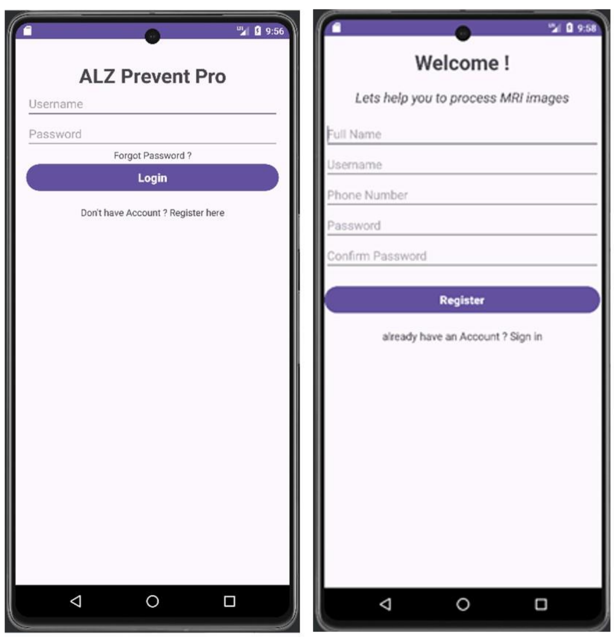

Fig. 2. Alzheimer prevention pro (i) login to system (ii) new user registration

TABLE II
SUMMARY OF KEY CHARACTERISTICS, STRENGTHS, AND WEAKNESSES OF MRI PREPROCESSING

Preprocessing Technique	Key characteristics	Strengths	Weaknesses
MRI Image Reorientation	Adjusts the orientation of MRI images to a standard anatomical alignment.	Simplifies subsequent analysis steps and ensures consistent orientation across datasets.	May introduce interpolation artifacts that, if not done carefully, are computationally intensive for large datasets.
Registration	Aligns MRI images to a standard space or template using rigid, affine, or nonlinear transformations.	Improves comparability across subjects and studies, essential for group analysis.	Affine and non-linear registration can be computationally intensive, and errors in alignment can propagate to subsequent analysis.
Skull Stripping	Removes non-brain tissues (e.g., skull, scalp) from MRI images to focus on brain tissue.	Reduces noise and computational load, improves the accuracy of brainfocused analyses.	May remove brain tissues if not accurate, errors can affect downstream processes like segmentation and registration.
Slicing	Converts 3D MRI volumes into 2D slices for specific analyses or visualization.	Facilitates specific types of image analysis, allows detailed inspection of individual slices.	Loses contextual 3D information, can introduce slice selection bias, less effective for volumetric analysis.

Upon completion of preprocessing, the GUI prompts users to specify storage preferences and provides options for organizing and accessing processed data. In the final step, the preprocessed 3D image is sliced based on the axis to obtain the axial, coronal, and sagittal planes. The *Results* is used to traverse through the sliced images. Furthermore, the GUI prioritizes security and privacy by implementing authentication mechanisms to restrict access to sensitive data. Users have control over their data, including the ability to delete or export processed images as needed. In the HTML part, the web interface has the same functionalities in mobile application, allowing users to access the application from a web browser. This web interface includes forms for *login*, if the user already has an account, and *registration* to register as a new user, uploading the MRI image or file to be processed. To integrate the preprocessing steps coded in Python, we use a Python library that can be called from your Android Studio and HTML code. We write the preprocessing logic in Python functions and then call these functions from your Android Studio and HTML code when the user clicks on the preprocess button.

In summary, designing a GUI for mobile devices to input MRI images, undergo user login or registration, upload MRI scans, trigger the preprocessing steps, store results, and finally allow the user to download the results requires careful consideration of usability, functionality, and security. This integration of GUI elements in Android Studio and HTML, along with using Python for the preprocessing steps, creates a comprehensive application for processing MRI images. The GUI can provide a seamless and efficient user experience for medical imaging applications by incorporating intuitive design, principles, responsive layout, and robust backend integration.

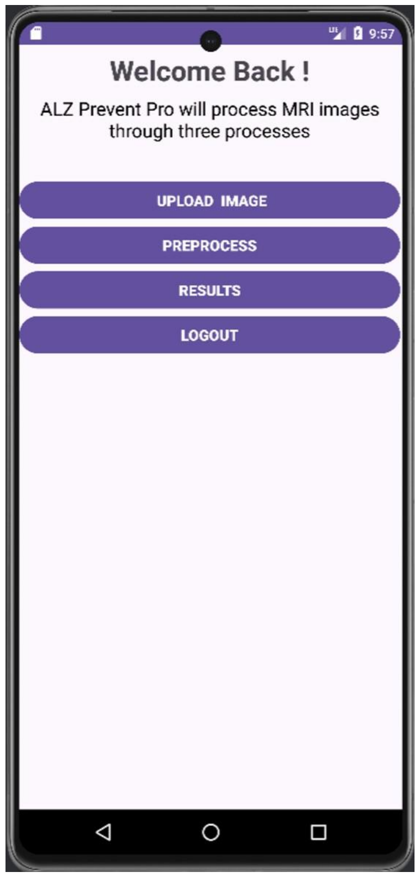

Fig. 3. Alzheimer prevention pro (i) login to system (ii) new user registration

IV. EXPERIMENTAL RESULTS

Reorientation [43]is the first step in the MRI preprocessing pipeline. It is crucial to ensure standardized alignment and orientation across image volumes in MRI scans. The process involves adjusting the spatial orientation of the acquired images to a consistent coordinate system, typically based on anatomical landmarks or reference planes within the brain. The first step in reorientation is identifying the orientation of the original image volumes, which may vary depending on the patient's positioning during the scan. Common orientations include sagittal, coronal, and axial planes. Next, a transformation matrix is computed to align the image volumes with a standardized coordinate system. This transformation is applied to each voxel in the image volume, ensuring that anatomical structures are accurately represented in the standardized orientation. Fig 4 shows a sample result of reorientation having the sagittal, coronal, and axial images.

Reorientation, ensures consistency in subsequent image processing tasks, such as registration, segmentation, and quantitative analysis. By aligning MRI scans to a standardized coordinate system, patient positioning and scanner orientation variations are mitigated, facilitating accurate comparison and analysis of images across different subjects and imaging sessions. Overall, reorientation enhances the reliability and interpretability of MRI data, enabling clinicians and researchers to make informed decisions and derive meaningful insights from neuroimaging studies.

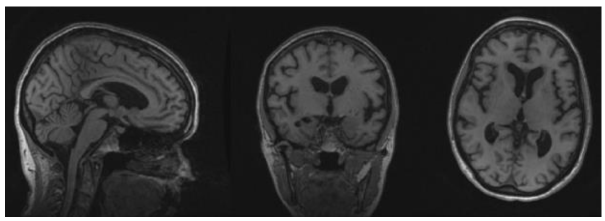

Fig. 4. Result of reorientation: sagittal, coronal, and axial planes

In the next step of processing, registration [44], is a critical step in MRI scans that aligns multiple image volumes or modalities into a common coordinate system. It involves identifying spatial transformations that bring images into spatial alignment, accounting for position, orientation, and scale differences. The registration process begins by selecting reference images or landmarks that serve as the basis for alignment. Common reference points include anatomical landmarks or visible features across all images. Next, a registration algorithm computes the transformation needed to align each image with the reference. This may involve rigid transformations, which only allow for translations, rotations, and scaling, or non-rigid transformations, which also account for local deformations. Fig 5 shows a sample result of registration with sagittal, coronal, and axial planes.

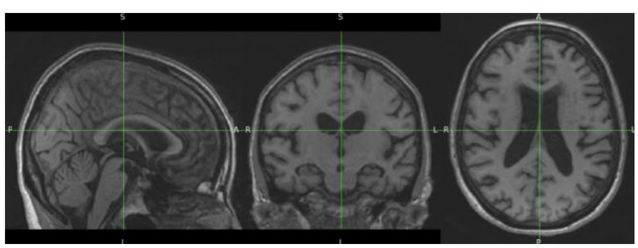

Fig. 5. Result of registration: sagittal, coronal, and axial planes

Registration algorithms optimize parameters to minimize differences between the reference and target images, typically using optimization techniques like gradient descent or mutual information maximization. Once the transformations are computed, they are applied to the target images, aligning them with the reference. This results in a set of registered images with a common coordinate system, facilitating comparison and analysis across subjects or imaging modalities. Registration is essential for various MRI applications, including longitudinal studies, image fusion, and multimodal analysis. It improves the accuracy and reliability of subsequent image processing tasks, enabling clinicians and researchers to extract meaningful insights from MRI data.

Reorientation and registration in MRI preprocessing yield spatially aligned image volumes, enabling accurate analysis and comparison. Reorientation ensures consistent orientation, while registration aligns multiple volumes into a common coordinate system for integration. However it is necessary to undertake skull stripping, the next preprocessing step, that removes non-brain tissues from MRI scans, enhancing the accuracy of subsequent analysis by isolating brain structures. Fig 6 shows a sample result of skull stripping with sagittal, coronal, and axial planes.

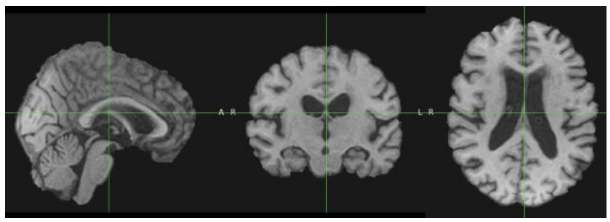

Fig. 6. Result of Skull stripping: sagittal, coronal, and axial planes

The process begins with intensity thresholding to identify brain tissue and non-brain regions. Next, morphological operations such as erosion and dilation are applied to refine the brain mask and remove remaining non-brain structures. Skull stripping is crucial for enhancing the quality of subsequent analysis by isolating brain structures and reducing interference from extraneous tissues and artifacts. This technique optimize MRI data for clinical diagnosis, research, and treatment planning by enhancing interpretability and reliability.

After reorientation, registration, and skull stripping of MRI scans, the outcome is a standardized and refined dataset optimized for accurate analysis. These preprocessing steps ensure consistent alignment and removal of non-brain tissues, enhancing the accuracy of AI algorithms for image analysis. AI techniques, such as deep learning, can then be applied to segmented MRI data to automate tasks like tumor detection, disease classification, and treatment planning.

Reorientation ensures consistent orientation, while registration aligns scans into a common coordinate system. Skull stripping [45]removes non-brain tissues, enhancing segmentation accuracy. The resulting dataset facilitates precise localization and characterization of abnormalities, aiding diagnosis and treatment planning. Overall, these preprocessing steps enhance the utility and reliability of MRI scans, advancing our understanding of neurological conditions and guiding clinical decision-making.

After reorientation, registration, and skull stripping of MRI scans, AI benefits from standardized and refined datasets. These preprocessing steps ensure consistent alignment and removal of non-brain tissues, enhancing the accuracy of AI algorithms for image analysis. However slicing after preprocessing MRI scans is essential as it allows precise localization and characterization of abnormalities or structures, aiding in accurate diagnosis and treatment planning.

After preprocessing MRI scans, slicing involves extracting two-dimensional images, or slices, from the three-dimensional volume for analysis and visualization. This process utilizes imaging software to select specific orientations (e.g., axial, sagittal, coronal) and slice thicknesses. These orientations allows clinicians and researchers to examine detailed crosssectional views of the brain and identify abnormalities or structures of interest. Additionally, sliced images can be used for quantitative analysis, such as volumetric measurements or region-of-interest analysis, to further characterize brain morphology and pathology. Fig 7 shows a sample result of slicing skull with sagittal, coronal, and axial planes.

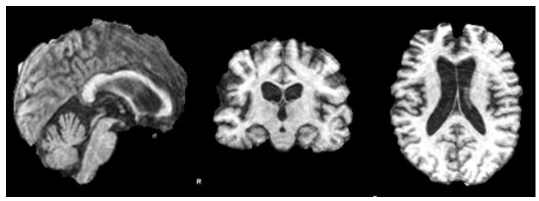

Fig. 7. Result of Slicing: sagittal, coronal, and axial planes

The use of the refined and sliced image dataset makes it easier to train and validate models, which in turn helps improve the performance of AI and its ability to generalize to new data. By segmenting MRI data, AI techniques like deep learning can be applied to automate tasks such as detecting tumors, classifying diseases, and planning treatments [47]. Ultimately, these preprocessing steps optimize MRI data for AI applications, accelerating medical image analysis and enabling more precise diagnosis and treatment strategies.

V. Conclusion

This research aims to enhance early AD prediction by leveraging preprocessing techniques to address irregularities in MRI scans. By identifying and mitigating these irregularities, we aim to improve the accuracy and effectiveness of AD prediction, potentially saving lives and reducing healthcare costs. This study contributes significantly to the understanding of AI's role in disease prediction and the implications of data irregularities on prediction accuracy. By developing preprocessed models and integrating them into a user-friendly GUI, we empower clinicians to make informed decisions and improve patient outcomes. Moreover, our research addresses the critical need for assessing the quality of MRI data, ensuring reliable predictions in medical applications. The potential benefits of our work extend beyond healthcare, with implications for advancing scientific knowledge and fostering innovation in multiple fields. As we continue to refine our preprocessing techniques, we anticipate broader applications in identifying and addressing irregularities in other medical biomarkers, ultimately leading to the development of more accurate predictive models and decision support tools for healthcare providers. Overall, our research contributes to advancing AI technologies in AD prediction, with significant implications for healthcare professionals and patients alike.

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