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Image Processing in MRI: A Methodology Review

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Abstract
Magnetic Resonance Imaging (MRI) plays a crucial role in medical diagnostics in modern times, allowing a non-invasive way to peer into and measure the intricately woven structures within the human body. Magnetic resonance imaging(MRI) and computed tomography (CT) are among the most used medical imaging modalities and give great insights into the internal organs and the tissues. Brain imaging has been particularly impressive in providing tools to aid in detection, diagnosis, and monitoring of conditions like tumors. However, the brain being highly complex in anatomy with high presence of noise and artifacts in medical images poses difficulty in precise diagnosis that offers detailed and high-resolution images of internal body structure. In this paper, an effort was put to review the techniques in MRI image processing. Radiology image processing improves diagnostic information and is a critical step in image processing that can make an image suitable for diagnostic preprocessing methods, such as noise reduction to enhance image quality making it more accurate for segmentation. Segmentation which isolates the areas of interest. Feature extraction to reduce dimensionality of data, various morphological operations and classification methods to reduce time of diagnosis and improving consistency in healthcare systems. To integrate advances in preprocessing, segmentation, and classification, this paper highlights the transformational impact of these methodologies on enhancing diagnostic accuracy, efficiency, and reliability in tumor identification.
Keywords: *Image processing; MRI; Radiology; Tumor*

1. Introduction
Medical images serve as significant channels of diagnosis. MRI is a non-invasive image technology in the field of medicine that produces three dimensional detailed anatomical structures. MRI includes many techniques to perform operations for preprocessing, segmentation, feature extraction, and classification in order to improve accuracy and effectiveness. [1] Preprocessing stands out as the building process for any kind of medical imaging pipeline. Here, raw medical images are made ready for further analysis by removing any noise, correcting intensity variations, and erasing any irrelevant part of the image like artifacts or labels. [2] Different methods such as histogram equalization, median filters, and skull stripping is used here for noise elimination and focusing should be on regions of interest. For example, skull stripping eliminates non cerebral structures for segmenting out brain tissue with clear margin. Preprocessing is designed to ensure that high-quality, clinically relevant data goes all the way through downstream processes, thereby reducing errors in subsequent procedures. Once preprocessing is done, the next task is segmentation. Segmentation is essentially forced partitioning of an image into the desired regions, such as those that separate the tumor tissue from the normal brain structures. Being one of the difficult and most core tasks- especially in medical imaging-segmentation is

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the process of isolating abnormal material. [3] After segmentation, feature extraction identifies and isolates the most important and informative properties of the MRI images that reduce the dimensionality of the data by focusing only on relevant features. Classification involves assigning labels to different regions or the entire image based on the extracted features. It determines what each part of the image represents, such as normal tissue, diseased tissue, or other specific categories to distinguish between healthy and abnormal areas. This paper explores the key methodologies employed in MRI image processing, focusing on reconstruction, classification, and segmentation techniques, and highlights their impact on advancing medical diagnostics

2. Preprocessing

The raw images from the scan cannot be directly used for the processing as various defects or artifacts may be present in them. Excluding preprocessing steps can lead to unclear images that could affect visibility of important structures, as without preprocessing steps like skull stripping, segmentation and classification would generate inaccurate results, which would further affect the accuracy in tumor detection or brain volume measurement. Therefore, it is necessary to preprocess it before examining. The preprocessing is useful in conversion, image resize, noise removal and enhances the quality and produces an image through which minute inconsistencies can be detected correctly. The major preprocessing techniques are Tracking Algorithm, Skull Stripping, Image Enhancement and Gray Scale Conversion. Figure 1 shows Preprocessing Methodology.

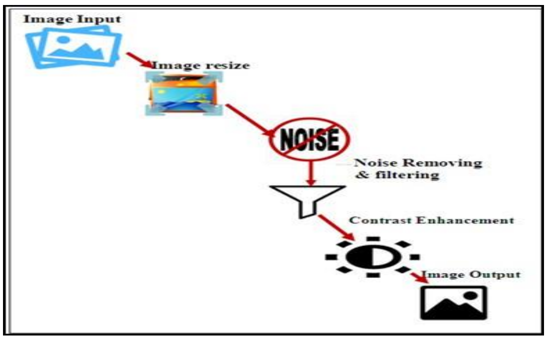
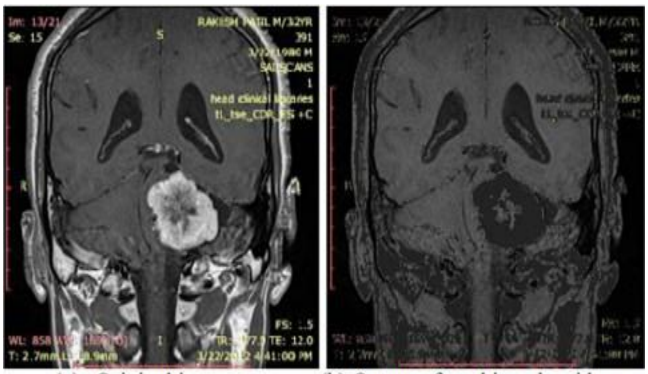


Figure 1 Preprocessing Methodology

2.1 Tracking Algorithm

This technique monitors and detects movement, growth or changes in specific brain structures such as tumors across different scan sequences. It then updates the position and size of the object over time, as the MRI images change between scans which monitor tumor progression or shrinkage over time. The disadvantage of the tracking algorithm is it uses the highest threshold for gray scale image which is 255. This will remove artifacts which have a gray value of 255 only leaving all other artifacts on the image. The Figure 2 Shows the difference between original image and image after applying tracking algorithm.



(a) Original image (b) Output of tracking algorithms

Figure 2 Comparison Between Original Image and After Applying Tracking Algorithm

2.2 Skull Stripping

This is a preprocessing step that improves results in brain image analysis, which involves removal of non-cerebral tissues of the brain. Contrast of this image is adjusted and then converted into binary to crop and locate brain regions. A low threshold is applied to this cropped image to create binary vision. The brain region is then extracted from surrounding tissues.

2.3 Image Enhancement

This step improves the quality of digital images to make them clear and suitable for analysis. After skull stripping, the brain cortex appears as a distinct dark ring around the brain tissues in MRI images. Image

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enhancement removes this dark ring and highlights the relevant features of the brain. This is achieved using noise filtering or brightening techniques. Morphological operations such as thicken, are done to refine the boundaries. This ensures that the resulting MRI image focuses only on the areas of interest, for better tumor detection and analysis. Figure 3 shows image after skull stripping and enhancing the image.

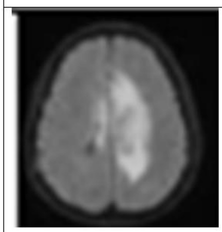
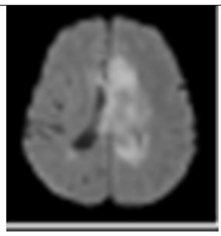
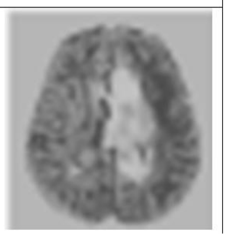
Original Image	Skull Stripped	Enhanced Image
		

Figure 3 Results of Skull Stripped Image, Enhanced Image of Tumor Images

2.4 Gray Scale Conversion

The grayscale image removes unwanted color information and focuses on key features like tumors, which are often defined by changes in intensity. These images are simpler to process as they contain only one channel. Firstly, an MRI image is taken in color, typically a 3-channel RGB image. The color channels are combined into a single grayscale image which is achieved by averaging or using a weighted sum of the three color channels based on their brightness perception. The output is a black-and-white (grayscale) image corresponding to intensity variations of the different tissues in the brain, such as tumors, skull, and brain matter.

3. Segmentation

MRI Segmentation refers to the process of dividing a brain scanned image into different regions based on tissue type, like gray matter, white matter, and cerebrospinal fluid, allowing for detailed analysis of specific anatomical structures and identification of abnormalities within the brain by separating different areas of interest from the overall image. Brain MRI segmentation is an essential basic step that has many applications in neurology such as quantitative analysis, operational planning, and functional imaging. Although MRI can describe the structures of the brain accurately, however medical image segmentation is a tough task because of poor spatial resolution, low contrast, ill- defined boundaries, inhomogeneity, partial volume effect, noise, variability of object shapes and some other acquisition artifacts in the retrieved data as well as the lack of models of the anatomy that entirely capture the possible deformations in each structure. Many researchers have classified schemes of image segmentation under different heads. One of such classifications are threshold-based, region-based, pixel classification and model-based techniques. Threshold-based methods are based on the postulate that the pixels that lie within a certain range belong to one class. Boundary-based methods use the assumption that pixel properties change abruptly at the boundary of two regions. [7] A number of methods are available to segment the tumor from brain MRI images. The highlights of this study are as follows:

- It presents an exhaustive study of recent methods for brain tumor segmentation from brain MRI images.
- It helps the clinicians to take the decision of correct diagnosis and further treatment accordingly.
- Quantitative analysis through different metrics shows the effectiveness and appropriateness of recent schemes.
- It also gives readers new directions of research for brain tumor segmentation.

3.1 Thresholding

Thresholding is one of the simplest techniques of image segmentation. It is fast, easy to implement and understand. It works upon the idea of converting a scalar image into a binary image, in which a threshold value is decided based upon the intensity values of the image. The intensity values of the pixels are compared with the threshold value. [7]

3.2 Region Based

Group pixels together based on their intensity similarity, gradually expanding pixels until boundaries are identified. User selects initial

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"seed" points within the region of interest, then the algorithm iteratively adds neighbouring pixels with similar intensity values to the region. It can handle complex tissue boundaries, allowing for more nuanced segmentation than simple thresholding. [8]

3.3 Pixel Classification

This process analyses each pixel individually using machine learning models to classify it based on its intensity and features, assigning a label like grey matter, white matter or CSF (Cerebrospinal Fluid). Trained models like Support Vector Machines (SVM) or Neural Networks are used to predict the tissue type of each pixel based on its intensity and potentially other features like texture. High accuracy in complex tissue structures, can incorporate more sophisticated features.

3.4 Model Based

It uses a pre-defined anatomical model of the tissue to guide segmentation, incorporating knowledge about the shape and structure of the organ. The 3D model of the target structure is registered to the MRI image, the model is used to constrain the segmentation process, ensuring the extracted region conforms to the expected anatomy. It improves segmentation accuracy by leveraging anatomical information, and can be useful for complex structures.

4. Feature Extraction

Feature extraction is important in image processing which involves identification and representation of distinctive structures of the brain. The primary task of pattern recognition is to take an input pattern and correctly assign it as one of the possible output classes. These features are vital for various downstream tasks such as object detection, classification, and image matching.

4.1 Principal Components Analysis (PCA)

PCA is a method which simplifies the data by reducing its dimensions while keeping the essential information. It is achieved by breaking down complex data into new sets of components with unique features. These components are chosen based on the amount of variation they capture. Firstly, the images are processed to extract important information which involve breaking down the image data into smaller parts called wavelet coefficients. It is done to transform the data into a smaller number of components that retain most of the information. During training, feature vectors which are representations of the MRI images, are generated and stored. These vectors are derived from the PCA components and serve as a database for comparison. When a new MRI image is tested, its features are also extracted using PCA. The system compares this test vector with the stored training vectors by measuring their similarity. If the test vector closely matches a stored vector, the system identifies the image correctly. If not, the identification is incorrect. This approach is used for tasks like classifying normal vs. abnormal MRIs. [9]

4.2 Transition feature

Transition features refer to points where pixel intensity changes from low (background) to high (foreground). These features are essential for identifying edges, boundaries, and structures like tumors or lesions. To detect them, the image is scanned in horizontal and vertical directions to locate areas with sharp intensity changes, such as the boundaries of abnormal regions. Instead of processing the entire MRI image, smaller sub-images focusing on specific areas of interest, such as a tumor, are used to improve accuracy and efficiency. These features are critical for segmenting the image into meaningful regions, making it easier to classify normal and abnormal tissues. [10]

are used to improve accuracy and efficiency. These features are critical for segmenting the image into meaningful regions, making it easier to classify normal and abnormal tissues. [10]

5. Classification of Images Using Transformer Models

Classifying MRI images is crucial in diagnosing brain condition, as doctors rely on precise categorization to determine effective treatment. Traditional methods often lack precision and require long training times, but self-learning transformer models have addressed these challenges. With their self-attention mechanism, transformer models identify intricate patterns and relationships between

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brain regions, significantly improving classification accuracy. These models are also cable of handling larger datasets, making them adaptable to the growing volume of brain MRI data. [11] Furthermore, their autonomous learning abilities enable them to detect nuanced details in MRI images that traditional approaches often overlook. This enhancement in precision is vital for ensuring accurate patient diagnoses and formulating treatment plans. Transducer models, another advancement in this domain, are adept at capturing long-term information and understanding complex patterns in brain data. Their ability to analyze MRI scans autonomously further highlights their potential in streamlining the diagnostics in the healthcare environment. [11]

5.1 Notable Research Contribution

Several studies highlight the advancements in this field:

- Stember et al. (2021) introduced a reinforcement learning(RL) approach combined with SBERT for extracting classification labels from radiology reports, achieving superior 3D image classification accuracy.
- Jun et al. (2021) developed theMedical transformer, a transfer learning framework that processes 3D images as 2D slices, enhancing spatial relationships and outperforming traditional methods in tasks like disease diagnosis and tumor segmentation.
- Tummala et al. (2022) used Vision Transformers(ViT) on MRI datasets, showing the effectiveness of ViT ensembles in tumor classification.
- Aloraini et al. (2023) proposed a model using feature fusion modules to enhance accuracy in brain tumor classification. [12]
- Dai et al. (2023) introduced Transformer-basedHierarchical Clustering(THC) in lesion prediction and brain network analysis.
- Brain tumors are a serious health concern, increasing rapidly worldwide. They occur due to uncontrolled cell growth in the brain and can be classified as primary or secondary. Tumors can be benign or malignant, with the latter being life-threatening. Early diagnosis and treatment are crucial for patient survival.
- MRI (Magnetic Resonance imaging) is the most widely used diagnostics technique for detecting brain tumors. It provides detailed soft tissue images, helping doctors differentiate between healthy and abnormal tissues. Other imaging methods include CT and PET scans, which complements MRI finding. Table 1 shows Comparative Analysis of the Image Processing Methods.

enables detailed visualization of soft tissues. The application of image processing techniques to MRI scans has led to significant advancements in diagnostic accuracy, treatment planning, and disease monitoring. Image processing in MRI involves a range of methodologies, from basic preprocessing techniques such as noise reduction and image enhancement, to more advanced techniques including segmentation, feature extraction, and machine learning-based analysis. Preprocessing aims to improve the quality of the acquired MRI data by removing artifacts, normalizing intensities, and adjusting for any distortions that may have occurred during scanning. Segmentation techniques are crucial for isolating regions of interest, such as tumors, lesions, or anatomical structures, and play a pivotal role in quantitative analysis for precise measurements and analysis. Advanced feature extraction and analysis techniques, including texture analysis and statistical modeling, help in identifying patterns that are not visible to the naked eye, improving the sensitivity and specificity of diagnostic procedures. The integration of artificial intelligence (AI) and deep learning has further transformed the field, allowing automated detection of abnormalities, prediction of disease progression, and personalized treatment planning. Moreover, post-processing methods that generate 3D reconstructions or visualize functional activity (like fMRI) allow clinicians to better understand the spatial and temporal dynamics of various brain activities or organ functions. As technology continues to evolve.

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Table 1 **Comparative Analysis of the Image Processing Methods**

Methodology	Technique	Explanation	Accuracy	Conclusion
Preprocessing	Tracking Algorithm	Removes artifacts by tracking and thresholding pixel intensities.	Removes artifacts effectively but may delete important details near region of interest (70-80%)	Useful for basic artifact removal
	Skull Stripping	Removes skull ribcage to isolate brain or other regions of interest	Provides accurate segmentation (90-95%)	Essential for medical imaging tasks like brain tumour.
	Image Enhancement	Adjusts contrast, brightness, or smoothing features to highlight important areas.	Effective in improving diagnostic clarity (85-90%)	Best used after noise removal or artifact elimination.
	Gray Scale Conversion	Converts color images to grayscale, reduces computational complexity	Simple and efficient, preserves intensity features (95%)	Fundamental step for preprocessing.
Segmentation	Thresholding	Converts a grayscale image into a binary image by assigning each pixel a value	Depends on the type of the data being analyzed.	Pixels with value 1 corresponds to object while pixels with value 0 corresponds to background
	Region Based	Divides an image into regions by grouping pixels with similar characteristics like color or intensity	Ranges from 70% to 90%	Grouping pixels for specialized formation of similar categories.
	Pixel classification	Allows a detailed object identification and analysis within an image	Falls within a range of 80% to 95% for well-trained models	Classification of pixels for identifying and detailing objects.
	Model Based	Uses a predefined “model” of an object shape or appearance to segment that object with an image	Can vary greatly depending on a specific model (80%-95%)	Models are use to engage object with image

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Feature Extraction	Principal Component Analysis (PCA)	Reduces data dimensionality, retains maximum variance.	Preserves essential data features while reducing redundancy. (97.2%)	Effective for dimensionality reduction, improves computational efficiency.
	Transition Feature	Analyzes the transitions	Performs well in	Captures edge and boundary
		between different intensities .	texture-based tasks by effectively capturing edge and boundary information. (93.5 %)	information.
Classification using transformer model	Reinforcement Learning(RL) with SBERT	Automated label extraction from radiology reports combined with RL and SBERT for 3D MRI classification	92%	Effective in training with small datasets and achieving precise classification of 3D images.
	Medical Transformer	Processes 3D images as 2D slices, maintaining spatial relationships While reducing parameters for efficient analysis.	AU 0.837	Enhances classification performance by leveraging 2D slice-based processing in medical imaging.
	Vision Transformer (ViT)[13]	Combination of ViT models for classifying meningiomas, gliomas, and pituitary tumours in MRI scans.	98.7%	Highly effective for tumor classification with large-scale data handling capabilities.
	Feature Fusion Module(FFM) & CNN[14]	Combines local and global features using CNN and transformer-based modules for classification.	99.10%	Achieves superior accuracy in brain tumor classification with fusion of feature extraction techniques.
	Transformer-Based Hierarchical Clustering (THC)[15]	Uses attention mechanisms to understand clustering assignments in brain networks for lesion detection.	89.4%	Effective for brain network analysis, but requires extensive hyperparameters turning for optimal performance.

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Conclusion

For preprocessing tasks in medical imaging, Skull Stripping combined with Image Enhancement achieves the highest diagnostic clarity and accuracy for segmentation. Gray scale conversion is essential but serves as a supportive preprocessing step rather than a standalone method. Model Based is the best method for Segmentation which usually works with complex and real world scenarios and is generally most accurate and versatile. Although, for fast and simple tasks thresholding remains effective. For feature extraction, PCA is more accurate and versatile, making it ideal for high-dimensional data and general-purpose tasks whereas transition features are better for applications requiring detailed edge and texture analysis. For classification, Feature Fusion Module (FFM) with CNN is the most suitable technique for brain tumor classification. The Vision Transformer (ViT) ensemble also demonstrates strong accuracy and can be effectively used for large datasets. Transformer-based models show great potential in improving precision and automation in MRI image classification.

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