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METHODS OF DIGITAL PROCESSING OF MRI IMAGES ON THE EXAMPLE OF THE BRAIN

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Abstract. *Magnetic Resonance Imaging (MRI) has become a cornerstone in medical diagnostics due to its superior soft tissue contrast and non-invasive nature. However, the complexity and vast amount of data generated by MRI necessitate advanced digital processing techniques to enhance image quality, facilitate interpretation, and extract meaningful clinical information. This article provides a comprehensive overview of the current methods employed in the digital processing of MRI images. Key topics include preprocessing techniques such as noise reduction and artifact correction, image segmentation, feature extraction, and advanced reconstruction methods. We also explore the application of machine learning algorithms in enhancing diagnostic accuracy and efficiency. By integrating these digital processing methods, MRI technology can significantly improve patient outcomes through more precise and reliable imaging.*

Keywords: *MRI, digital processing, noise reduction, artifact correction, image segmentation, feature extraction, image reconstruction, machine learning, medical imaging, diagnostic accuracy.*

МЕТОДЫ ЦИФРОВОЙ ОБРАБОТКИ ИЗОБРАЖЕНИЙ МРТ НА ПРИМЕРЕ ГОЛОВНОГО МОЗГА

Аннотация. *Магнитно-резонансная томография (МРТ) стала краеугольным камнем в медицинской диагностике благодаря превосходному контрасту мягких тканей и неинвазивности. Однако сложность и огромный объем данных, генерируемых МРТ, требуют передовых методов цифровой обработки для повышения качества изображений, облегчения интерпретации и извлечения значимой клинической информации. В этой статье представлен всесторонний обзор современных методов, используемых при цифровой обработке изображений МРТ. Ключевые темы включают методы предварительной обработки, такие как шумоподавление и коррекция артефактов, сегментация изображений, извлечение признаков и передовые методы реконструкции. Мы также исследуем применение алгоритмов машинного обучения для повышения точности и эффективности диагностики. Интегрируя эти методы цифровой обработки, технология МРТ может значительно улучшить результаты лечения пациентов за счет более точной и надежной визуализации.*

Ключевые слова: *МРТ, цифровая обработка, шумоподавление, коррекция артефактов, сегментация изображений, извлечение признаков, реконструкция изображений, машинное обучение, медицинская визуализация, точность диагностики.*

Introduction

Magnetic Resonance Imaging (MRI) has revolutionized the field of medical diagnostics,

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offering detailed images of soft tissues, organs, and other internal structures without the use of ionizing radiation. Its ability to produce high-contrast images and its versatility in capturing various types of tissue make MRI an invaluable tool in the diagnosis and monitoring of numerous medical conditions, including neurological, cardiovascular, and musculoskeletal disorders.

Despite its advantages, the raw data acquired from MRI scans often contain noise, artifacts, and other imperfections that can obscure critical details and complicate diagnosis. To address these challenges, digital processing methods are employed to enhance the quality and interpretability of MRI images. These methods encompass a range of techniques, from basic preprocessing steps like noise reduction and artifact correction to more complex processes such as image segmentation, feature extraction, and advanced image reconstruction.

In recent years, the advent of machine learning and artificial intelligence has introduced new possibilities for the digital processing of MRI images. These technologies have shown promise in automating and improving the accuracy of image analysis, thereby aiding radiologists and medical professionals in making more informed decisions.

This article aims to provide a detailed exploration of the various digital processing methods applied to MRI images. By understanding these techniques, we can appreciate how they contribute to the overall enhancement of MRI as a diagnostic tool, ultimately leading to better patient care and outcomes.

MRI Image Classification Methods

The MRI image classification can be done in supervised manner as well as in un-supervised manner. The process of classification of MR images is challenging and can be achieved various ways. The supervised techniques mainly used are artificial neural network (ANN) based on back-propagation neural network (BPNN), convolutional neural network (CNN), probabilistic neural network (PNN), and apart from ANN, there are support vector machine (SVM) and k-nearest neighbor (KNN) which are most preferred. Figure 1 illustrates the comparison of normal brain image and abnormal brain image. The second image clearly depicts brain tumor. MRI image classification can be used in detection of large variety of diseases.

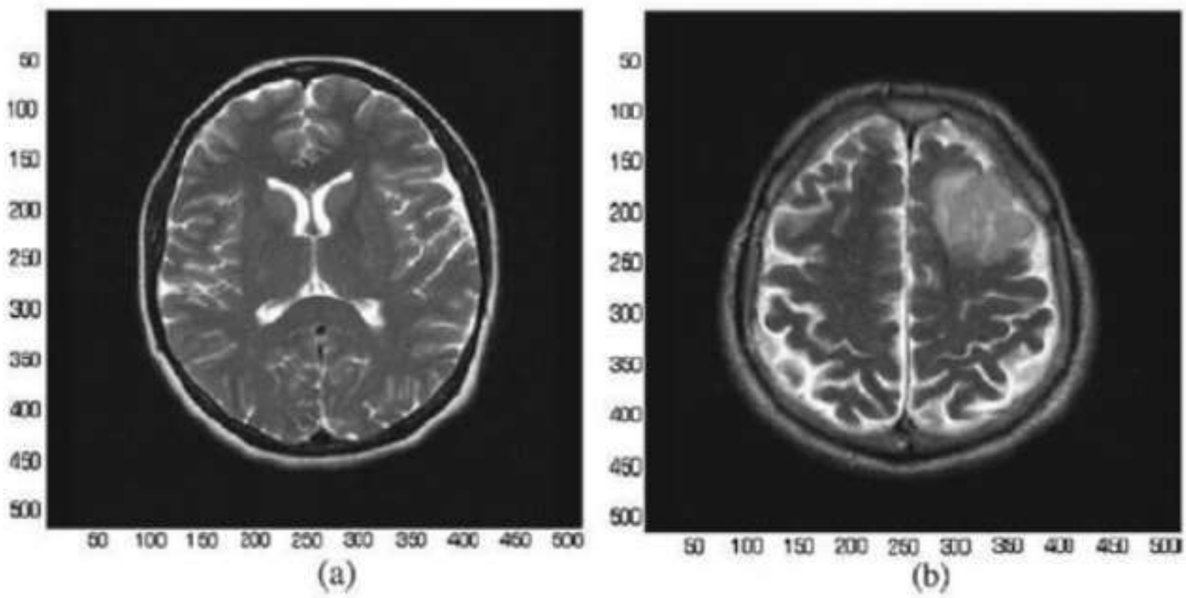


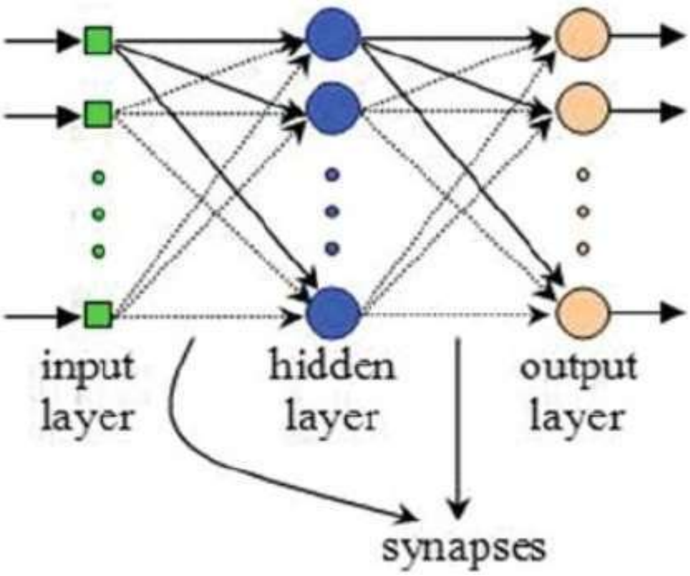
Fig. 1 a) Normal brain MRI image, b) Abnormal brain MRI image.

ANN-based classifiers are the most preferred for the classification of MR images. The ANN classifier consists of massively interconnected processing elements. The elements and layers are organized such that the whole architecture resembles the human brain.

An ANN seems to be massively parallel distributed processor. Figure 2 illustrates a simple ANN having three layers with feed-forward connections. The most frequently used training algorithm is BPNN. The signals are sent forward by the neurons, while the errors are sent backwards. The process continues until the ANN learns the training data.

The BPNN is supervised learning, and its main aim is to reduce the error. The BPNNs are useful for brain tumor detection from MRI brain images.

Fig. 2 Simple ANN architecture.



Histogram

A histogram is a list that runs the length of the number of intensities values and counts the frequency of each pixel intensity for a given image. An example of a histogram showing the 8-bit pixel value distribution of a slice can be seen in Figure 1b and 1c. Approaches that use intensity distributions are popular and a standard way many research studies correct bias in MR images.3

The nonparametric nonuniform normalization method (N3) has, since its inception in 1998, been shown to produce the best bias correction. Since then, the N3 method has been upgraded, and the current standard for bias correction is the N4 method. A popular software that contains the N4 bias correction can be found in the Nippy Python package.

Chang and coworkers used the N4 bias correction in deep learning-based study utilizing TensorFlow to predict isocitrate dehydrogenase status in low- and high-grade gliomas.8 Although there are several approaches to address bias correction, the area still remains one of the active research projects.

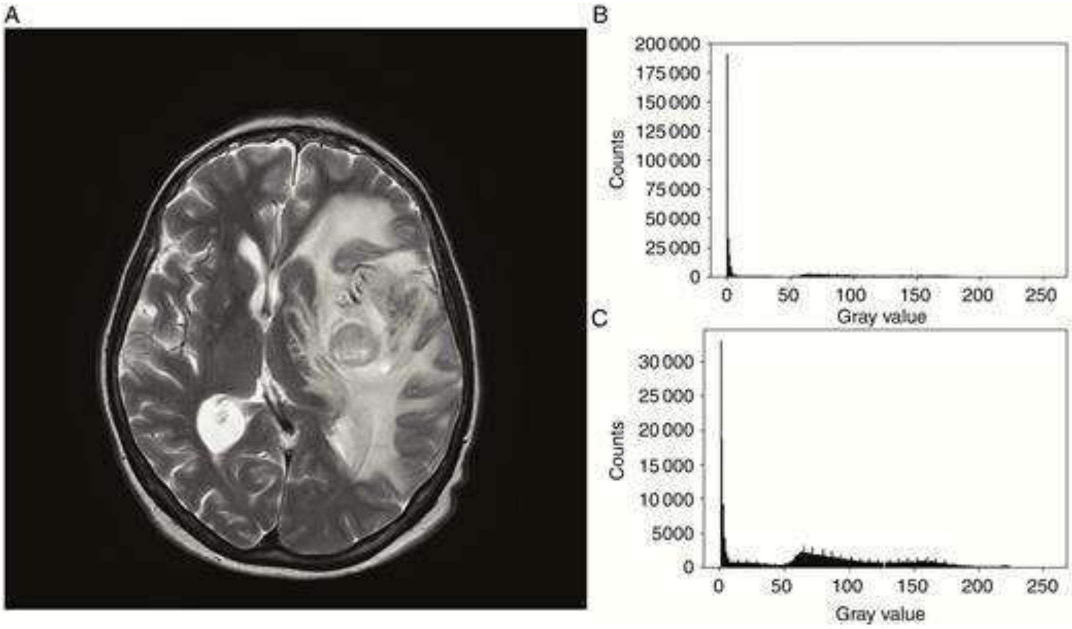


Figure3. (a) An axial slice near the middle of the brain and its associated histograms. (b) A histogram of all gray-level values (0–255). (c) A histogram of all gray-level values but 0 (1–255).

Image segmentation.

MRI images need segmentation to make it easier to get accurate information. Because with

digital MRI image segmentation, it can obtain pixels or objects according to their texture or color to separate objects and backgrounds or MRI images can also be divided into several segments so that the processed image is easier to analyze. Image segmentation consists of pixel-based, edge- based, and region-based segmentation, where segmentation is done based on the three types of

segmentation according to the purpose of obtaining information related to the digital image being processed.

Segmentation is an image is divided into disparate, nonoverlapping regions whose texture features share degrees of homogeneity. In patients with brain cancers, the goal would be to

delineate the ROI containing tumor, edema, or other distinguishing features. Segmentation of

tumors is a very important part of general clinical diagnosis that also forms the basis of imaging studies.

In most segmentation challenges, segmentation algorithms are assessed by the accuracy of

segmentation of white matter, gray matter, and cerebrospinal fluid. Over the years, segmentation strategies have been developed and are categorized in different ways. There are 3 main types of segmentation that range in their degree of computer-aided automation: manual segmentation,

supervised, and unsupervised.

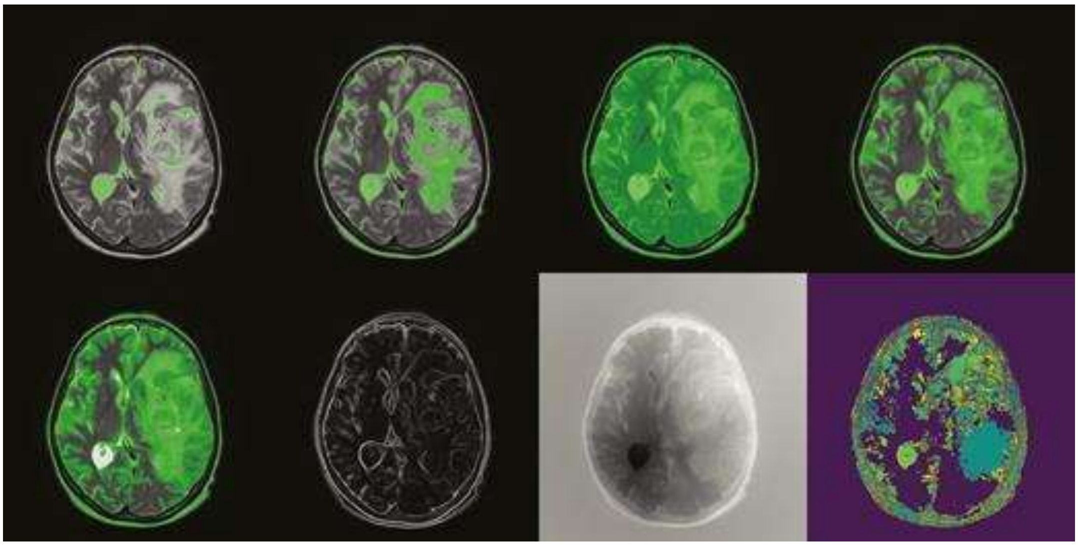


Figure 4. The application of 4 common filters used for segmentation in Insight ToolKit.

From left to right and top to bottom, the filters are as follows: simple thresholding, binary thresholding, Otsu's thresholding, region growing, confidence connected, the gradient magnitude, fast marching, and watershed. It is important to note that none of the parameters have been tuned for any of these filters.

Table 1. Three types of segmentation

Segmentation Techniques	Consists of	Explanation
Pixel Based	Thresholding : -Otsu	Grayscale images are converted to binary images by selecting a threshold value
Edge Based - Region-Based	Clustering: - K – means - Fuzzy C-Mean Edge Detection, Gradient Mode, Active Contours, Level Sets. Region Growing, Split/Merge, Graph Cut (hybrid)	Clustering where objects are put together into groups based on their characteristics. The edge detection technique is to determine the pixel value at the boundary. Segmentation. The result is an image in the binary form Region-based segmentation groups pixels by region

Deep Learning in MR Image Processing.

Deep learning is a branch of machine learning based on the use of multiple layers to learn data representations, and can be applied to both supervised and unsupervised learning. These multiple layers allow the machine to learn multiple level features of data in order to achieve its desired function. Figure 5a presents a simplified version of a neural network, which has been the most widely used deep learning architecture over the last decade. Each layer of deep learning architecture consists of a set of nodes, and each node is represented by a digitized number. The nodes of the previous layer can be connected to each node of the next layer either fully or locally, as shown in Figure 5b and c, respectively. Figure 5d shows a locally-connected layer with two different channels. In this case, individual channels have their own connections.

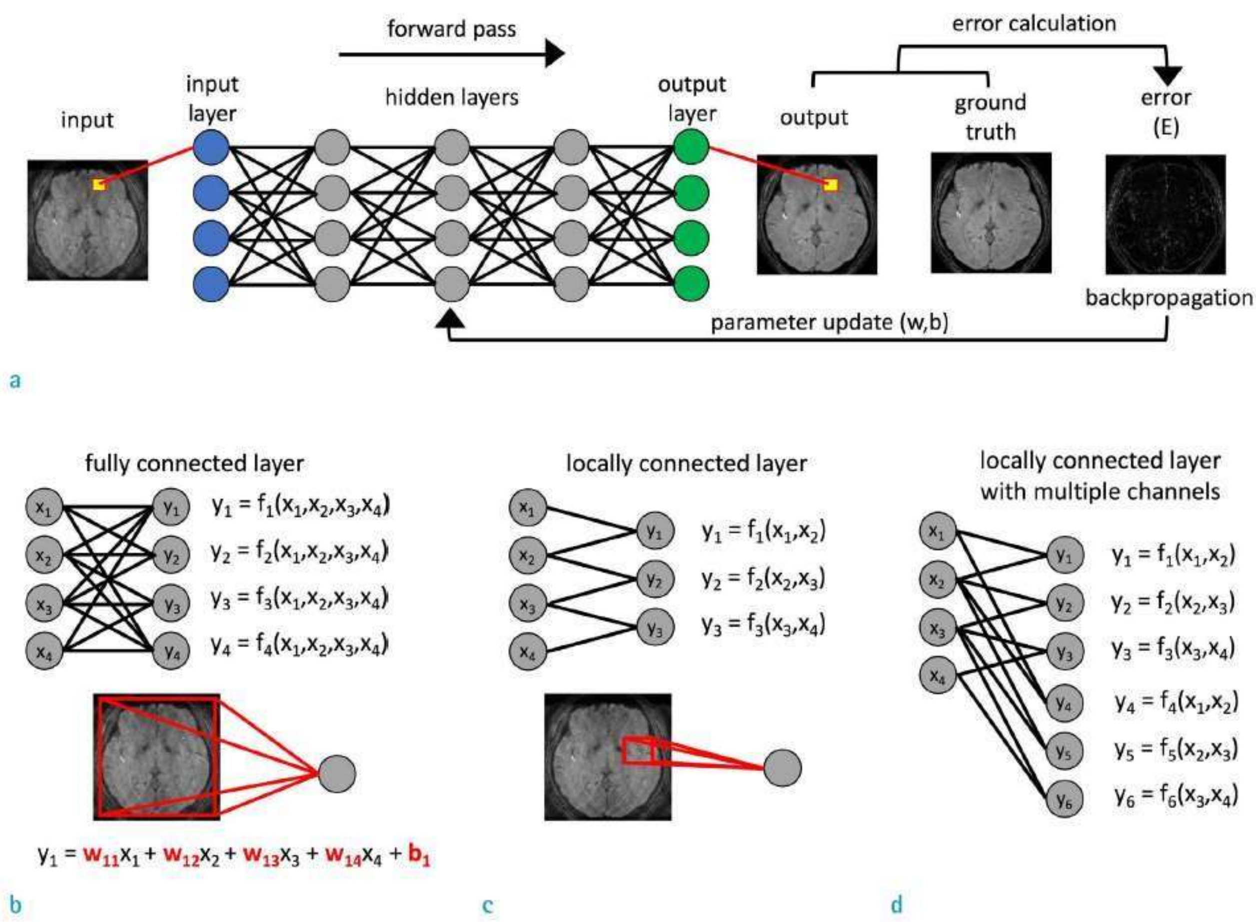


Fig. 5. (a) Overall process of the learning process for the simplified version of the neural network, which is the most widely used deep learning architecture in image processing applications. The nodes of the previous layer can be connected to each node of the next layer in various ways. (b) Fully-connected layer. (c) Locally-connected layer. (d) Locally-connected layer with multiple channels.

Biomarker Recording

All of the features discussed quickly create a massive matrix of data, making it difficult to properly maintain records of each biological feature, or biomarker. To address this data management problem, the image standardization biomarker initiative (IBSI) was founded to devise a set of rules to standardize the extraction and naming of imaging biomarkers, enhance reproducibility, suggest workflows, and establish biomarker reporting guidelines.

The IBSI has proposed a general scheme for biomedical image processing workflows. As the field is dynamic, this scheme is not permanent but rather a guideline for investigators. This review has been structured in a way that follows IBSI’s scheme: data acquisition, preprocessing, segmentation, image interpolation (optional), feature extraction, and feature data. A high-level visualization of this workflow can be found in the flowchart in Figure 6. Interpolation is optional in cases where patients do not have the same number of slices. This often occurs in multi-institutional studies.

Interpolating missing images for parity is sometimes necessary, depending on the type of analysis to be performed.

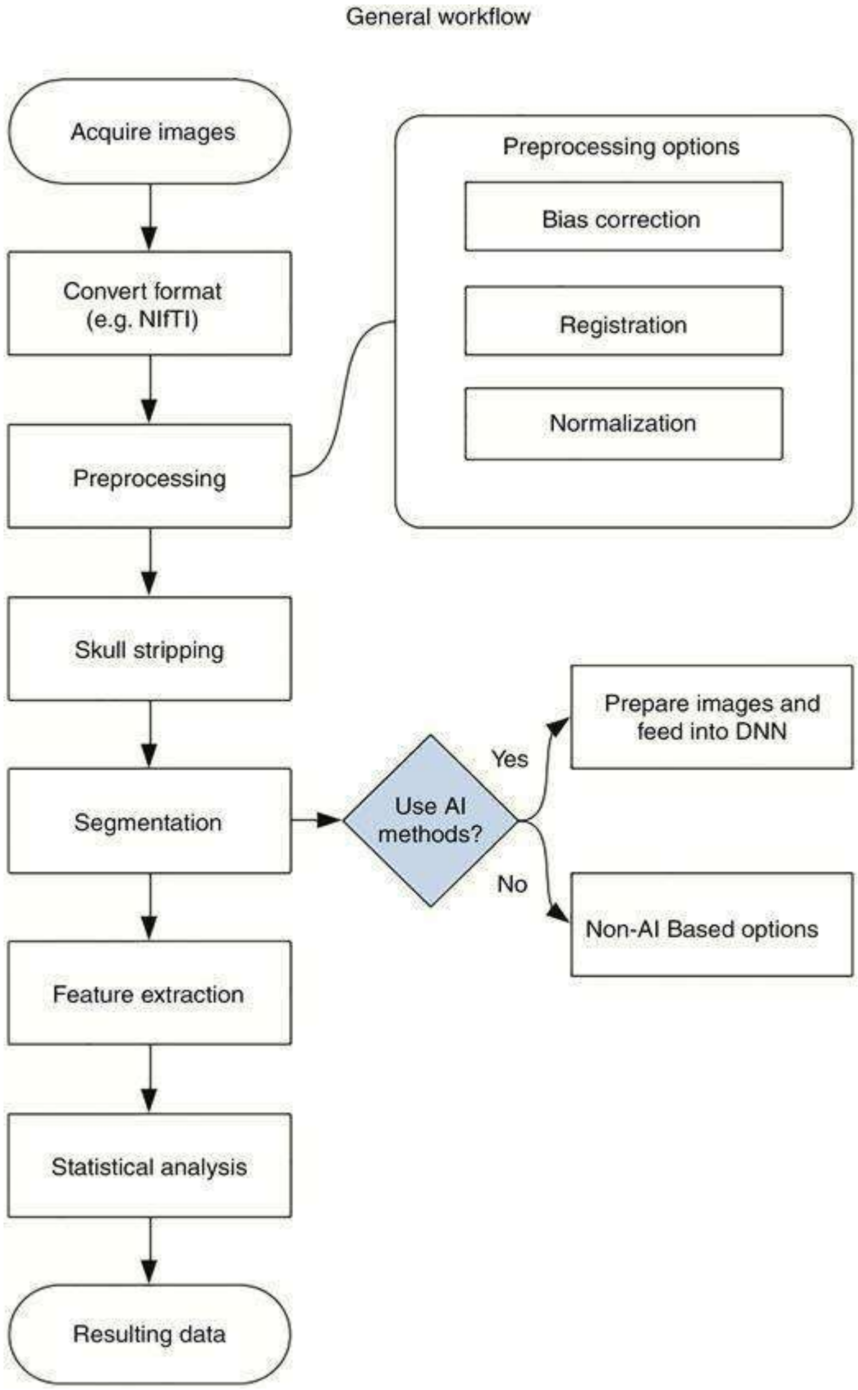


Figure 6.A flowchart of a general MR image analytics workflow and a potential use of AI-based methods in the segmentation process block.

Conclusion.

This paper studied the current trends in the classification of MRI images. A general overview of various supervised and unsupervised classification methods was discussed. The analysis was mainly focused on MRI brain images classification methods.

The classification accuracy of MRI brain images played important role for the diagnosis of various diseases with accuracy. The field of medical image diagnosis is full of challenges as the technique's available lags in various aspects, so there is always a scope for the further enhancements in the performance of the existing methods. The survey will be useful for researchers and new learners who aim for the advancement in MRI image classification methods.

MRI imaging analysis advanced significantly since the advent of computer vision and computer graphics. AI is being applied to many areas, including MRI imaging analysis, which is now moving at an accelerated pace as new deep learning-based research is conducted. This application of AI will undoubtedly open new areas of research and investigation, particularly for challenging diseases such as brain tumors.

MRI image processing methods for detecting and classifying brain tumors are the right solution in the medical field It can help the medical team to identify and classify brain tumors using MRI images. And from the existing algorithm, it can be seen that the Support Vector Machine is the best method for classifying brain tumors based on MRI images supported by some preprocessing and feature extraction as well as the Radial basis function (RBNFF) method. It is hoped that in the future MRI image processing can combine various existing image processing methods to obtain the best results for reading MRI images for the detection and classification of brain tumors.

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