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MRI Image Analysis for Brain Tumor Segmentation Using Convolutional Neural Network

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Abstract: In medical imaging, the analysis of Brain Tumor Segmentation is one of the most challenging Problems. To reduce the death rate, the defects in the region of a Human Brain should be reported immediately. The segmentation of the abnormal region helps to monitor and plan the treatment. Isolating normal and abnormal tissues is a critical step in Segmentation. Magnetic Resonance Imaging (MRI) is a widely used, noninvasive modality for early diagnosis of Brain abnormalities. Several Deep Learning based methods have been applied to Brain Tumor Segmentation and achieved promising results. Deep Learning techniques such as the Convolutional Neural Network (CNN) are used to obtain the best results in Brain Tumor Segmentation. The building blocks of CNN algorithms are specifically designed for image segmentation tasks. Looking ahead, Deep Learning-based Brain Tumor Segmentation holds significant potential to revolutionize the diagnosis and treatment of Brain Tumors, paving the way for more accurate and personalized healthcare solutions.

Keywords: Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Deep Learning (DL)

1. Introduction:

The analysis of medical imaging involves clinical treatment and basic medical research for computer-aided diagnosis, medical robots, and image-based applications. For understanding diseases and investigating clinical challenges to improve healthcare quality, medical image analysis provides useful guidance for medical professionals. Brain tumor segmentation has attracted much attention in the research community among various tasks in medical image analysis. Due to various challenges in location uncertainty, morphological uncertainty, low contrast imaging, annotation bias, and data imbalance accuracy the brain tumor segmentation remains to be solved. The most common imaging methods that used before and after surgery are Magnetic Resonance Imaging (MRI).

Brain Tumor is an abnormal and uncontrolled growth of cells within the brain or its surrounding structures. These tumors can be classified into two main types: primary tumors, which originate in the brain itself, and secondary (or metastatic) tumors, which spread to the brain from cancers in other parts of the body. Primary Brain tumors may be benign (non-cancerous) or malignant (cancerous), with common types including gliomas, meningioma, pituitary adenomas, and medulloblastomas.

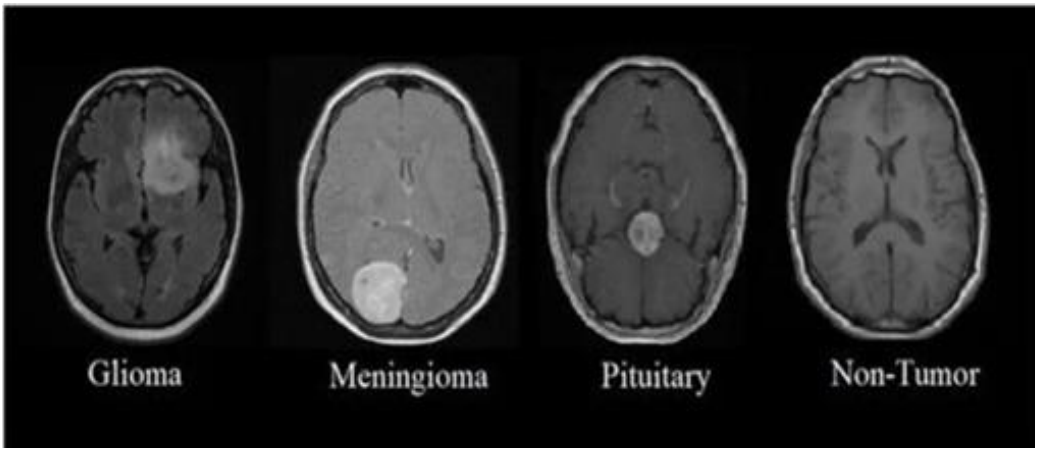

Fig: 1.1 Types of Brain Tumor

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Gliomas, especially glioblastomas, are among the most aggressive and deadly forms. Symptoms of brain tumors vary depending on their size, location, and rate of growth, but may include persistent headaches, seizures, vision or hearing problems, nausea, personality changes, and difficulties with movement or coordination. The exact cause of brain tumors is often unknown, but factors like genetic mutations, exposure to radiation, a family history of brain tumors and certain immune conditions may increase risk. Diagnosis typically involves neurological examinations and imaging techniques such as MRI or CT scans, often followed by a biopsy for confirmation. Treatment options depend on the type of tumor and location, and may include surgery, radiation therapy, chemotherapy, targeted drug therapies, or immunotherapy. In recent years, the integration of artificial intelligence-particularly deep learning models such as (CNNs) has significantly enhanced the accuracy and efficiency of brain tumor detection and segmentation from MRI images, aiding clinicians in diagnosis and treatment planning.

2. Magnetic Resonance Imaging

A Brain tumor is a mass or group of aberrant cells surrounding the brain; any development inside this constrained area might be problematic. There are two types of brain tumors: Benign (not cancerous) and Malignant (cancerous). Brain injury may result from an increase in intracranial pressure brought on by the growth of benign or malignant tumors.

Numerous medical imaging methods, including single-photon emission computed tomography, CT, PET, magnetic resonance spectroscopy (MRS), and MRI, are utilized to offer helpful information regarding size, shape, and location. The most common method for diagnosing brain tumors in medicine is magnetic resonance imaging (MRI). Additionally, the MRI significantly influences better growth rate prediction, treatment planning, and diagnosis.

One of the most effective and widely used techniques for assessing individuals who exhibit symptoms and indicators of a brain tumor is magnetic resonance imaging (MRI). It can determine the position and size of tumors, design the best course of therapy, and evaluate the effectiveness of that treatment because of its exceptional contrast accuracy. Different tissue contrast pictures are produced by MRI modalities, offering useful structural data that can be utilized for brain tumor diagnosis and segmentation.

3. Proposed Methodology

3.1 THE PROPOSED WORK

The proposed work presents a detailed methodology for brain tumor segmentation from MRI images using a Convolutional Neural Network (CNN)-based approach. The process begins with the collection of a brain MRI image dataset, which serves as the foundational input for the entire system. These MRI images contain various brain structures and potentially tumor regions that need to be accurately segmented for clinical analysis and diagnosis.

The first stage involves pre-processing the input MRI images to enhance their quality and make them suitable for feature extraction and learning. Pre-processing typically includes steps such as image resizing, contrast adjustment, noise filtering (e.g., using median or Wiener filters), and normalization. These steps help in standardizing the images and removing artifacts that may affect the performance of the CNN.

Following pre-processing, the system performs feature extraction, where the most relevant information from the MRI scans is identified. This can involve manual techniques such as Histogram of Oriented Gradients (HOG) or texture-based features, or it can be integrated into the CNN's initial layers to automatically learn these features. Feature extraction is a critical step because it allows the network to focus on the most important visual patterns that distinguish tumor tissues from healthy brain tissues.

The extracted features are then passed into the Convolutional Neural Network, which is the core of the proposed system. The CNN consists of multiple layers including convolutional layers, activation functions (like ReLU), pooling layers, and fully connected layers or up-sampling blocks for pixel-level classification. The CNN is trained using a labelled dataset of MRI images and corresponding segmentation masks, allowing it to learn how to distinguish tumor regions from the rest of the brain. Depending on the design, the CNN can perform semantic segmentation, producing a detailed map where each pixel is classified as tumor or non-tumor.

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Finally, the CNN outputs segmented images, where the tumor regions are clearly identified and separated from the rest of the brain tissue. These segmented results can be visualized as overlays on the original images, helping radiologists and clinicians in assessing the size, shape, and location of the tumor. This proposed CNN-based framework significantly improves the accuracy, consistency, and speed of brain tumor segmentation compared to traditional methods and serves as a valuable tool in computer-aided diagnosis and treatment planning.

3.2 BLOCK DIAGRAM

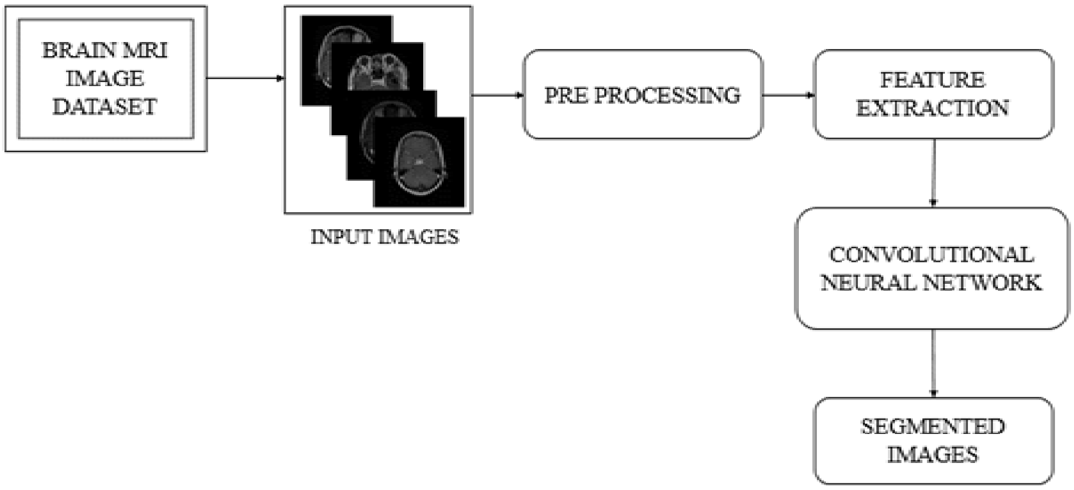

Fig 3.1: The Block Diagram of Proposed Work

3.3 Working

The diagram illustrated in Fig 3.1 is the general workflow for Brain Tumor Segmentation using MRI images. It starts with a Brain MRI Image Dataset, from which input images are taken. These images undergo preprocessing to enhance quality and remove noise. After that, feature extraction is performed to identify significant patterns and regions in the images. The extracted features are then fed into a Convolutional Neural Network (CNN), which learns to identify tumor regions. Finally, the CNN outputs segmented images, highlighting the tumor areas for further medical analysis or diagnosis.

3.3.1 Brain MRI Image Dataset

This is the foundation of the entire process. It contains MRI scans of the Human Brain. These images may include various MRI modalities like T1, T2, FLAIR and T1c, which provide different tissue contrasts and are critical for identifying abnormalities like tumors.

- T1-weighted images (T1): Good for anatomical detail.
- T2-weighted images (T2): Highlights fluids; useful for identifying tumors.
- FLAIR (Fluid Attenuated Inversion Recovery): Suppresses fluid to enhance lesion visibility.
- T1-contrast (T1c or T1-Gd): Taken after injecting a contrast agent to enhance tumor borders.

The dataset is often labeled or annotated by radiologists, marking tumor boundaries or regions of interest. This ground truth is used for supervised training of deep learning models. High-quality, well-labeled datasets ensure that deep learning models are both clinically relevant and technically robust.

3.3.2 Input Images

The MRI scans from the dataset are read and converted into a usable format. These input images are fed into the system one by one or in batches. They may vary in size, orientation, and modality, and are often standardized before further processing. Each image is a digital representation of a cross-sectional view of the brain, where abnormalities like tumors can be visually and computationally analyzed.

3.3.3 Pre-Processing

In brain MRI image analysis, pre-processing techniques play a crucial role in enhancing image quality and improving the performance of subsequent segmentation tasks. MRI images often suffer from various types of noise introduced during acquisition due to scanner imperfections, patient movement, or variations in acquisition parameters. This noise can obscure critical anatomical structures especially the boundaries of brain tumors leading to imprecise segmentation and potentially flawed clinical assessments. To mitigate these challenges, advanced filtering and contrast enhancement techniques are applied prior to segmentation. Two widely used methods are Wiener filtering and Histogram Equalization.

3.3.3.1 Wiener filtering

- The Wiener filter is particularly effective in adaptive noise reduction while preserving critical structural details such as edges.
- It applies strong noise suppression in smooth (low-variance) regions and retains sharpness in high-variance regions like edges.
- This is crucial because tumor boundaries usually exist in high contrast regions and preserving them ensures accurate segmentation.
- MRI images often suffer from Gaussian noise, especially in low-signal areas, which the Wiener filter is well-suited to handle.
- By improving the signal-to-noise ratio (SNR), Wiener filtering enhances the quality of MRI images used for diagnostic purposes.
- It ensures that important anatomical features are retained, supporting better analysis and decision-making in medical imaging.

3.3.3.1 Histogram Equalization

- Histogram Equalization is a contrast enhancement technique that redistributes the pixel intensity values across the image to span the full range of possible intensities.
- It is especially beneficial in medical imaging, where the tumor and surrounding brain tissue often exhibit similar intensity values, making it difficult to distinguish between them.
- This process helps in making subtle and hidden structures, such as small Tumors or poorly contrasted tissue boundaries, more visible and distinguishable.
- The technique improves the dynamic range of pixel intensities, which facilitates more accurate and efficient segmentation by deep learning models or other image analysis techniques.
- Overall, histogram equalization is a critical pre-processing step that supports better visualization and enhances the performance of tumor detection algorithms.

3.3.4 Feature Extraction

In this stage, relevant features are extracted from the pre-processed images. These features may include edges, textures, shapes, and intensity patterns, which help differentiate between healthy and abnormal tissues. Although modern CNNs learn features automatically, traditional techniques like GLCM (Gray Level Co-occurrence Matrix) may still be used in some hybrid methods. The aim is to convert raw pixel data into a form that highlights critical characteristics of the tumor region.

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3.3.4.1 Gray Level Co-occurrence Matrix

The Gray Level Co-occurrence Matrix (GLCM) is a statistical method used to analyse the texture of an image by examining the spatial relationship between pairs of pixels. In the context of image segmentation, GLCM helps distinguish different regions based on their texture characteristics rather than just intensity or colour. The method involves creating a matrix that counts how often pairs of pixel values (gray levels) occur at a specified spatial relationship (defined by direction and distance) within a region of the image. For example, if we choose a direction (like horizontal) and a distance (like 1 pixel), the GLCM tallies how frequently a pixel with gray level i occurs adjacent to a pixel with gray level j. Once the GLCM is constructed, several texture features can be derived from it, such as contrast, correlation, energy, homogeneity and entropy which describe aspects like texture smoothness, regularity, and complexity. These features are especially useful in segmentation tasks, where they help differentiate between regions with different textures, such as distinguishing healthy tissue from tumors in medical images. By analysing the GLCM-derived features over different parts of an image, a classifier can be trained to segment and label areas based on their underlying textural properties, making GLCM a powerful tool for identifying subtle structural patterns in images.

3.3.5 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have become a powerful tool for brain tumor segmentation in MRI images due to their ability to automatically learn complex features directly from the data. Unlike traditional methods such as thresh-holding or clustering, which rely on manually designed features, CNNs extract hierarchical patterns like edges, textures, and shapes that are crucial for accurately identifying tumor boundaries. In segmentation tasks, CNNs perform pixel-wise classification, producing masks that delineate tumor regions from healthy tissue. Typically, a CNN-based segmentation model consists of multiple convolutional layers that extract features, pooling layers that reduce spatial dimensions, and up-sampling layers that restore the original image size to output a mask of the same resolution as the input. Training these models requires a set of MRI scans paired with ground truth tumor masks, and they are optimized using loss functions such as Dice loss, which is particularly effective for handling the imbalance between tumor and non-tumor pixels. MATLAB’s Deep Learning Toolbox supports designing, training, and evaluating CNNs for segmentation, enabling researchers to build custom architectures without relying on standard models like U-Net. Overall, CNN-based segmentation significantly improves the accuracy and reliability of brain tumor detection compared to traditional image processing techniques.

3.3.6 Segmented Images

The output of this CNN-based segmentation process is a set of segmented images, where the tumor regions are clearly identified and separated from the surrounding brain tissues. This automated segmentation significantly reduces manual effort, enhances diagnostic accuracy and facilitates early detection and treatment planning.

4. Software Requirements

4.1 MATLAB

MATLAB is an interpreted, high-level, general purpose programming language created by Guido Van Rossum and first released in 1991; MATLAB's design philosophy emphasizes code Readability with its notable use of significant Whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. MATLAB is dynamically typed and garbage collected. It supports multiple programming paradigms, including procedural, object-oriented and functional programming.

4.2 MATLAB R2019B

In MATLAB R2019b, convolutional neural networks (CNNs) can be effectively used for brain tumor segmentation by leveraging the Deep Learning Toolbox, which provides functions and tools to design, train, and evaluate CNN architectures. Although R2019b does not include some of the latest deep learning features available in newer releases, it still supports building custom CNN models for pixel-wise segmentation tasks. Users can create a CNN by defining a series of layers, including convolutional layers for feature extraction, ReLU activation, pooling layers for spatial down-sampling, and transposed convolutional layers for up-sampling the feature maps back to the original image size. The toolbox also allows using pixel classification layers with appropriate loss

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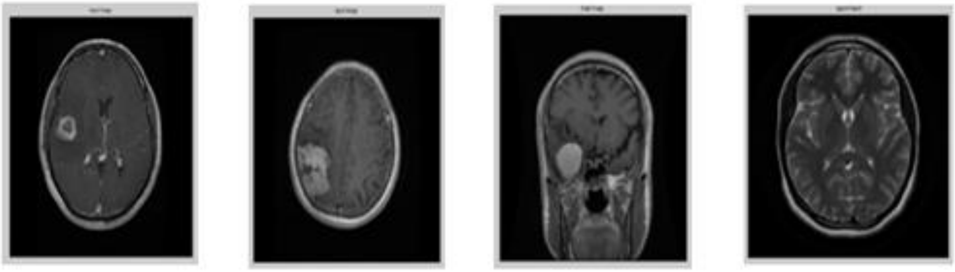
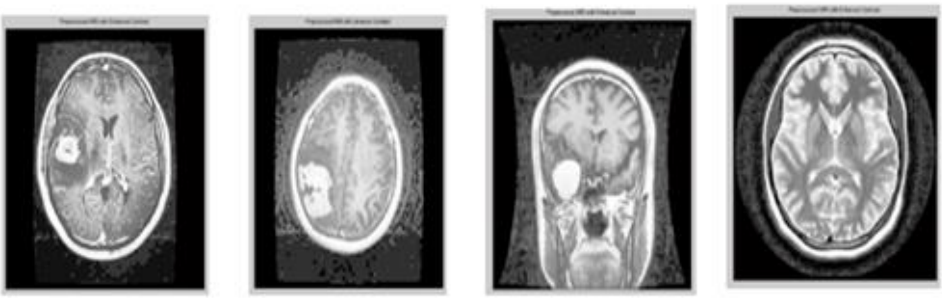
functions such as Dice or cross-entropy loss to train the network on MRI images paired with ground truth tumor masks. MATLAB's built-in functions like train-Network facilitate the training process with options for data augmentation and validation. Thus, MATLAB R2019b provides a solid environment for researchers and engineers to implement CNN-based brain tumor segmentation without needing advanced architecture like U-Net, allowing customization to fit specific datasets and requirements.

5. Results and Discussion

5.1 Pre-Processing



Original Images of Glioma, Meningioma, Pituitary Tumor and Non-Tumor



Original Images of Glioma, Meningioma, Pituitary Tumor and Non-Tumor are Pre-processed using Wiener Filter and Histogram Equalization

Fig: 5.1: Pre-Processed Images

Table 5.1: Comparison Table for Weiner Filter and Histogram Equalization

Feature	**Wiener Filter**	**Histogram Equalization**
Purpose	De-noising	Contrast enhancement
Target	Gaussian noise	Intensity spread
Effect on tumor edges	Preserves edges during de-noising	Makes edges and regions more visible
Order in Pre-processing	Applied early	Applied after noise reduction

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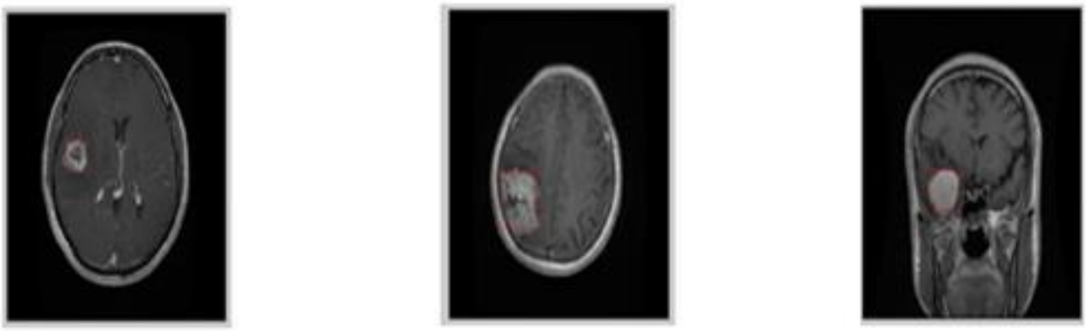
5.2 Feature Extraction

Table 5.2: Features Extracted From Pre-Processed Image

FEATURE	GLIOMA	MENINGIOMA	PITUITARY TUMOR	NON-TUMOR
Contrast	0.88462	0.49948	0.3758	0.6510
Correlation (mean)	0.54707	0.71247	0.7943	0.7055
Energy	0.02194	0.04016	0.0433	0.0613
Entropy	2.53331	2.22144	1.9135	2.1151
Homogeneity (mean)	0.70606	0.80443	0.8658	0.8492
Homogeneity (product)	0.69231	0.79995	0.8620	0.8394
Sum Average (horizontal)	7.26923	7.73758	7.9100	4.3263

5.3 Convolutional Neural Networks

Tumor Recognition of Glioma, Meningioma, Pituitary Tumor



Segmentation of Glioma, Meningioma, Pituitary Tumor using CNNs

Fig: 5.2: Segmented Images Using CNNs

6. Conclusion

The output of this CNN-based segmentation process is a set of segmented images, where the tumor regions are clearly identified and separated from the surrounding brain tissues. This automated segmentation significantly reduces manual effort, enhances diagnostic accuracy, and facilitates early detection and treatment planning. The CNN model is designed to automatically learn complex hierarchical representations of the input features and segment the tumor region with high precision. Its layered architecture allows the model to focus on both low-level and high-level features crucial for effective segmentation. The proposed method efficiently integrates preprocessing, feature extraction, and CNN-based segmentation into a unified workflow. This not only improves the reliability and robustness of brain tumor detection but also paves the way for real-time clinical applications. The use of CNNs in this framework marks a substantial advancement over traditional methods by offering greater accuracy, automation, and adaptability to complex medical imaging challenges

7. Future Work

Future work will focus on extending the CNN-based segmentation approach to include tumor classification and detection. After accurately segmenting the tumor regions, these areas can be analyzed using CNN classifiers to determine the tumor type or grade, enhancing diagnostic detail. Detection models can be integrated to localize and identify tumors across slices, enabling a complete automated system. This advancement will improve clinical decision-making, support early diagnosis, and pave the way for real-time, end-to-end brain tumor analysis in medical imaging

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