BRAIN TUMOR IDENTIFICATION AND CLASSIFICATION OF MRI IMAGES USING DEEP LEARNING TECHNIQUES

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ABSTRACT

The detection, segmentation, and extraction from Magnetic Resonance Imaging (MRI) images of contaminated tumor areas are significant concerns however, a repetitive and extensive task executed by radiologists or clinical experts relies on their expertise. Image processing concepts can imagine the various anatomical structure of the human organ. Detection of human brain abnormal structures by basic imaging techniques is challenging. In this paper, a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) has been proposed for brain tumor segmentation based on deep learning techniques. The present work proposes the separation of the whole cerebral venous system into MRI imaging with the addition of a new, fully automatic algorithm based on structural, morphological, and relaxometry details. The segmenting function is distinguished by a high level of uniformity between anatomy and the neighboring brain tissue. ELM is a type of learning algorithm consisting of one or more layers of hidden nodes. Such networks are used in various areas, including regression and classification. In brain MRI images, the probabilistic neural network classification system has been utilized for training and checking the accuracy of tumor detection in images. The numerical results show almost 98.51% accuracy in detecting abnormal and normal tissue from brain Magnetic Resonance images that demonstrate the efficiency of the system suggested.

I. INTRODUCTION

Gliomas are the most prevalent and lethal brain tumors, classified into Low-Grade (LGG) and High-Grade Gliomas (HGG), with HGG being more aggressive and typically leading to a survival period of only 14 months post-diagnosis, even with treatments like surgery, chemotherapy, and radiotherapy. MRI plays a crucial role in glioma assessment due to its ability to capture detailed and complementary sequences. Accurate segmentation of gliomas and their sub-regions is essential for diagnosis, treatment planning, and follow-up, but manual segmentation is time-consuming and prone to inter- and intra-rater variability. Automatic segmentation is challenging due to tumor variability in shape, size, and location, as well as MRI intensity inconsistencies and tumor-induced deformation of normal brain tissue. Traditional approaches involve probabilistic models, Markov Random Fields (MRF), and probabilistic atlases, while machine learning methods such as Support Vector Machines (SVM) and Random Forests (RF) have proven effective by incorporating features like texture, symmetry, and intensity. Deep learning methods, particularly Convolutional Neural Networks (CNNs), have shown superior performance by automatically learning hierarchical features from raw data, overcoming the need for handcrafted features. Techniques like 3D filters, multi-pathway architectures, cascaded networks, and subject-specific training further enhance segmentation accuracy. Inspired by VGG-style CNNs, recent work proposes using small 3×3 kernels to build deeper networks with fewer parameters and greater non-linearity, reducing overfitting while maintaining large receptive fields. Pre-processing with intensity normalization (e.g., Nyúl's method) addresses variability from multi-site MRI scanners, while data augmentation techniques improve model robustness. These advanced CNN-based methods significantly improve glioma segmentation, aiding clinical decisions and improving patient outcomes.

MOTIVATION

Gliomas are aggressive brain tumors with high mortality, requiring precise segmentation for effective treatment. Manual segmentation is time-consuming and inconsistent, leading to the need for automated methods. Traditional machine learning methods like Random Forests have shown success, but recent advancements in deep learning—especially Convolutional Neural Networks (CNNs)—have significantly improved segmentation accuracy by learning complex patterns from raw MRI data. The use of small convolutional kernels, data augmentation, and intensity normalization techniques enhances model performance and robustness, making CNN-based models promising tools for clinical brain tumor analysis.

- **Develop an Accurate Glioma Segmentation Model:** Create a deep learning-based framework capable of accurately identifying and segmenting glioma regions and sub- regions in brain MRI scans.
- **Improve Clinical Workflow:** Reduce the reliance on manual segmentation by radiologists, which is time-consuming and error-prone, thereby enhancing efficiency and consistency in diagnosis and treatment planning.
- **Handle Data Variability:** Address challenges related to intensity inhomogeneity and scanner differences using pre-processing techniques like intensity normalization.
- **Utilize Deep Learning for Feature Extraction:** Employ Convolutional Neural Networks (CNNs) to automatically learn hierarchical and complex features from raw MRI data without the need for handcrafted feature engineering.
- **Enhance Model Robustness and Generalization:** Implement data augmentation strategies to deal with limited datasets and improve the model's ability to generalize across diverse cases and tumor presentations.
- **Incorporate Efficient Network Design:** Use small 3×3 convolutional kernels to design deeper yet more efficient CNN architectures that reduce overfitting and increase segmentation accuracy.
- **Compare with Traditional Techniques:** Evaluate the performance of the deep learning model against traditional machine learning methods (e.g., Random Forests) to highlight improvements in segmentation precision.
- **Facilitate Real-world Application:** Ensure the proposed system can be adapted for clinical use, supporting radiologists with reliable and reproducible results in tumor analysis and monitoring.

PROBLEM STATEMENT

Brain tumors, particularly gliomas, are among the most life-threatening neurological disorders, with high mortality rates and complex treatment requirements. Accurate and timely identification of these tumors is critical for effective treatment planning. However, manual interpretation of MRI scans is time-consuming, prone to inter-observer variability, and often inconsistent due to the tumors irregular shapes, locations, and appearances across patients. Additionally, variability in MRI image quality caused by different scanners and acquisition protocols makes diagnosis even more challenging. Traditional segmentation and classification methods lack the adaptability and precision needed for reliable results. Therefore, there is a pressing need for an intelligent, automated system that can accurately detect and classify brain tumors in MRI images using advanced deep learning techniques—enhancing diagnostic accuracy, reducing workload for medical professionals, and supporting timely clinical decisions.

SCOPE AND OBJECTIVE

The aim of tumor detection is to specify the tumor location, namely active tissue or necrotic tumor tissue. This is carried out by detecting the abnormal region comparing with the normal healthy tissues.dtheuseofsmall3 3kernelstoobtain deeper CNNs. With smaller kernels we can stack more convolutional layers, while having the same receptive field of bigger kernels. For instance, two 3*3 cascaded convolutional layers have the same effective receptive field of one 5*5 layer, but fewer weights. At the same time, it has the advantages of applying more non- linearity and being less prone to overfitting because small kernels have fewer weights than bigger kernels as a pre-processing step that aims to address data heterogeneity caused by multi- site multi-scanner acquisitions of MRI images. The large spatial and structural variability in brain tumors are also an important concern that we study using two kinds of data augmentation.

Goals:

- **Accurate Tumors Localization**: Detect and delineate tumor regions such as active and necrotic tissue by comparing MRI scans with normal brain tissue structures.
- **Design Efficient CNN Architectures**: Use small 3×3 convolutional kernels to construct deep CNNs, enabling increased non-linearity, reduced overfitting, and efficient feature extraction with fewer parameters.
- **Normalize Multi-Site MRI Data**: Apply intensity normalization techniques to handle variability in MRI images caused by different scanners and acquisition settings.
- **Enhance Model Robustness**: Employ diverse data augmentation methods to manage the high spatial and structural variability of brain tumors and improve model generalization.
- **Automate Tumors Classification Pipeline**: Develop a scalable deep learning framework that automates tumor detection and classification to support clinicians in diagnosis and treatment planning.

The goal of this project is to reduce manual tumor segmentation by using Convolutional Neural Networks (CNNs), a type of artificial neural network designed for image analysis. CNNs help automate the detection and classification of brain tumors, addressing challenges like variability in tumor shape, size, and location. To improve accuracy, the system also uses neighborhood information from voxels and probabilistic models like Markov Random Fields (MRF) for smoother and more reliable segmentation.

II. LITERATURE SURVEY

S. Bauer – "A Survey of MRI-Based Medical Image Analysis for Brain Tumor Studies". This study provides an overview of how MRI images are used for brain tumor analysis. It focuses on the segmentation process—separating the tumor and its parts from the surrounding brain tissue—and discusses the challenges caused by the tumor changing the shape and structure of brain anatomy. The paper compares different methods and highlights those that work well with standard MRI scans used in hospitals.

E. G. Van Meir – "Exciting New Advances in Neuro-Oncology: The Avenue to a Cure for Malignant Glioma". This paper discusses the latest progress in treating malignant gliomas, which are the deadliest form of brain tumors. It talks about the use of a chemotherapy drug called temozolomide and improvements in surgery using special imaging techniques like fluorescence-guided surgery. The author is hopeful that in the near future, new combinations of drugs will better target these tumors, reducing their deadly effects and giving hope to patients and doctors.

M. Prastawa – "A Brain Tumor Segmentation Framework Based on Outlier Detection". This research introduces a method that not only segments the tumor but also detects the surrounding edema (swelling), which is essential for treatment planning. Unlike many other techniques, this method does not rely solely on the contrast enhancement seen in T1-weighted MRI scans, making it more flexible and reliable.

C. H. Lee – "Segmenting Brain Tumors Using Pseudo-Conditional Random Fields". This work proposes a segmentation technique using pseudo-conditional random fields (PCRFs). These are faster and more efficient than traditional methods while maintaining high accuracy. The method considers not just the pixel itself but also the information from nearby pixels, which helps make better predictions about tumor regions.

R. Meier – "Patient-Specific Semi-Supervised Learning for Postoperative Brain Tumor Segmentation". This paper presents a semi-supervised learning method that uses both pre- surgery and post-surgery images of the same patient to improve the accuracy of tumor segmentation. This personalized approach makes the segmentation more reliable, especially when dealing with changes in the brain after surgery.

D. Zikic – "Segmentation of Brain Tumor Tissues with Convolutional Neural Networks". The authors explore using Convolutional Neural Networks (CNNs) to segment brain tumors directly from MRI images. They feed the network small image patches with multi-channel intensity data. Only basic pre-processing is used to adjust for different MRI scanners, showing that CNNs can effectively handle real-world data variability and perform accurate tumor segmentation.

EXISTING SYSTEM

There are many image processing method, for example, histogram equalization, picture segmentation, image enhancement, morphological operation, feature choice and obtaining the features, and order.

A wide range of image processing techniques was used in segmenting brain tumor tissues. Some researchers used basic approaches for segmentation such as thresholding segmentation techniques. Another basic approach is edge detection which was used to detect the change of luminance intensity around the tumor to segment the tumor region. Region growing algorithm was also used for detecting and segmenting brain tumor in MRI images.

DISADVANTAGES

1. **Increased Complexity:** Using various filters, Fourier transforms, and discrete transforms increases the computational complexity of the processing system.
2. **High Equipment Cost:** The specialized equipment required for advanced image processing and diagnosis is expensive.
3. **Need for Skilled Personnel:** The presence of trained medical personnel is necessary to interpret the results correctly and make accurate decisions.
4. **Limited Equipment Availability:** Diagnosis and processing can be performed only with particular, often highly specialized, equipment.
5. **Time-Consuming Process:** Some segmentation methods (like region growing or manual thresholding) can be slow and require manual intervention.
6. **Sensitivity to Image Quality:** Techniques like edge detection and thresholding are sensitive to noise and variations in MRI image quality, potentially leading to inaccurate segmentation.
7. **Low Generalization:** Basic methods like thresholding or edge detection might not perform well across different datasets or varying tumor shapes, sizes, and intensities.

PROPOSED SYSTEM

Fully Automatic Heterogeneous Segmentation using Support vector machine (FAHS-SVM) for brain tumor detection and segmentation. Figure 2 describes the proposed FAHS-SVM method architecture. Magnetic Resonance Imaging is a diagnostic tool for human anatomy study and testing. Increased tumor vascularity leads to preferential uptake of the contrasting agent and can be utilized better to view the tumors of the normal tissue around them. When the contrast injections are performed repeatedly, the dynamic nature of contrast uptake can be tested, which can increase the distinction between malignant or benign diseases.

Implementation:

- To propose Fully Automated Heterogeneous Segmentation using Support Vector Machine (FAHSSVM) for brain tumor detection and segmentation.

- To design an Extreme learning machine algorithm for the classification and feature extraction of MRI images.
- The experimental results show high accuracy in detecting brain tumors with the help of datasets.

III. MODULE DESCRIPTION

Preprocessing

The image is loaded as the .mat format and the image is in the form of MRI. MRI image is in either RGB or gray scale. The image is resized and converted to grey if the image was in color. After that DWT (Discrete Wavelet Transform) will be applied.

Feature Extraction

In this part, we extract features of images to use in classification part. For feature extraction and feature selection, we use convolution neural network (CNN). As previously described to classification the images in the first step, CNN extracts the features of the dataset and perform the classification based on these features. In KE-CNN method we use CNN for feature extraction. Our configuration for CNN is the same model used in the previous method for convolutional neural networks. In this configuration, we have four convolution layers, four maxpooling layers with 1 fully connected layer.

Image Segmentation

It is a labelling process for each pixel in a medical image data set for indicating the type of tissue or the structure of anatomy. The labels that result from this approach have a vast area of applications in visualization and medical research. The method of dividing an image into sets of pixels which is also called super pixels is the image segmentation. The chief objective of segmentation is to identify the tumor's location. It is along chosen by the pixel powers themselves, yet in addition by the neighboring pixel powers and locations. Thought of these neighboring pixels extraordinarily controls the impact of noise.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

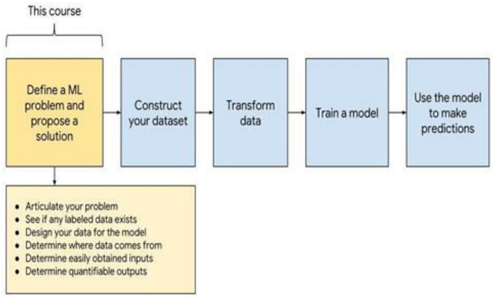

FIG: System architecture for brain tumor detection using CNN

V. OUTPUT SCREENS

HOME PAGE

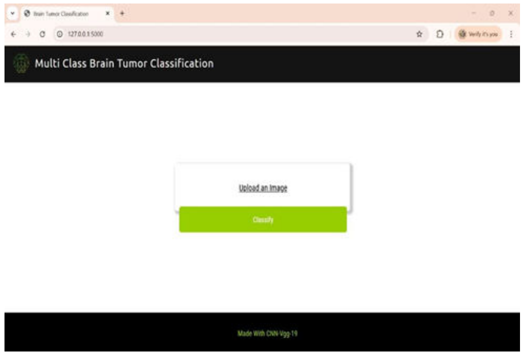

FIG: HOME PAGE

SELECT IMAGE

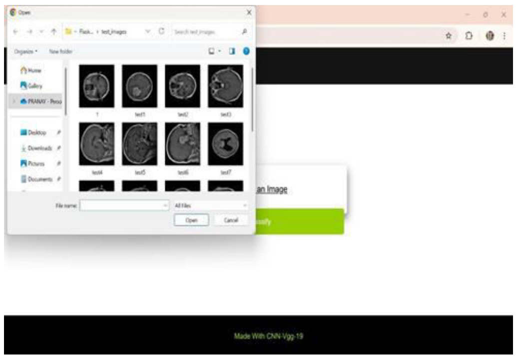

FIG:SELECT IMAGE

TUMOR DETECTED

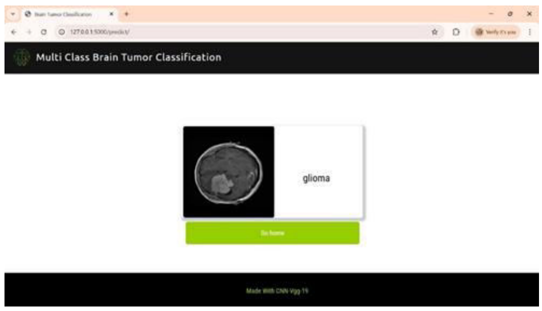

FIG:TUMOR DETECTED

NO TUMOR DETECTED

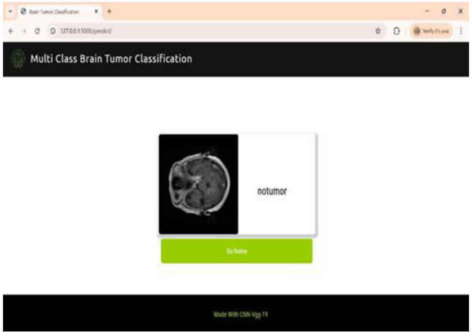

FIG: NO TUMOR DETECTED

VI. CONCLUSION

We propose a novel CNN-based method for the segmentation of brain tumors in MRI images, consisting of three main stages: pre-processing, classification via CNN, and post-processing. Initially, MRI images are normalized by computing the mean intensity value and standard deviation across all training patches extracted for each sequence, and then patches are normalized to have zero mean and unit variance. The CNN architecture effectively relates both local and global features, enabling accurate segmentation. Training and testing speeds are improved through the use of max pooling, maxout, and dropout techniques, which also complement the learning process. Furthermore, reducing features in the fully connected layers not only increases speed but also minimizes overfitting by lowering the number of parameters. The results demonstrate that the proposed method accurately detects enhancing tumors and precisely specifies the tumor region. This accurate segmentation not only aids clinical diagnosis but also contributes to improving the patient's lifetime

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