Brain Tumors Detection Using Deep Learning

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Abstract - Brain Tumors are one of the most challenging diseases to cure among the different ailments encountered in medical study. Early classification of brain Tumors from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify Tumors in the brain. MRI is commonly used for such tasks because of its unmatched image quality. The traditional method of identifying Tumors relies on physicians, which is time-consuming and prone to errors, putting the patient's life in jeopardy. Identifying the classes of brain Tumors is difficult due to the high anatomical and spatial diversity of the brain Tumors's surrounding region. An automated and precise diagnosis approach is required to treat this severe disease effectively. The relevance of artificial intelligence (AI) in the form of deep learning (DL) has revolutionized new methods of automated medical image diagnosis. As a result, good planning can protect a person's life that has a brain TUMORS The proposed project aims to revolutionize the field of brain Tumors detection in Magnetic Resonance Images (MRI) by introducing a Graph Convolutional Neural Network (GCNN) architecture. Unlike traditional methods that rely on handcrafted features and conventional machine learning algorithms, which might not effectively capture the intricate spatial relationships present in MRI data, the GCNN leverages the inherent graph structure of brain images. In this innovative approach, each voxel in the MRI represents a node interconnected by spatial relationships, forming a graph representation of the image. The GCNN architecture is specifically tailored to extract hierarchical features from this graph, enabling accurate and efficient Tumors detection. Extensive experimentation and evaluation on benchmark datasets have been conducted to validate the effectiveness of the proposed method. Results indicate superior performance compared to existing approaches, showcasing its potential as a reliable and early diagnostic tool for brain Tumorss in MRI images.

***Key Words*:** Image recognition,MRI,GCNN

1.INTRODUCTION

The brain is a complex organ that controls thought, memory, emotion, touch, motor skills, vision, breathing, temperature, hunger and every process that regulates our body. Together, the brain and spinal cord that extends from it make up the central nervous system, or CNS.

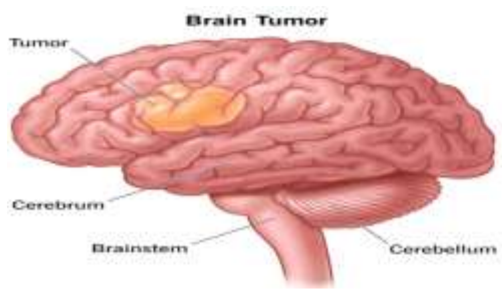


Figure 1.1. Brain

Weighing about 3 pounds in the average adult, the brain is about 60% fat. The remaining 40% is a combination of water, protein, carbohydrates and salts. The brain itself is a not a muscle. It contains blosod vessels and nerves, including neurons and glial cells.

Brain Tumors

A brain Tumors is a growth of abnormal cells in the brain. The anatomy of the brain is very complex, with different parts responsible for different nervous system functions. Brain Tumors can develop in any part of the brain or skull, including its protective lining, the underside of the brain (skull base), the brainstem, the sinuses and the nasal cavity, and many other areas. There are more than 120 different types of Tumors that can develop in the brain, depending on what tissue they arise from.

2. OBJECTIVE

The objective of the proposed project is to develop an automatic brain Tumors detection system for Magnetic Resonance Images (MRI) using a Graph Convolutional Neural Network (GCNN) architecture. Traditional methods for brain Tumors detection often rely on handcrafted features and conventional machine learning algorithms, which may struggle to capture the complex spatial relationships inherent in MRI data. The objective is to overcome these limitations by leveraging the graph structure of brain images, where each voxel represents a node interconnected by spatial relationships, to effectively capture intricate patterns.

3.EXISTING SYSTEM

Region growing method

This is a traditional approach in which segmentation begins with the manual sorting of seeds from the image of interest. The manual dealings to attain the seed point are the area growing's
restriction. However, split-and-merge is a region-growing algorithm that does not need a seed point. Region growth is also vulnerable to noise, resulting in gaps in partitioned areas. This problem is solved by the hemitropic region-growing algorithm. However, this technique requires user intervention for seed selection.

Watershed algorithm

Watershed is a segmentation system dependent on gradients. Similar gradient values are analysed as heights. When a hole is drilled into each local minimum and immersed in water, the water rises before it reaches the local maximums. When two bodies of water intersect, a barrier is constructed between them, and the water level increases before both points are combined. The picture is segmented by dams, which are referred to as watersheds.

Clustering method

Clustering is an unsupervised learning task that groups items based on a similarity criterion. There are two types of clustering algorithms: hard clustering and fuzzy clustering. The hard clustering process seldom assigns a pixel to a single cluster. Due to the presence of partial volume effects in MRI, this cannot be used for MRI segmentation. In fuzzy clustering, a single pixel may be allocated to several clusters. Fuzzy C Means (FCM) is a common fuzzy clustering tool. Although the FCM algorithm performs very quick and simple segmentation, it does not guarantee good accuracy for noisy or irregular images

3.1DISADVANTAGES

Manual segmentation depends on clinicians' experience, and is laborious and time consuming.

- Handcrafted Features
- Difficult to segment these brain Tumors regions automatically.
- High Computational Process
- Misclassification due to improper segmentation
- Performance in Brain Tumors detection was not satisfactory.
- Computational complexity is severely increased
- Time spent in feature extraction
- False prediction of Brain Tumors Grades

4.PROPOSED SYSTEM

This project proposes a novel approach for the automatic detection of brain tumors in Magnetic Resonance Images (MRI) using a Graph Convolutional Neural Network (GCNN) architecture. Traditional methods for brain tumor detection often rely on handcrafted features and conventional machine learning algorithms, which may struggle to capture the complex spatial relationships inherent in MRI data. In contrast, the proposed GCNN leverages the graph structure of brain images,where each voxel represents a node interconnected by spatial relationships, to effectively capture these intricate patterns.

The main goal behind the development of our proposed model is to automatically distinguish people with brain tumors, while reducing the time required for classification and improving accuracy. We propose a novel and robust DL framework GCNN for detecting brain tumors using MRI datasets. The proposed model is a four step process, in which the steps are named: 1). Pre-processing, 2). Features Extraction, 3). Features Reduction, and 4). Classification. Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull, in the pre-processing step. During this stage, the images are converted from grey scale to coloured images for further processing. In second step, it uses Grey Level Co-occurrence Matrix GLCM) technique to extract different features from the images. In third stage, Color Moments (CMs) are used to reduce the number of features and get an optimal set of characteristics. Images with the optimal set of features are passed to GCNN classifiers for the classification of BT Type and their grades.

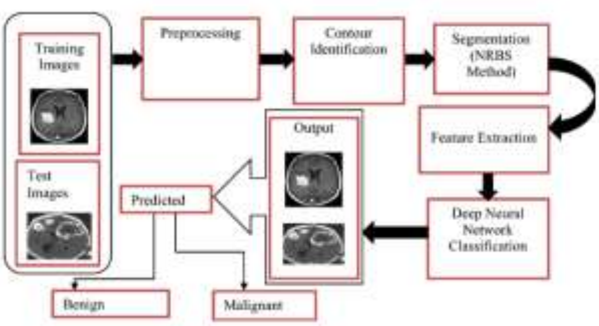
4.1ADVANTAGES

A fast and accurate fully automatic method for brain tumor classification which is competitive both in terms of accuracy and speed compared to the state of the art.
The method is based on deep neural networks (DNN) and learns features that are specific to brain tumor types.
Segmentation technique accomplishes the better segmentation results with the maximum accuracy of 99%.
Automatic Feature Extraction
Low Computational Overhead
This method in clinical oncology can help radiologists and oncologists to get various tumor regions, sizes and shapes, and assist them in improving tumor diagnosis, treatment plan and prognosis.
Cancer Rehabilitations program to the infected patients with brain tumor.

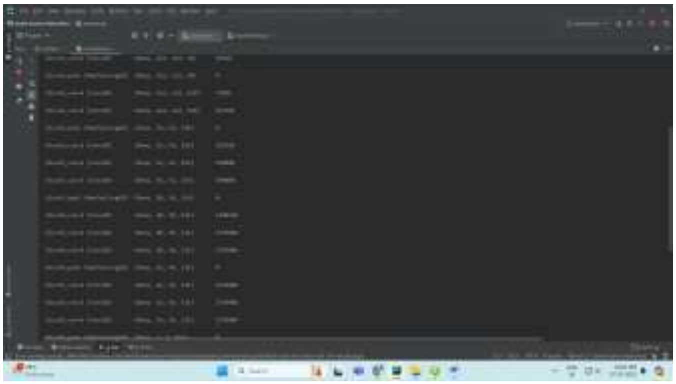
5.SYSTEM ARCHITECTURE

The organized design of a system that specifies its elements, interactions, and data flow to accomplish a particular goal is referred to as system architecture. It offers a roadmap for the effective cooperation of various system modules. Scalability, dependability, and optimal performance are guaranteed by a well-designed system architecture, which also preserves ease of maintenance and system integration. It usually consists of components like user interfaces, communication protocols, data processing, and storage.

A robust system design is modular in nature, with each module carrying out a distinct task and interacting with other modules via clearly defined interfaces. Layers including input processing, data analysis, decision-making, and output generation are frequently involved. Architectures can be distributed or centralized, using real-time processing methods, cloud computing, or artificial intelligence, depending on how complicated the system is. A carefully thought-out architecture guarantees smooth operation across many contexts and applications, lowers redundancy, and improves system economy.



IMPLEMENTATION AND RESULT:



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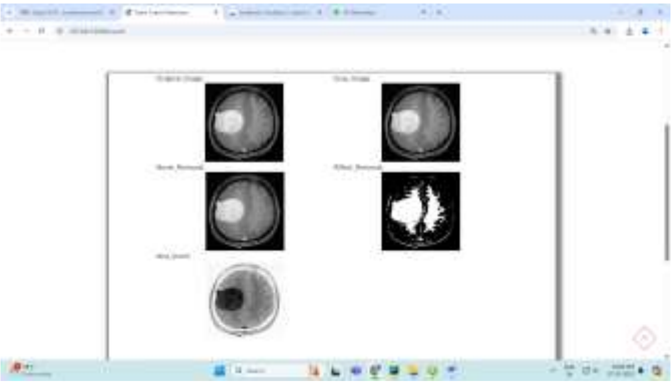

6.CONCLUSIONS

This project demonstrates that CNN can effectively leverage the natural graph structure of MRI data to improve brain tumor detection. By representing each voxel as a node connected by spatial relationships, the model extracts and utilizes hierarchical features for better classification.
Experimental results on benchmark datasets confirm that the proposed method outperforms traditional techniques, providing a more reliable and efficient diagnostic tool. This enhanced accuracy and reduced dependency on handcrafted features mark a significant advancement in automated medical imaging.

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