NeuroDepthNet: A Deep Learning-Based System for Brain Tumor Classification and Depth Estimation

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Abstract - *Early and accurate detection of brain tumors is critical for improving patient outcomes. This paper presents a dual-module approach for optimized brain tumor detection and classification, integrated with a novel estimation of tumor depth using 3D reconstruction. The system combines the power of deep neural networks (DNNs) for classification with medical image processing using SimpleITK and VTK for depth value estimation through 3D reconstruction. The proposed architecture addresses the critical gap in tumor localization and depth analysis, enhancing surgical planning and clinical diagnostics. The pipeline has been evaluated on MRI datasets with promising results in accuracy, visual quality of reconstructions, and computational efficiency.*

Key Words: **Brain tumor detection, classification, 3D reconstruction, VTK, SimpleITK, Deep Neural Networks, tumor depth estimation, medical imaging.**

1.INTRODUCTION

Brain tumors pose a significant risk to human life due to their invasive nature and the complexity of surgical intervention. The medical community heavily relies on Magnetic Resonance Imaging (MRI) for the diagnosis and treatment planning of brain tumors. However, traditional 2D slice-based analysis often lacks depth perception, making it difficult to assess the tumor's full extent.This paper introduces an optimized framework that not only automates tumor detection and classification using deep learning but also estimates the depth value by reconstructing the tumor in 3D using SimpleITK and VTK libraries. This dual-module system aims to bridge the gap between classification and spatial quantification, offering a more holistic view for radiologists and neurosurgeons.

1.1 OBJECTIVE

To develop a dual-module system that Detects and classifies brain tumors using a DNN classifier Estimates tumor depth through 3D reconstruction using SimpleITK and VTK Enhances diagnostic decision-making by integrating classification results with 3D spatial information.

1.2 MOTIVATION TO TAKE UP THE PROJECT

Deep Neural Networks (DNNs), particularly Convolutional Neural Networks (CNNs), have become foundational in the advancement of artificial intelligence, especially in medical imaging. Their hierarchical architecture enables the automatic extraction of complex features from high-dimensional data such as MRI scans. CNNs have demonstrated superior performance in image classification, segmentation, and detection tasks, making them highly suitable for brain tumor diagnosis. In the context of this research, the motivation lies not only in accurately detecting and classifying brain tumors but also in addressing the critical need for spatial depth analysis—an aspect often overlooked in 2D imaging approaches. By integrating DNN-based classification with 3D reconstruction using tools like VTK and SimpleITK, this work aims to bridge the gap between precise tumor identification and spatial understanding, ultimately contributing to improved clinical decision-making.

1.3 CHALLENGES TO BE ADDRESSED

Artificial intelligence (AI) has emerged as a pivotal force in technological advancement, with applications extending into nearly every field—including medicine. Within this landscape, Deep Neural Networks (DNNs) have demonstrated exceptional capability in pattern recognition and classification tasks, particularly in medical imaging. Despite their promise, several challenges must be addressed to effectively integrate DNNs into brain tumor diagnostics. One key issue is the limited availability of annotated medical datasets necessary for training robust models. Additionally, conventional 2D MRI-based analysis often lacks spatial context, making it difficult to estimate tumor depth—a crucial factor for surgical planning. This project seeks to overcome these challenges by combining DNN-based classification with 3D reconstruction techniques using VTK and SimpleITK, thereby offering a more comprehensive and interpretable diagnostic tool for brain tumor detection.

1.4 CNN and DNN

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed to process grid-like data such as medical images. They utilize multiple layers, including convolutional, pooling, normalization, and fully connected layers, to automatically extract and learn hierarchical features from input data with minimal manual preprocessing. CNNs are often referred to as shift-invariant artificial neural networks (SIANNs) due to their ability to recognize patterns regardless of spatial translation, a property that mirrors the biological organization of the visual cortex in animals. In these networks, individual neurons respond only to stimuli within a localized region of the input, mimicking the receptive fields found in the brain's visual processing areas.

This architecture makes CNNs highly effective for analyzing visual data, such as MRI scans, where detecting structural abnormalities is critical. In the context of brain tumor detection and classification, CNNs can identify tumors based on spatial variations in intensity, shape, and texture. Traditional diagnostic approaches often rely on manual interpretation by radiologists, which can be time-consuming and subject to variability. However, advances in deep learning—particularly the use of 3D CNNs—have significantly improved the automation and accuracy of tumor detection. These models process volumetric data directly, enabling the network to learn spatial relationships across MRI slices, thereby enhancing the detection and characterization of brain tumors.

1.5 LITERATURE SURVEY

Significant advancements have been made in the field of brain tumor detection and classification, with several studies contributing to the development of improved methodologies. One notable study by [1] demonstrated an average Dice Similarity Index (DSI) of 0.82, showing promising results in tumor segmentation. This approach outperformed previous techniques by offering better overlap between the segmented tumor regions and those manually delineated by radiologists, which suggests higher precision in tumor identification.

Pradeep Singh Yadav et al. [2] proposed a method based on X-ray imaging, highlighting that cancer-affected regions exhibit high-intensity pixels, while normal tissues correspond to low-intensity pixels. This principle underlies thresholding, a simple but effective technique for segmentation. Thresholding categorizes tumor regions based on intensity levels, and while this method is basic, it provides a foundation for more advanced tumor detection techniques. Additionally, morphological operations, such as "imerode" and "imdilate," were used to extract tumors from the X-ray images. In the proposed technique, these operations, combined with the identification of regions of interest (ROIs), allow for the extraction of relevant tumor features, improving tumor recognition.

Nishant Verma et al. [3] emphasized region-growing techniques for image segmentation, proposing a method where pixels with similar intensity values are grouped into a single region. This process relies on 4-connected or 8-connected pixel areas to determine if adjacent pixels belong to the same region. The region-based segmentation method is noted for its resilience to noise in X-ray images, which contributes to more robust tumor segmentation compared to other methods.

Deepthi Murthy T.S. et al. [4] focused on thresholding and morphological operations for efficient brain tumor segmentation. However, the thresholding value in their method was fixed, making it semi-automated and requiring human intervention for optimal results. This limitation points to the need for more adaptive techniques to handle variations in brain scan data.

L. Ramya et al. [5] explored region-growing segmentation techniques and applied them to identify tumors in brain MRI images. Their method incorporates skull removal, combined with morphological operators, to enhance the accuracy of brain tumor detection. This approach highlights the importance of preprocessing steps like skull removal, which significantly improve the accuracy of tumor identification.

2. EXISTING SYSTEM

Brain tumor detection plays a crucial role in the early diagnosis and treatment planning of patients. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated promising results in automating this process. Among the various CNN architectures, ResNet50 stands out due to its depth and the use of skip connections, which address the vanishing gradient problem and facilitate more efficient feature learning.

Despite the promising results achieved, there are several limitations that need to be addressed. Ongoing research and development are essential to overcome these challenges and facilitate the integration of these deep learning-based systems into routine clinical practice. The future direction should focus on improving model generalization, handling diverse and noisy medical images, and optimizing system performance to meet the clinical needs of healthcare professionals.

3. PROPOSED SYSTEM

The proposed system aims to optimize brain tumor detection and classification by integrating two key modules: the tumor detection and classification module and the tumor depth value estimation module. This dual approach leverages the power of Deep Neural Networks (DNNs) for efficient detection and classification of brain tumors, while utilizing 3D reconstruction techniques with VTK (Visualization Toolkit) and SimpleITK to estimate tumor depth and provide spatial information critical for precise diagnosis and treatment planning.

3.1 Tumor Detection and Classification Module

The first module focuses on automating the process of brain tumor detection and classification. This is achieved using a Convolutional Neural Network (CNN) architecture, specifically designed for medical image analysis. The CNN is trained to differentiate between tumor and non-tumor regions in MRI scans, classifying the detected tumors into benign or malignant categories. The model utilizes transfer learning from pre-trained networks such as ResNet50 to extract high-level features from the input medical images. These features are crucial for distinguishing various tumor types and for accurate classification.

3.2 Tumor Detection and Classification Module

The second module addresses the critical aspect of tumor depth estimation, which is essential for determining tumor growth patterns and planning treatment strategies. This is achieved by reconstructing the 3D volume of the tumor using VTK and SimpleITK. The system first segments the tumor from the MRI scan, creating a 3D model of the affected region. Using the depth estimation algorithms, the system calculates the depth value of the tumor, providing more accurate information about its location within the brain, which can be vital for surgical planning or radiation therapy.

The tumor's depth value is determined by calculating the distance from the surface of the brain tissue to the deepest point of the segmented tumor region. This information is then integrated with the tumor's classification to provide a comprehensive assessment of the tumor's severity, size, and location.

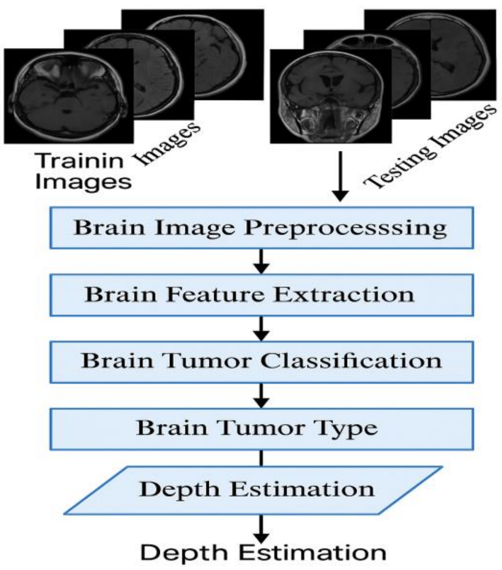

Fig -1: Proposed System

4. SYSTEM ARCHITECTURE

The proposed system architecture consists of two integrated modules designed to enhance the diagnosis of brain tumors. The first module uses a deep learning model, specifically a DNN algorithm, to classify MRI brain images into four categories: glioma, meningioma, pituitary tumor, or no tumor. It extracts features from the images and uses a Softmax layer to predict the tumor type accurately. Once classified, the second module takes over to estimate the tumor's depth by reconstructing a 3D model from 2D MRI slices. Using segmentation techniques from SimpleITK, the tumor region is isolated and passed to VTK for 3D visualization. These slices are then stacked to build a volumetric image of the tumor. The system calculates depth by measuring the distance from the brain surface to the tumor's deepest point. This helps provide spatial context, supporting better surgical planning.

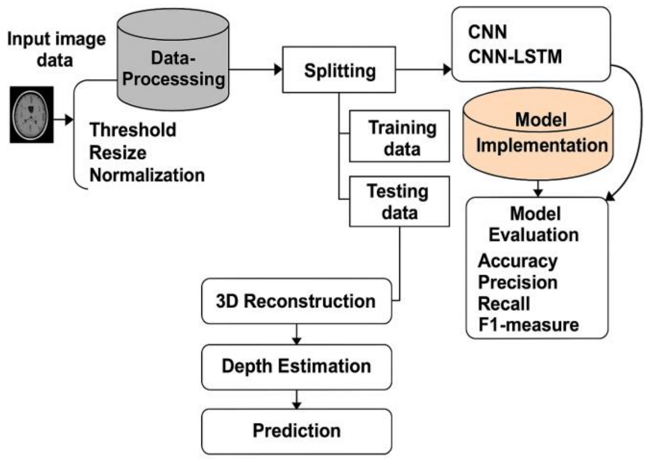

Fig-2: System Architecture

5. DATASETS

1.A dataset is a structured compilation of data, often organized to serve specific tasks such as machine learning, analysis, or research. In this context, it provides the foundation for training and evaluating brain tumor detection and classification models.

2.Once the dataset is collected, it typically undergoes preprocessing steps such as image normalization, resizing, noise reduction, and data augmentation. These processes help ensure the data is clean, consistent, and suitable for use in deep learning frameworks.

3.The dataset used in this study comprises 7,017 MRI images of the human brain, categorized into four distinct classes: glioma, meningioma, pituitary tumor, and no tumor. These categories are essential for training a multi-class classification model.

4. Glioma: 300 images , Meningioma: 305 images, No Tumor: 404 images ,Pituitary Tumor: 300 images .These images are used for testing.

5.Glioma: 1,320 images, Meningioma: 1,338 images, No Tumor: 1,594 images, Pituitary Tumor: 1,456 images. These images are used for training.

6. IMPLEMENTATION AND RESULT

The proposed system is implemented using a supervised Deep Neural Network (DNN), designed to effectively classify brain tumors based on MRI images. The DNN processes image data to learn complex patterns that distinguish between various tumor types and normal brain conditions. For image preprocessing and enhancement, the framework incorporates OpenCV, which optimizes image clarity and speeds up processing. In addition to classification, the system utilizes VTK and SimpleITK libraries for 3D reconstruction of the tumor, enabling accurate depth value estimation by generating a volumetric model from 2D slices. This integration allows the system not only to detect the presence of a tumor but also to provide insights into its spatial dimensions within the brain. The model was trained on a comprehensive dataset and achieved a confidence level of 99.8% in correctly classifying tumor types. This high accuracy, combined with precise depth analysis, makes the dual-module system a robust tool for both diagnostic and surgical planning purposes.

Datasets	Glioma	Meningioma	No tumor	Pituitary
Training	1320	1338	1594	1456
Testing	300	305	404	300

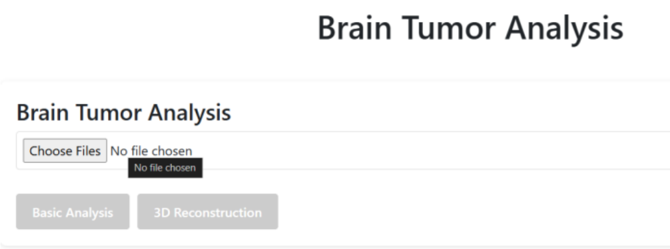

Fig-3: Home page

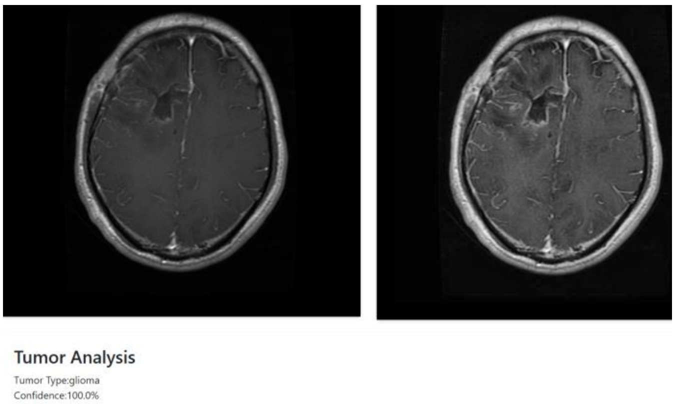

Fig-4: Classification result

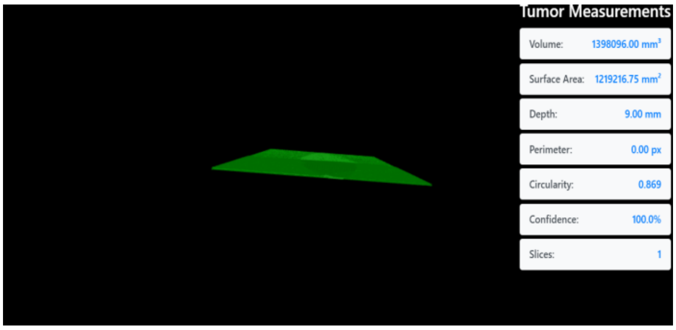

Fig-5: Depth value

7. CONCLUSIONS

This study presents a dual-module system that effectively combines deep learning with medical image reconstruction to improve brain tumor detection and analysis. Using a Deep Neural Network (DNN), the system accurately classifies brain MRI images into various tumor types, achieving a high confidence level of 99.8%. Alongside classification, the integration of VTK and SimpleITK enables the generation of 3D tumor models, which help in estimating the depth and spatial position of the tumor within the brain. This depth analysis is valuable for understanding tumor severity and guiding treatment decisions. By working with actual medical image data, the system offers both diagnostic accuracy and clinical relevance. It simplifies the workflow for radiologists by providing both a tumor type prediction and a visual 3D reference in one system. Although the results are promising, further improvements could make the model more adaptable to a wider range of cases and patient data. The project demonstrates how combining machine learning with 3D imaging tools can bring real value to medical diagnostics. With more data and continued refinement, this approach can support doctors in early diagnosis, better treatment planning, and improved patient outcomes in brain tumor care.

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