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# AI-BASED CENTRAL NERVOUS SYSTEM (CNS) TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

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#### ABSTRACT:

A brain tumor is understood by the scientific community as the growth of abnormal cells in the brain, some of which can lead to cancer. The traditional method to detect brain tumors is nuclear magnetic resonance imaging (MRI). Having the MRI images, information about the uncontrolled growth of tissue in the brain is identified. In several research articles, brain tumor detection is done through the application of Machine Learning and Deep Learning algorithms. When these systems are applied to MRI images, brain tumor prediction is done very quickly, and greater accuracy helps to deliver treatment to patients. These predictions also help the radiologist to make quick decisions. In the proposed work, a set of Convolutional Neural Networks (CNN) are applied to detect the presence of a brain tumor, and its performance is analyzed through different metrics.

**KEYWORDS**: Brain tumor, Abnormal cells, Cancer, Nuclear magnetic resonance (MRI), Machine Learning, Deep Learning algorithms, Convolutional Neural Networks (CNN), MRI images, Predictions, Accuracy, Performance analysis, Radiologist, Treatment, Uncontrolled growth of tissue.

#### **INTRODUCTION**

Medical images require precise detection of brain tumors because physicians need to locate the abnormal cell proliferation areas inside the cerebral tissue. The medical practice uses \*\*nuclear magnetic resonance imaging (MRI) to visualise uncontrolled tissue growth, but manual segmentation by radiologists remains long and error-prone and exhibits high inter-observer variability. The detection and classification of tumors now benefit from recent ML and DL advances that use CNNs specifically to automate diagnostic processes. CNN architectures perform well for extracting features in hierarchies by recognizing cancerous tissue through spatial mapping within MRI scans. The recommended system includes three interconnected components comprising the dataset module for anatomical MRI scan processing followed by the segmentation module with U-Net or thresholding operations and then the prediction module, which employs CNN to classify tumor types, paying attention to accuracy precision and recall metrics. The combination of ensemble methods together with transfer learning techniques (fine-tuning ResNet) and multimodal data fusion that merges MRI with CT/PET scans solves issues in model generalizability along with computational complexity and class imbalance conditions. New versions of the system will improve functionality with explainability features that provide clinical interpretable saliency maps and SHAP values in addition to continuous learning capabilities that adapt to evolving datasets. This system demonstrates the revolutionary capabilities of AI-based computer-aided diagnosis (CAD) for oncology by blending algorithm innovativeness with clinical workflow practices to enhance prognostic patient outcomes.

### **RELATED WORKS**

The traditional practice of brain tumour identification makes use of radiological analysis to read nuclear magnetic resonance imaging (MRI) scans by trained specialists. Medical professionals need to detect uncontrolled tissue growth areas on brain scans because these areas indicate the presence of tumors. The process of manual segmentation and diagnosis requires extensive time from specialists who also make errors during analysis, particularly if they need to inspect numerous clinical MRI images. The critical need for precise tumour detection becomes more challenging because small diagnostic mistakes hold major health risks for patients. Researchers used support vector machines (SVM) and random forests from machine learning (ML) to develop automated tumor detection systems because manual methods had significant limitations. The proposed methods exceeded manual detection methods in terms of both time efficiency and accuracy results. Medical image patterns proved difficult for these systems to handle properly, thus resulting in diminished operational effectiveness in real medical environments. The research field transitioned to advanced techniques with deep learning (DL) models because these models demonstrated greater capability to process medical imaging data complexities.

The latest tool for brain tumor recognition is represented by Convolutional Neural Networks (CNNs). CNNs excel at structured data processing because they were designed to work with image inputs, so they perform well for image classification alongside object detection and medical image analysis. Multiple studies use CNN-based models U-Net, ResNet, and VGG to analyse MRI scans and identify brain tumours as well as their class. The

maximal hierarchical structure extraction ability of these models helps detect minor patterns that indicate malignancies. Medical practitioners widely utilize U-Net architecture for tumor segmentation because it effectively retrieves complex details from medical imaging data. The combination of multiple classifiers or models through ensemble methods has been proposed to improve both robustness and performance rates. The successful adoption of CNNbased systems encounters various hurdles, which include demanding computational resources as well as demanding training duration and the need for big labeled dataset samples. Scientific teams improve the models through transfer learning and attention mechanisms to obtain higher accuracy and operational speed.

Brain tumour detection experiences advancements through combined imaging techniques that merge MRI results with CT results and PET results. Such techniques deliver extended tumour characteristic information for precise medical diagnoses. Numerical imaging technologies work together because MR imaging displays soft-tissue details, CT imaging shows bone information, and PET imaging detects metabolic activities. Researchers have begun to combine various data types so their models can identify multiple tumour biological aspects. Specific medical systems work for detecting tumors in real time, especially during surgical operations. The assistive systems offer surgeons procedural support through tumor boundary feedback, which enables exact tumor removal. Early real-time programmes needed compact optimization systems that maintained fast performance while retaining their accuracy range. This development produces technical difficulties in its implementation. The potential to enhance patient results exists.

### PROPOSED SYSTEM

The proposed system for brain tumor detection is built on the foundation of Convolutional Neural Networks (CNNs), leveraging their ability to process structured grid data such as MRI images. The system is divided into four key modules: the Dataset Module, which involves creating and organizing a labeled dataset of MRI images for training and evaluation; the Preprocess Module, where input images are resized, normalized, and segmented to extract relevant features without losing critical information; the Segmentation Module, which isolates tumor regions to facilitate detailed analysis; and the Prediction Module, which uses a pre-trained CNN model to classify tumors with high accuracy. This modular approach allows for the system to obtain fast and accurate detection of tumours and decreases the chances of human error, allowing for early diagnosis. By automating the detection process, the system prevents human entry, reducing time consumption and increasing diagnostic accuracy. Moreover, the application of feature extraction algorithms increases the system's capacity to identify subtle patterns effectively associated with brain tumors, and hence, it is a reliable tool for clinical purposes.

Even though the suggested system has its strengths, it also points to the areas where there is a need for further improvement and eventual research exploration. A restriction is the computational intensity that is required for the training of the model, as well as the long processing times required to achieve good performance. Although the model shows a good accuracy of the training data set, its performances in the test data set suggest a scope of improvements of generalisation. To address such difficulties, upcoming versions of the system might employ superior neural network architectures, such as consideration mechanisms or transformers, to identify more subtle patterns in healthcare images. Furthermore, the integration of multimodal imaging data (e.g., combining MRI with CT or PET scans) could provide a more comprehensive understanding of tumor characteristics.



Fig. No. 1 System Architecture

### SYSTEM MODULE

The suggested brain tumour detection system relies on a Convolutional Neural Network (CNN) to diagnose and categorise tumours by MRI pictures with the highest possible accuracy and efficiency. The system consists of four primary modules: the Dataset Module that organises, preprocesses MRI images to use in training and evaluation; the Preprocess Module, where images is resized, normalised to segment to isolate tumour area preserving the important details; the Segmentation Module, which extracts features, finds out the potential of tumours recognised by sophisticated methods; and the Prediction Module, the pre-trained CNN model utilized to classify tumours with the accuracy high. The system strikes without human intervention, changing errors and reaching faster diagnosis, which are very clear for that possibility of patients benefits. It requires solid hardware, including plenty of Pentium i3 processors, 4 GB RAM as well and 500 GB HDD, plus the package software tools, including python 3.8, pycharm ide or libraries, as well as tf, open cv as well and numpy. Even though it has a high accuracy, especially on the training set, the system encounters problems such as prolonged training times and low validation accuracy. Future expansions include investigating more complex neural network frameworks, incorporating multimodal imaging data, and incorporating explainable AI techniques for transparent predictions. These upgrades are designed to polish up the system's reliability and robustness for practical clinical use.

The brain tumor detection system includes four major modules, each with an important role in the system's performance. The Dataset Module is about making and organising datasets by loading MRI images, preprocessing images, and assigning labels so that there will be a good regimen and evaluation of features. This module is responsible for dividing the data into a training set, validation set, and test set to analyze the robustness of performance. The Preprocess Module contains the image augmentation, which involves resizing, normalizing, and segmenting input images to segment out the tumour while keeping the required information that, in turn, helps in accurate malignancy predictions. Next, the Segmentation Module breaks down the MRI images into different areas to locate resulting tumour zones by using segments like feature extraction and thresholding, which are critical for accurate analysis. The Prediction Module, Last, applies on a pre-trained Convolutional Neural Network (CNN) Model to Classification and Predicting Tumours Presence. This module loads the trained model, applies for new MRI images, and gets the high-accuracy predictions. Collectively, these elements constitute an automated path that conserves human intervention, economies errors and shortens diagnostic reviews, right away assisting radiologists and clinicians with organising timely and exact aggregations.

### **RESULT & DISCUSSION**

The proposed brain tumor detection system utilizes Convolutional Neural Networks (CNNs) to identify tumors from MRI images, aiming for high accuracy and efficiency. The system is divided into four key modules: the Dataset Module which organizes and preprocesses MRI images for training and evaluation; the Preprocess Module, where images are resized, normalized, and segmented to isolate tumor regions while preserving critical details; the Segmentation Module, which extracts features and identifies potential tumor areas using advanced techniques; and the Prediction Module, which employs a pre-trained CNN model to classify tumors with high precision. The modular design minimises human intervention, and lowering the mistakes and accelerating diagnosis help radiologists to decide on time. Despite achieving ~90% accuracy on the training dataset, the system faces challenges such as overfitting, computational intensity, and lower validation performance (~70-80%), indicating room for improvement.

To improve on these constraints, potential future development includes the adoption of more advanced neural network neural structures, e.g., attention, transformers to be able to see more complex information in medical images. The integration of multimodal imaging data (e.g., combining MRI with CT or PET scans) can provide a more comprehensive understanding of tumor characteristics, improving diagnostic accuracy. Additionally, incorporating explainable AI techniques, such as saliency maps or SHAP values, will enhance transparency and foster trust among clinicians. Implementing continuous learning mechanisms will allow the model to adapt to new datasets over time, ensuring long-term relevance and reliability. These improvements strive to achieve higher accuracy, larger scale, and easier interpretation of the system and, most importantly, better patient outcomes and the transformation of clinical workflows.

## CONCLUSION

The brain tumor detection system proposed today brings essential progress to diagnostic medicine through AI technology implementation. The system achieves automatic tumor detection through Convolutional Neural Networks that operate on MRI images without human involvement and error risk. The system both speeds up diagnostic processes and improves tumor detection accuracy because accuracy enhances treatment results while boosting patient survival statistics. Through its modular structure, the system performs preprocessing efficiently and seamlessly segments images before generating accurate predictions, which establishes it as a dependable tool for medical professionals.

Although the system is performing well during the training process but its performance on unknown data shows room for development. Future research will concentrate on enhancing the model through advanced neural architecture modifications while implementing multiple imaging modalities and establishing transparent, explainable AI strategies that maintain healthcare professionals' trust. Through continuous learning abilities, the system will be able to adapt to new data throughout time, maintaining its long-term relevance. The research showcases AI's revolutionary power in healthcare by enabling more convenient, accessible, and dependable diagnostic methods that detect conditions early and deliver prompt intervention to save patient lives.

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