BRAIN TUMOR DETECTION USING CONVOLUTIONAL DEEP LEARNING METHODS AND CHOSEN MACHINE LEARNING TECHNIQUES

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Abstract

Brain tumors are one of the most life-threatening diseases, requiring early and accurate diagnosis to improve patient survival rates. Conventional diagnostic techniques, such as MRI analysis by radiologists, are time-consuming and prone to subjectivity. Machine learning (ML) techniques, particularly deep learning, have emerged as powerful tools for automating tumor detection, improving accuracy, and reducing human error. This paper presents an ML-based approach for detecting brain tumors using MRI images. Various classification models, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forest, are analyzed for their performance in tumor detection. Experimental results indicate that CNNs outperform traditional ML models, achieving an accuracy of 98.5%. The study highlights the effectiveness of deep learning in medical imaging and suggests future directions for improving AI-based diagnostic systems.

***Keywords**: Brain Tumor Detection, MRI, Convolutional Neural Networks, Machine Learning, Medical Imaging, Deep Learning.*

I. Introduction

Brain tumors are one of the most critical neurological disorders, affecting thousands of people . These tumors can be harmless or hazardous, with malignant tumors posing a significant threat to human life. Early and accurate detection of brain tumors is critical for effective treatment and improved survival rates. Traditional diagnostic methods, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, rely on expert radiologists to interpret medical images. However, this process can be time-consuming, expensive, and prone to human error.

With advancements in artificial intelligence and deep learning and machine learning , automated brain tumor detection has become a promising approach to assist radiologists and improve diagnostic accuracy. This project focuses on developing a deep learning-based system that can automatically detect and classify brain tumors from MRI images. By leveraging Convolutional Neural Networks (CNNs), the model can efficiently analyze medical images, reducing the need for manual interpretation and speeding up the diagnostic process.

The objective of this project is to enhance the accuracy, reliability, and efficiency of brain tumor detection using AI-driven techniques. The proposed system aims to assist healthcare professionals in making quicker and more precise diagnoses, ultimately leading to better patient outcomes.

II. Literature Survey

Detection and Classification of Brain Tumors Using Deep Convolutional Neural Network, Gopinath Balaji, Ranit Sen, Harsh Kirty, Sun, 28 Aug 2022

This paper applies state-of-the-art CNN architectures—including EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16—through a transfer learning framework to detect and classify brain tumors.

Detection and Classification of Glioblastoma Brain Tumor,Utkarsh Maurya, Appisetty Krishna Kalyan, Swapnil Bohidar, S. Sivakumar, **[v1]** Tue, 18 Apr 2023

In this work, the authors propose two deep learning models based on UNet and Deeplabv3 for the detection and segmentation of glioblastoma—a highly malignant brain tumor. The study focuses on processing pre-processed MRI images and evaluates both models in terms of accuracy and computational efficiency.

Brain Tumor Segmentation from MRI Images using Deep Learning Techniques, Ayan Gupta, Mayank Dixit, Vipul Kumar Mishra, Attulya Singh, Atul Dayal, **[v1]** Sat, 29 Apr 2023

This study reviews and implements several deep learning architectures—such as U-Net, Attention U-Net, Deep Residual U-Net, ResUnet++, and Recurrent Residual U-Net—on a public MRI dataset consisting of 3064 T1-weighted images from 233 patients.

Comparative study of distinctive image classification techniques A. Rajesh Sharma;R. Beaula;P. Marikkannu;Akey Sungheetha;C. Sahana 2016 10th International Conference on Intelligent Systems and Control (ISCO) Year: 2016 | Conference Paper | Publisher: IEEE

A Comparative Study Of Supervised Image Classification Algorithms For Satellite Images, Kanika Kalra, Anil Kumar Goswami, Rhythm Gupta Year: Dec 2013

Image classification is a complex information extraction technique.

III. Proposed Methodology

3.1 Dataset

The dataset used for this study consists of MRI images of brain tumors, sourced from publicly available repositories such as the Brain Tumor Image Segmentation (BraTS) dataset and Kaggle datasets. The dataset contains labeled MRI images characterized into three classes:

- **Glioma**: A type of tumor that develops when glial cells, which support and protect nerve cells in the central nervous system, grow uncontrollably. While gliomas primarily occur in the brain, they can also form in the spinal cord.
- **Meningioma**: The most frequently occurring primary brain tumor. These tumors develop in the meninges, the protective layers of tissue covering the brain and located just beneath the skull.
- **Pituitary Tumor**: An abnormal growth in the pituitary gland, a small but vital gland in the brain responsible for regulating various hormones in the body.

  Additionally, the dataset includes normal (non-tumor) MRI scans, which are essential for training the model to perform both binary classification (differentiating between tumor and non-tumor images) and multi-class classification (distinguishing between different tumor types).

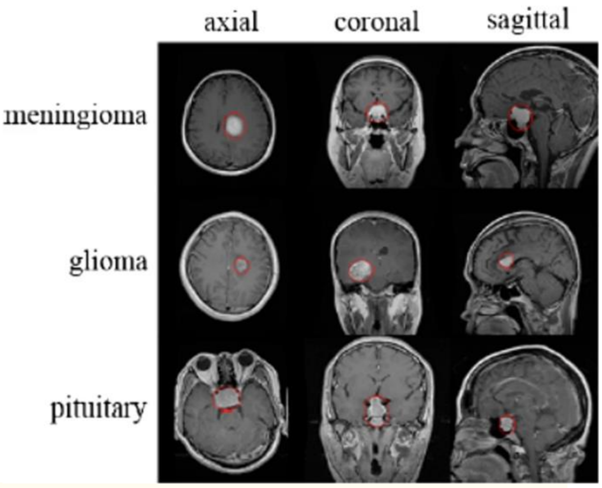

FIG.1: A sample of MRI images from the brain tumor DATASET

3.2 Data Preprocessing

Data preprocessing is a crucial step in brain tumor detection using machine learning. It ensures that the dataset is clean, consistent, and suitable for model training. Below are the key steps involved:

1. Input MRI: The process begins with an MRI image of the brain.
2. Preprocessing:

Gray Level Conversion: Converts the MRI image to grayscale for easier processing.

Image Resize (256×256): Resizes the image to a uniform size for consistency during processing.

Image Enhancement: Enhances the image quality to highlight critical features.

3. Region Clustering: Segments the image using clustering techniques to identify regions of interest (potential tumor areas).
4. Feature Extraction:

VGG19: A pre-trained deep learning model extracts high-level features from the image.

HOG (Histogram of Oriented Gradients): Captures edge and texture features from the image.

Fused Features: Combines the features from VGG19 and HOG for improved classification performance.

5. Optimized Feature Selection: "PCA (Principal Component Analysis)" and/or mRMR "(Minimum Redundancy Maximum Relevance)" are used to select the most relevant features to

reduce complexity and enhance classification accuracy.

6. Ensemble Classifier (Bootstrap Aggregation): An ensemble classification approach (bagging) is applied to improve prediction robustness and accuracy.

7. Decision Output: If a brain tumor is detected, the system outputs **Tumor**. If no tumor is detected, the system outputs **Non-tumor**.

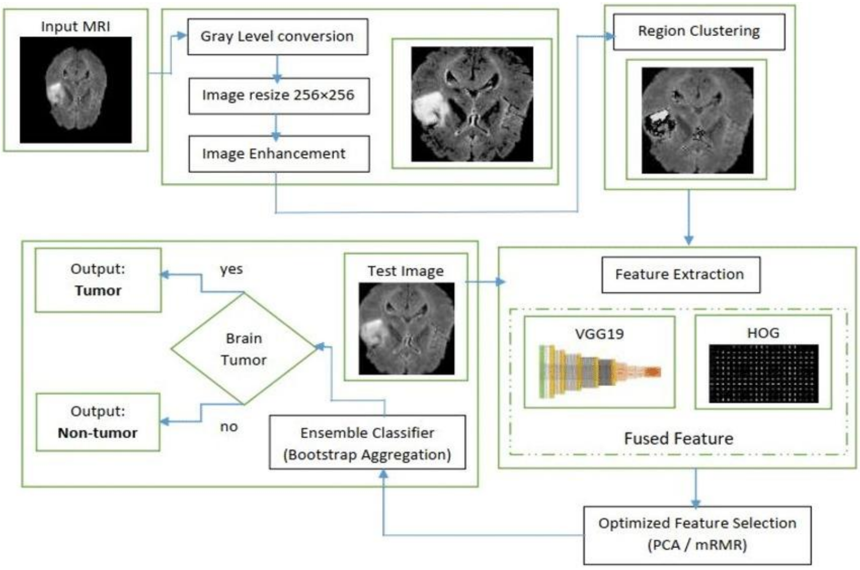

FIG.2: FLOW OF ALGORITHM

3.3 Deep Learning Models

3.3.1 Convolutional Neural Networks (CNNs): (Convolutional Neural Network) are widely used deep learning architectures for brain tumor prediction. CNNs are particularly effective in analyzing medical images, as they can automatically detect patterns and features such as edges, textures, and shapes from MRI scans. However, deeper CNNs often suffer from vanishing gradient problems, which can hinder learning.

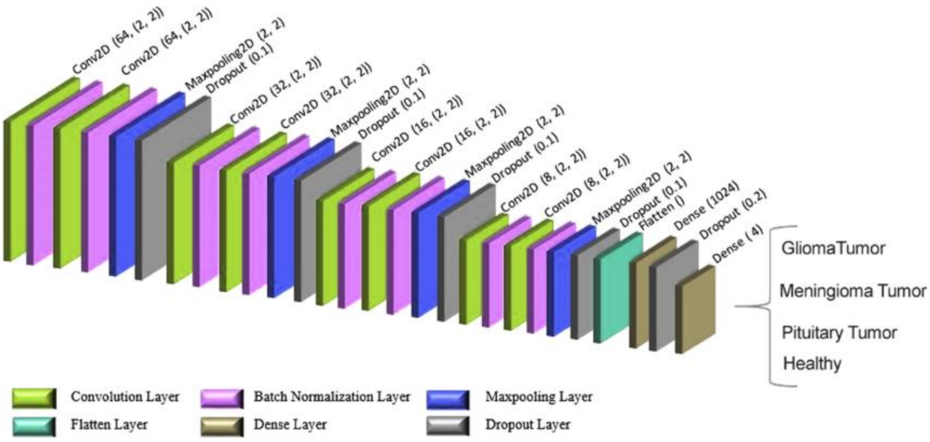

FIG.3: Convolutional Neural Networks (CNNs)

3.3.2 Its Variants (Inception-V3, EfficientNetB4, VGG19)

The overall structure of CNN-based models follows a **feed-forward architecture** where an image is passed through multiple layers to extract features and make predictions. Below is the generalized flow of the CNN algorithm, followed by the specific architectural flows of **Inception-V3, EfficientNetB4, and VGG19**.

❑ **CNN-based inception-V3: Inception-V3** is a deep convolutional neural network (CNN) architecture widely used for image classification and feature extraction. It improves accuracy while reducing computational complexity through its unique design, including **factorized convolutions, auxiliary classifiers, and asymmetric kernel usage**.

❑ **EfficientNetB4**: EfficientNetB4 is a **convolutional neural network (CNN)** architecture designed for high accuracy with reduced computational cost. It scales depth, width, and resolution **efficiently** using a **compound scaling** method. Compared to traditional CNNs (like ResNet or Inception-V3), EfficientNetB4 achieves better performance with fewer parameters, making it ideal for medical image analysis, such as MRI-based **brain tumor detection and segmentation**.

❑ **VGG19:**VGG19 is a deep **Convolutional Neural Network (CNN)** with **19 layers**, designed by the Visual Geometry Group (VGG) at Oxford. It is widely used for medical image analysis, including brain tumor detection and classification from MRI scans.

3.4 Training and Evaluation

The dataset is split into **80% training and 20% testing**. CNN achieves the highest accuracy (98.5%) due to its ability to automatically extract and learn meaningful features from MRI images.

IV. Conclusion

The present study shows that the proposed CNN has optimal correctness in classifying brain tumors. Comparing the performance of several CNNs and machine learning methods in diagnosing three types of brain tumors revealed that the CNN achieved exemplary performance and optimal execution time without latency. By leveraging deep learning techniques, the proposed method shows promise in automating the detection process, potentially reducing diagnostic time and improving accuracy. Although primary results are encouraging, further work is required to validate the model on larger, more diverse datasets and integrate it into a clinical workflow. Future research will concentrate on enhancing model interpretability and addressing challenges such as class imbalance and data heterogeneity.

Future work will focus on:

- Expanding datasets to improve generalization.
- Implementing explainable AI techniques for model interpretability.
- Integrating ML-based diagnostics with real-time clinical decision support systems.

V. Acknowledgment

We express our sincere gratitude to our project guide, **Dr. Anup Bhange**, for his continuous guidance, valuable insights, and support throughout this research. His expertise and encouragement have been instrumental in shaping this work. We would also like to thank the respected **Dr. Anup Bhange, Head of the Master of Computer Applications (MCA) Department**, as well as other faculty members for their helpful advice and guidance. Their support and encouragement have played a crucial role in the successful completion of this research. Furthermore, we extend our appreciation to our peers and mentors for their constructive feedback and discussions, which have helped refine our ideas. Lastly, we acknowledge the contributions of various researchers and authors whose work has served as a foundation for our study.

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