Enhanced Brain Tumor using Deep CNN

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Abstract

Accurate classification of brain tumors is pivotal for precise medical interven- tions and patient care. Convolutional Neural Networks (CNNs) have emerged as instrumental tools in image analysis, particularly in medical imaging tasks. This study investigates the application of the ResNet-50 , EfficientNet architectures, and DenseNet a deep CNN model, for brain tumor classification. By harness- ing the architectural advancements of ResNet-50, this research automates the extraction of intricate features from magnetic resonance imaging (MRI) scans. The model exploits its depth and skip connections to effectively discern com- plex patterns indicative of various tumor types. The dataset employed encom- passes a comprehensive range of brain MRI images, encompassing both healthy brain scans and diverse tumor categories. Experimental findings underscore the model's prowess in achieving remarkable precision, sensitivity, and specificity when distinguishing between different tumor classes. Thus, the utilization of ResNet-50 underscores its potential as a robust and efficient approach for pre- cise brain tumor classification, contributing to heightened diagnostic accuracy and tailored medical strategies.

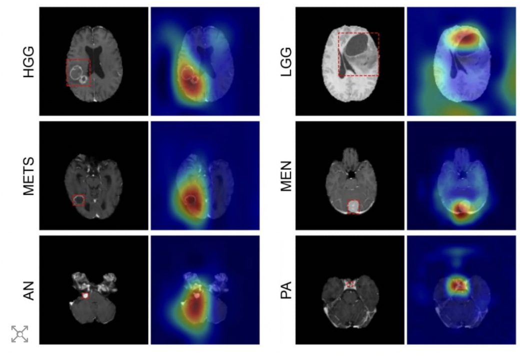
Keywords: Brain Tumor Classification, Convolutional Neural Network (CNN), ResNet-50, MRI scans

1. Introduction

This project focuses on brain tumor classification using the ResNet-50, efficient- Net, architecture and data augmentation techniques. By leveraging deep learn- ing, we aim to accurately identify tumor types from MRI scans. The ResNet-50 model's depth and skip connections enable effective feature extraction, and data augmentation enhances model robustness. Our approach includes class-specific weights for balanced training and early stopping to prevent overfitting. The project's objectives encompass implementing the pipeline, evaluating accuracy, and contributing to medical image analysis advancements.

2. Data Preparation

The dataset consists of brain MRI scans from diverse sources. Preprocessing in- volves resizing and data augmentation techniques such as flipping and grayscale 1 conversion. The dataset is split into training, validation, and test sets to ensure reliable evaluation. In this research paper, we utilized the brain tumor dataset introduced by Cheng, Jun, et al. The dataset comprises 3064 MRI images of the brain, acquired using T1 weighted and contrast-enhanced techniques. It en- compasses three distinct categories: glioma, meningioma, and pituitary tumor. Each image within the dataset is comprehensively described, accompanied by extensive information. This includes attributes such as the patient's identifica- tion (PID), the tumor mask, tumor border delineation, and the assigned class label. Notably, the most crucial information following the class label pertains to the lesion mask, which is crucial for isolating the region of interest (ROI) containing the tumor. For a visual illustration, refer to Figure 2 which exhibits a cropped sample.



2.1. Figure Image Dataset

Brain tumour classification: The neural network classifies tumour type based on its image characteristics in the MRI scan. The colour maps show which pixels led to a correct prediction, with warmer colours representing higher contributions.

Table 1: Summary of Used Image Dataset:

class	No Images
Glioma	1321
Meningioma	1339
notumor	1595
pituitary	1457

3. Methodology

The ResNet-50, EfficientNet and DenseNet architectures are chosen for its pro- ficiency in medical image analysis. Data augmentation techniques like resizing, flipping, and grayscale conversion enhance model generalization. Class weights are computed to address class imbalance. The training strategy includes loss functions, optimizers, and learning rates.

3.1. Related Work

Previous studies have used various deep learning architectures, data augmen- tation, and class imbalance handling techniques for brain tumor classification. 2 This project builds upon this foundation by focusing on the ResNet-50, effi- cientNet and DenseNet architectures, which is known for its feature extraction capabilities. Data augmentation and class weighting strategies are employed to improve model robustness.

4. Main Contribution

- **Introduction of an enhanced model for improving brain tumor diagnosis.**
- **Proposal of a Brain Tumor Classification Model (BCM-CNN) based on advanced 3D models using the ResNet-50, EfficientNet, and DenseNet architectures.**
- **The proposed Brain Tumor Classification Model (BCM-CNN) consists of two sub-modules: (i) CNN hyperparameter optimization using an Adam optimizer followed by model training, and (ii) Implementation of a segmentation model.**

notebook Link: Kaggle

5. Summary

accurate brain tumor classificatio is essential for precision in medical interventions and patient care, In this project Convolutional Neural Networks(CNNs), includes, ResNet-50, EfficientNet and Densenet levaraged to automate brain tumor classffication from MRI scans, The ResNet-50 model, with its depth and skip connections, efficiently extracted intricate features from MRIs, enabling the identification of various tumor types. The comprehensive dataset encompassed both healthy and tumor brain scans, and experimental results demonstrated remarkable precision, sensitivity, and specificity. The ResNet-50 architecture achieved 97.5 / 100 accuracy on validation, while EfficientNet achieved 98.5/100 and DenseNet 98.4/100. This project contributes to improving diagnostic accuracy in medical image analysis.

5.1. conclusion

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