Brain Tumor Detection Using Deep Learning

Name: Rawan Emad, Noha ezzat, Mariam kandeel, Rokaia emad

May 2024

Abstract

Brain tumors are a serious health concern, often requiring early detection for effective treatment. In this study, we investigate the application of various deep learning models, including CNN, ResNet, VGG16, Inception, and MobileNet, to classify brain tumors using a publicly available dataset. We describe the dataset, preprocessing steps, and the methodology used for training and evaluation. The performance of these models is compared in terms of accuracy and computational efficiency. Our findings demonstrate the strengths and limitations of each model in the context of brain tumor classification. **Keywords:** Brain tumor, deep learning, CNN, ResNet, VGG16, MobileNet, Inception, image classification.

1 Introduction

Brain tumors are a significant medical challenge affecting many individuals worldwide. Accurate and early diagnosis is crucial for effective treatment and management. Traditional diagnostic methods rely on clinical evaluation and imaging techniques, which can be time-consuming and subjective. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in automating and enhancing the diagnostic process through the analysis of medical images.

In this study, we apply several state-of-the-art deep learning models to a brain tumor dataset to evaluate their performance in classifying tumor types such as "glioma," "meningioma," "no tumor," and "pituitary." The models compared include a simple CNN, ResNet, VGG16, Inception, and MobileNet. We aim to identify which model provides the best trade-off between accuracy and computational efficiency for this specific task.

2 Related Work

Numerous studies have investigated the application of deep learning techniques for brain tumor detection and classification.

Hossain et al[1] utilized a deep learning framework involving a combination of CNNs and Support Vector Machines (SVM) to classify brain tumors into glioma, meningioma, and pituitary categories, achieving significant improvements in classification accuracy.

Cheng et al[3] developed a CNN-based model for brain tumor classification and demonstrated the effectiveness of CNNs in capturing tumor-specific features from MRI images. Their approach significantly outperformed traditional machine learning methods in terms of accuracy and robustness.

Zhang et al[2] explored the use of a ResNet-based architecture for brain tumor segmentation and classification. Their model leveraged deep residual connections to enhance feature extraction, leading to superior performance compared to standard CNN architectures.

Sekhar et al[1]investigated the performance of VGG16 and MobileNet for brain tumor detection. They found that while VGG16 provided high accuracy, MobileNet was more efficient in terms of computational resources, making it suitable for deployment in real-time clinical settings.

Mohsen et al[3] applied Inception networks to the task of brain tumor classification and demonstrated that the complex architecture of Inception models allowed for improved classification performance by capturing multi-scale features effectively.

These studies collectively highlight the potential of deep learning models in enhancing the accuracy and efficiency of brain tumor detection and classification, motivating further exploration and comparison of various architectures in this domain.

3 Data

The dataset used in this study is the Brain Tumor Dataset, which consists of MRI images labeled as "glioma," "meningioma," "no tumor," and "pituitary." The dataset is split into training and testing sets to evaluate model performance.

3.1 Preprocessing Steps

- **Data Extraction:** The dataset was extracted from a ZIP file and organized into training and testing directories.
- **Image Rescaling:** All images were rescaled to a pixel range of [0, 1].
- **Target Size:** All images were resized to 224x224 pixels to match the input size required by the models.

4 Methodology

Five deep learning models were employed for the classification task:

- **CNN:** A basic convolutional neural network with several convolutional and pooling layers.

- **ResNet:** A Residual Network that uses skip connections to improve training depth and accuracy.
- **VGG16:** A deep network with 16 layers, known for its strong performance in image classification tasks.
- **Inception:** A deep learning model designed by Google with a complex architecture that includes multiple convolutional kernels.
- **MobileNet:** A lightweight model designed for mobile and embedded vision applications, providing a good balance between accuracy and efficiency.

All models were trained using the Adam optimizer and categorical cross-entropy loss. not need for data augmentation as our dataset was balanced. The models were evaluated based on accuracy, F1-score loss, validation accuracy,an validation loss.

5 Results

The results section presents the findings of our experiments. We compare the performance of different models across the dataset. ResNet achieved the highest accuracy, demonstrating the effectiveness of deep networks with skip connections for medical image analysis. VGG16 also performed well but required longer training times. MobileNet provided a good balance between accuracy and computational efficiency, making it suitable for deployment in resource-constrained environments.

6 Conclusion

This study compared the performance of CNN, ResNet, VGG16, Inception, and MobileNet models in classifying brain tumors using MRI images. ResNet achieved the highest accuracy, demonstrating the effectiveness of deep networks with skip connections for medical image analysis. VGG16 also performed well but required longer training times. MobileNet provided a good balance between accuracy and computational efficiency, making it suitable for deployment in resource-constrained environments. Future work will explore the integration of these models into clinical workflows and their performance on larger, more diverse datasets.