Project Report - ECE 176

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Abstract

Automated brain tumor classification from MRI scans is essential for accurate diagnosis and treatment planning. In this project, I investigate four CNN architectures: ResNet, DenseNet, a simple CNN, and a Multiscale CNN model. This study aims to develop a robust system capable of accurately identifying brain tumor types.Surprisingly, simpler CNN architectures outperform ResNet and DenseNet, achieving testing accuracies of approximately 92.68% and 92.3%, respectively. This study contributes to automated brain tumor classification using deep learning. The findings suggest that simpler CNN architectures show promise for further research and integration into clinical practice

1 Introduction

Object recognition is a cornerstone of computer vision, as it holds immense significance and impact on a wide variety of other computer vision tasks such as object detection, semantic segmentation, and a wide variety of other visual tasks. This ability to accurately identify objects within images not only facilitates general computer vision tasks, but also plays a pivotal role in advancing biomedical research and clinical applications. Biomedical research and diagnosing utilizes a wide variety of medical imaging data to gain insights into complex phenomena.

One such effort is the use and analysis of magnetic resonance imaging (MRI) scans for tumor detection. MRI scans provide detailed anatomical information and are widely used for diagnosing various medical conditions, but they currently require manual analysis which is time-consuming and prone to human error.

The development of automated image classification techniques through Convulational Neural Networks (CNNs) offers a promising solution to this challenge. CNNs can learn to recognize patterns and features indicative of tumor presence and types within MRI images, which could provide more rapid and accurate diagnosis assistance for research and clinical purposes. Further efforts could even be done to enable earlier signs of tumors to better accelerate research and development of medications to slow, prevent, and eventually treat certain types of tumors.

In this study, I focus on the application of four distinct CNN models: (1) ResNet; (2) DenseNet; (3) simplified CNN; and (4) a multiscale CNN model to harness and compare the performance of these alternative, popular methods. By utilizing multiple architectures, I aim to develop a robust and efficient system for tumor classification to contribute to improvements in computer vision techniques for biomedical efforts by highlighting promising architecture for further development and utilization.

2 Related Work

There has been a wide variety of efforts and techniques to automate MRI analysis through computational and statistical methods. Efforts include the utilization of classical supervised learning algorithms, neural networks, and other software developed to detect and/or assist human analysis efforts in real time.

AFNI (Analysis of Functional NeuroImages)
AFNI[1] is an environment developed to interact, process, and display MRI data, and is maintained under the National Institutes of Health. Like most imaging software, AFNI was originally developed with the intent to assist with improving human capabilities in interacting with and visualizing MRI data for research and analysis. Most of its functions and capabilities are built around user experience such as displaying images and graph development, but it does have some more simple analysis capabilities such as development of activation maps using correlation methodology (AFNI).

Supervised Machine Learning Efforts
In their study, Venkatesh and M. Judith Leo[2] proposed a unique approach using a k-NN algorithm, distinct from alternative supervised learning models and neural networks. Their method combines K-means clustering with k-NN classification to detect tumor pixels within MRI brain images. However, while effective in distinguishing between benign and malignant tumors, this approach is limited to binary classification and does not differentiate tumor types such as glioma or metastatic tumors. Moreover, the effectiveness of their model heavily relies on the selection and utilization of features, as noted in their paper.

3 Method

For this project, I used four CNN architecture models to train and evaluate Brain Tumor MRI scans from a dataset that includes different tumor types such as glioma, meningioma, pituitary tumors, as well as a class indicating the absence of tumors. The dataset contains a wide range of MRI imaging data and is a crucial component of medical image analysis. My strategy involved utilizing four distinct neural network architectures. ResNet, DenseNet, CNN, and MultiscaleCNN are all deep neural network architectures.

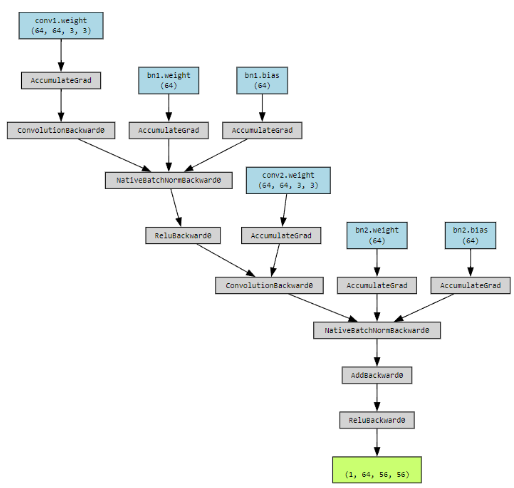

Figure 1: Overview of the Resnet-18 architecture.

3.1 ResNet

ResNet, short for Residual Network, is a particularly effective architecture due to its use of residual blocks. These blocks contain skip connections that allow the gradient to flow more efficiently during training, which helps alleviate the vanishing gradient problem. Each residual block consists of two convolutional layers followed by batch normalization and ReLU activation functions. My ResNet model comprises four convolutional layers with varying depths, followed by fully connected layers for classification. This architecture is particularly suited for capturing complex patterns and features within the MRI images.

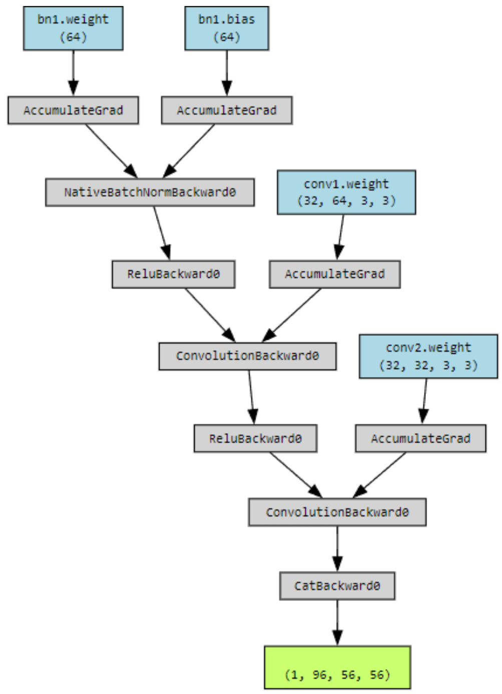

Figure 2: Overview of the DenseNet architecture.

3.2 DenseNet

DenseNet, short for Dense Convolutional Network, is a notable architecture due to its dense connectivity pattern that promotes feature reuse and enhances gradient flow throughout the network. No changes in content have been made. The design of DenseNet is based on dense blocks, where each layer receives input from all preceding layers within the block, leading to feature concatenation. To control the dimensionality and complexity of the model, transition blocks are incorporated. This architecture enables effective feature extraction from MRI images by leveraging dense connections and facilitating gradient propagation.

3.3 CNN

A fundamental Convolutional Neural Network (CNN) architecture is employed to establish a baseline for comparison with more complex models. CNNs are well-suited for image classification tasks due to their ability to automatically learn hierarchical features from raw pixel data. My CNN architecture comprises two convolutional layers with max-pooling operations followed by fully connected layers for classification. While less complex than ResNet and DenseNet, CNN serves as a valuable benchmark for evaluating the performance of more sophisticated models.

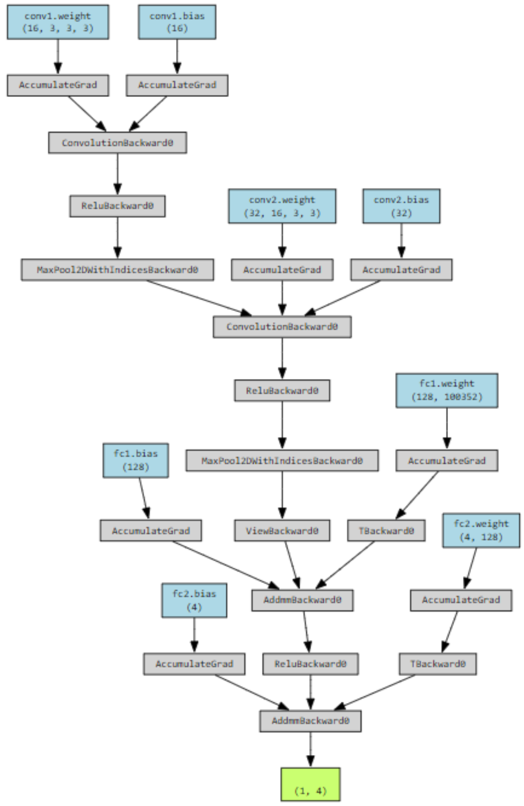

Figure 3: Overview of a simple CNN architecture.

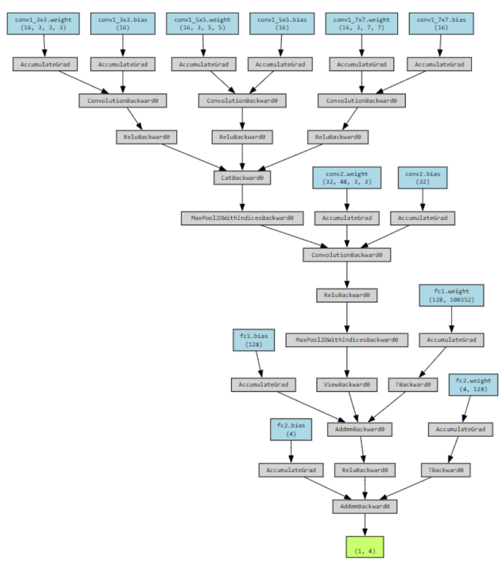

Figure 4: Overview of a multiscale CNN architecture.

3.4 Multiscale CNN

The MultiscaleCNN architecture is introduced to leverage features from multiple kernel sizes, thereby capturing both fine and coarse details within the MRI images. This architecture employs three convolutional layers with different kernel sizes (3x3, 5x5, and 7x7), allowing the model to extract features at multiple scales. The extracted features are then concatenated and processed through max-pooling and fully connected layers for classification. By incorporating features from different scales, MultiscaleCNN aims to enhance the model's ability to discriminate between tumor types and healthy tissue regions.

4 Experiments

4.1 Dataset: Brain Tumor MRI

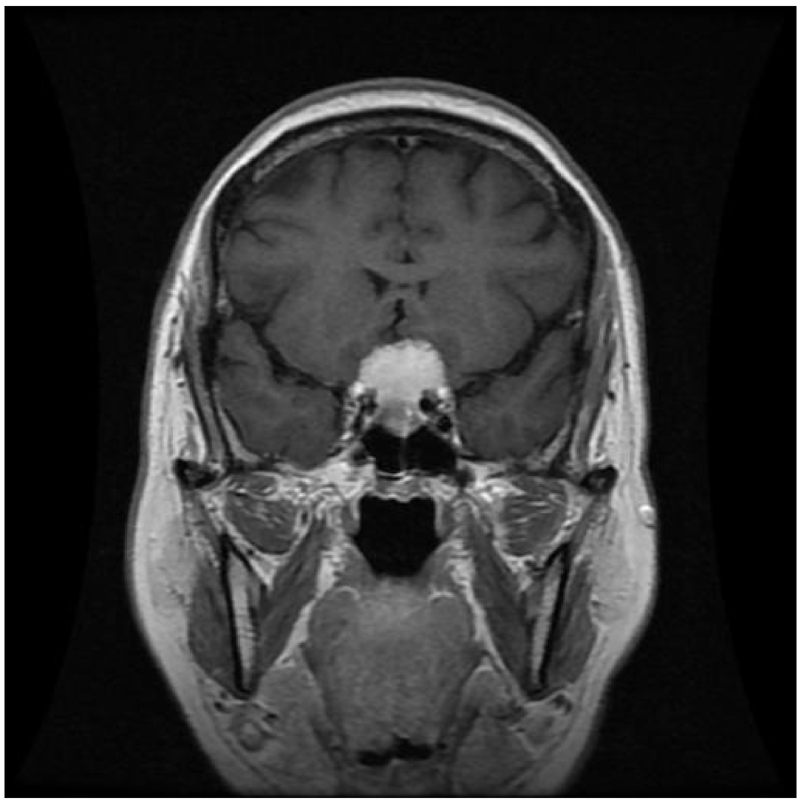

Figure 5: Sample image taken from the dataset. This image displays the presence of a pituitary tumor.

The dataset used for this effort was a Brain Tumor MRI dataset taken from Kaggle, which was a combination of three further datasets (figshare, SARTAJ, Br35H). In total, the data composes of 7,023 images of human brain MRI images, and is pre-organized into Testing and Training folders by the classification: glioma, meningioma, notumor, pituitary. For training purposes, 20% of the training data was split into a validation dataset of the same structure for validation during training.To effectively use the images for neural network development, the data was first normalized to size (224,224) with similar coloring before being loaded for model training and testing.

4.2 Results

Model Type	Testing Accuracy
ResNet-18	75.36%
DenseNet	83.45%
Simple CNN	92.68%
Multiscale CNN	92.30%

Each model was run on 10 epochs, with each iteration returning a validation accuracy. The Simple CNN and Multiscale CNN architectures significantly outperformed the more popular ResNet and DenseNet models, with testing accuracies of around 92.68% and 92.3% respectively. This suggests that for the purposes of MRI analysis, that the simpler architectures may be the better route of further development and research to achieve fully automated diagnosing software for clinical and biomedical research.

References

[1] https://afni.nimh.nih.gov/

[2] https://iopscience.iop.org/article/10.1088/1742-6596/1362/1/012073/pdf