CSC3109 Machine Learning Project Report

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1 Introduction

Machine learning (ML) has become a transformative technology, driving innovation across numerous fields such as healthcare, climate science, and energy management. Within ML, deep learning has emerged as a particularly powerful subset, enabling machines to perform tasks that require human-like perception and decision-making. This project aims to harness deep learning techniques to tackle real-world challenges in healthcare, specifically focusing on the classification of brain MRI images. By applying deep learning methodologies to this task, the project bridges theoretical concepts with practical applications, thereby advancing our understanding and capabilities in advanced ML techniques.

2 Problem Statement

Brain magnetic resonance imaging (MRI) is a non-invasive imaging technique that plays a crucial role in diagnosing and monitoring various brain conditions, including tumors. The interpretation of brain MRI images is a complex and time-consuming process, requiring expert knowledge and experience. Accurate classification of brain MRI images is essential for timely diagnosis and treatment planning, as different types of brain tumors have distinct characteristics and treatment strategies. Patients may receive imaging studies as part of their routine care or to investigate specific symptoms, such as headaches, seizures, or cognitive changes [1]. In many cases, the radiologist's report on the MRI findings is critical for guiding clinical decisions and patient management.

Accurate classification of brain MRI images is a significant challenge in the medical field. Brain MRI scans are essential for diagnosing and monitoring various neurological conditions, yet the complexity and variability of these images make classification difficult. Misclassifications can lead to delays in diagnosis and treatment, impacting patient outcomes. Thus, there is a critical need for robust classification models that can reliably distinguish between different types of brain tumors.

As the availability of MRI data increases, the demand for automated tools to assist radiologists in interpreting these images grows. Current manual methods are time-consuming and prone to human error, highlighting the need for efficient, automated solutions. This project seeks to address this problem by developing, evaluating, and comparing multiple deep learning models to achieve high accuracy in classifying brain MRI images. By leveraging deep learning techniques, the project aims to reduce the workload on healthcare professionals, enhance diagnostic efficiency, and improve patient care through early detection and timely medical interventions.

3 Objective

The overarching objective of this project is to develop deep learning models that aid radiologists and doctors in the efficient diagnosis of brain tumors, facilitating early intervention and improving patient outcomes. By applying and extending advanced deep learning techniques, this project aims to produce models capable of accurately classifying brain MRI images. These models will support healthcare professionals by reducing diagnostic time and enhancing the accuracy of diagnoses, ultimately

contributing to more timely and effective medical interventions.

4 Data Preprocessing

Data preprocessing is a vital step in the data mining process, particularly in the context of deep learning for image classification. This step involves techniques such as image augmentation, affine transformations, and resizing, which are essential for enhancing model performance. For this project, preprocessing is applied to the provided dataset (dataset_19) to ensure it is suitable for the brain tumor classification task. The specific steps involved in the preprocessing of this dataset are outlined below.

4.1 Dataset

The dataset, referred to as dataset_19, comprises a folder containing four subfolders, each representing a different class of brain tumors. Each subfolder includes 120 MRI images of 512x512 pixels. The dataset distribution is illustrated in Figure 1.
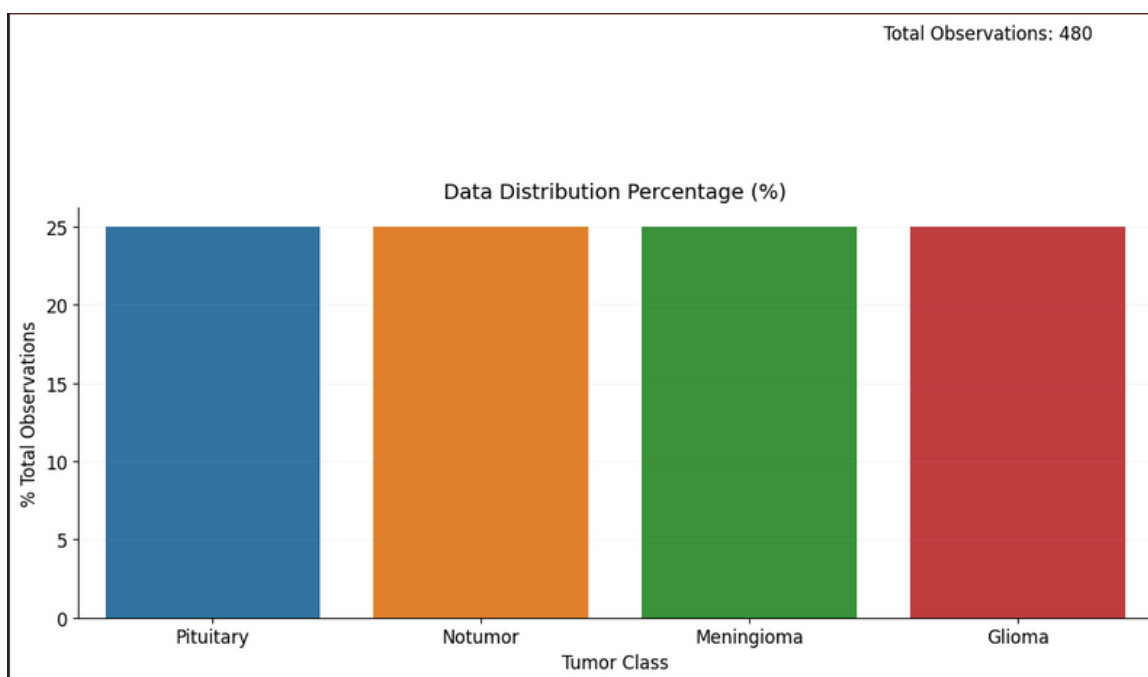

Figure 1: Distribution of images in dataset_19.

To prepare the dataset for the classification task, it is preprocessed and subsequently divided into training and validation sets, with the training set comprising 80% of the data and the validation set

20%. This split is shown in Figure 2. The training set is used to train the model, while the validation set is used to evaluate its performance.
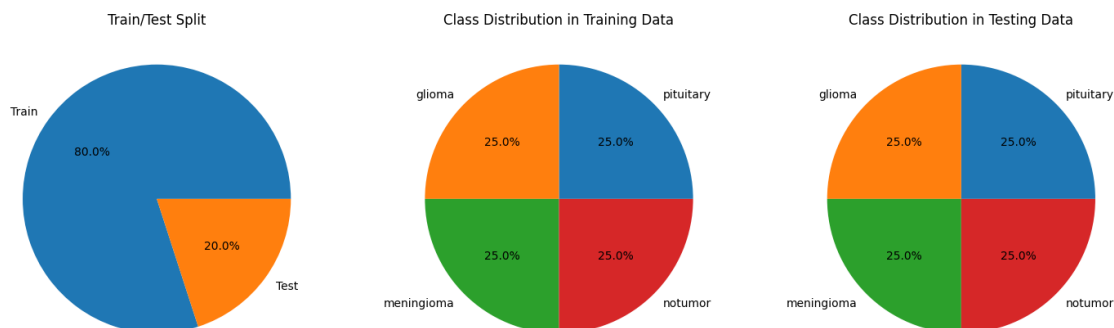

Figure 2: Splitting the dataset into training and validation sets.

Image augmentation is performed using the `ImageDataGenerator` class from the Keras library. This technique artificially increases the dataset size by applying various transformations to the images, thus improving model performance by providing more training data. The `ImageDataGenerator` class offers several parameters for image augmentation.

The preprocessing pipeline involves initially performing horizontal flips on the images, followed by random rotations. Each image is then normalized by dividing pixel values by 255. After these transformations, the dataset is split into training and validation sets as previously described.

4.2   Summary and Justifications

Given the relatively small size of dataset_19 (480 images in total), data augmentation is crucial for enhancing the dataset's variability and improving the model's generalization capabilities. Flipping images horizontally is justified based on the anatomical symmetry of the brain's hemispheres, allowing for effective augmentation without misrepresenting tumor locations [2]. This technique increases the diversity of the training data, which is particularly important given the limited size of the dataset compared to larger datasets, such as those used in the BraTS competition.

Similarly, random rotations are applied since brain images can be rotated in various directions, further increasing the dataset's variability and aiding in model training. The augmentation strategies, including horizontal flipping and random rotations, are essential for compensating for the smaller dataset size by exposing the model to a wider variety of image orientations and perspectives. This approach helps create a more robust model capable of accurately classifying brain tumors despite the limited amount of original training data.

5 Data Mining

In this section, various data mining techniques are employed to extract meaningful insights from the preprocessed data.

5.1 Overview

All models were trained on Google's Colab plaform, utilizing the GPU runtime for faster training. In the following subsections, we will discuss the data mining techniques used to model the brain tumor classification task. The techniques include data augmentation, data splitting, and model selection.

5.2 Model Selection

Model selection is a critical step in developing an effective machine learning model, especially for complex tasks like brain tumor classification. The choice of model impacts the accuracy, efficiency, and overall performance of the solution. This section discusses the use of transfer learning with pretrained models such as VGG16 and EfficientNet, as well as deep learning approaches like U-Net, which have demonstrated high performance in related tasks such as the BraTS Competition.

The BraTS (Brain Tumor Segmentation) Competition has established itself as a benchmark for brain tumor segmentation tasks over several years. The competition has highlighted various models and techniques that consistently achieve superior results. Among the most commonly used models by top teams in the competition are U-Net, VGG16, and EfficientNet. These models have been chosen due to their proven ability to effectively handle medical imaging tasks, making them ideal candidates for our project.

Transfer Learning with Pretrained Models: Transfer learning involves leveraging pretrained models, which have already been trained on large datasets, and fine-tuning them for specific tasks. This approach is particularly useful when dealing with small datasets, as it allows the model to benefit from the knowledge gained during pretraining.

VGG16: VGG16 is a convolutional neural network (CNN) known for its simplicity and effectiveness. It has been pretrained on the ImageNet dataset, which contains millions of images across thousands of categories. For our brain tumor classification task, VGG16 can be fine-tuned to learn the specific features of MRI images, leveraging its deep architecture to capture intricate details.

EfficientNet: EfficientNet is another pretrained model that has gained popularity for its performance and efficiency. It scales up in a balanced manner across depth, width, and resolution, providing an optimized architecture that achieves high accuracy with fewer parameters. EfficientNet's ability to maintain performance while being computationally efficient makes it a suitable choice for our dataset.

Deep Learning with U-Net: U-Net is a deep learning model specifically designed for biomedical image segmentation. Its architecture consists of a contracting path to capture context and a symmetric expanding path for precise localization. U-Net has been widely used in medical imaging due to its

ability to segment images accurately. In the context of brain tumor classification, U-Net can be adapted to highlight and classify different regions of MRI scans, making it a powerful tool for our project.

Model Selection Process: The model selection process involves evaluating the suitability of each model based on the dataset characteristics and the specific requirements of the classification task. Given the relatively small size of our dataset (dataset_19), models that can generalize well from limited data are preferred.

By leveraging these models, we aim to achieve high accuracy in classifying brain MRI images, thereby supporting healthcare professionals in the efficient diagnosis of brain tumors and facilitating early intervention. The combination of transfer learning and deep learning techniques ensures that our approach is both robust and effective, despite the limited size of the dataset.

5.3   unet
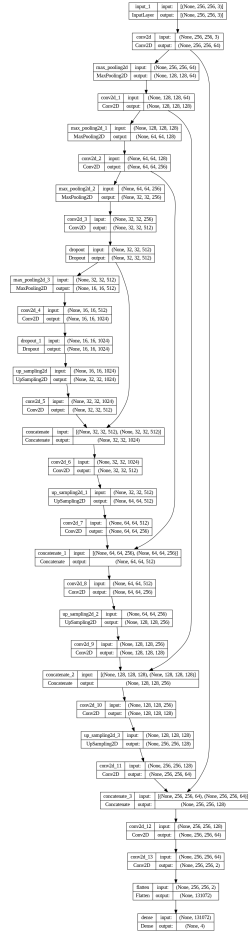
This is a simple implementation of the U-Net architecture.

Figure 3: unet Architecture

5.4 VGG16

This is a simple implementation of the VGG16 model

6 Conclusion

7 Future Work

References

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