CSC3109 Machine Learning Project Report

Woon Jun Wei (2200624)[1], Benjamin Loh Choon How (2201590)[1], Low Hong Sheng Jovian (2203654)[1], Ong Zi Xuan Max (2200717)[1], and Cleon Tay Shi Hong (2200649)[1]

[1]Team 19

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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 Dataset Exploration

The dataset, referred to as `dataset_19`, consists of a collection of MRI images organized into four subfolders, each representing a distinct class of brain tumors. Each subfolder contains 120 images, resulting in a well-balanced dataset with a total of 480 images. This balance is essential for training deep learning models, as it mitigates the risk of bias towards any particular class, ensuring that the model learns to distinguish among all categories effectively.

The dataset is composed of images representing four types of brain tumors: glioma, meningioma, pituitary tumors, and cases with no tumors. Specifically, it includes:

- **Glioma Tumor**: 120 images
- **Meningioma Tumor**: 120 images
- **Pituitary Tumor**: 120 images
- **No Tumor**: 120 images

Each image in the dataset captures the brain from different perspectives, including axial, coronal, and sagittal views. These diverse views are crucial as they provide comprehensive information about the tumor's location, size, and relation to surrounding structures. For instance, axial views offer a horizontal slice of the brain, coronal views provide a frontal slice, and sagittal views give a side slice. Including these various perspectives ensures that the model can learn robust features and improve its ability to generalize across different cases.

The distribution of images across these classes is depicted in Figure 1. This visual representation underscores the dataset's balance and uniformity, further highlighting its suitability for developing a deep learning model for brain tumor classification.

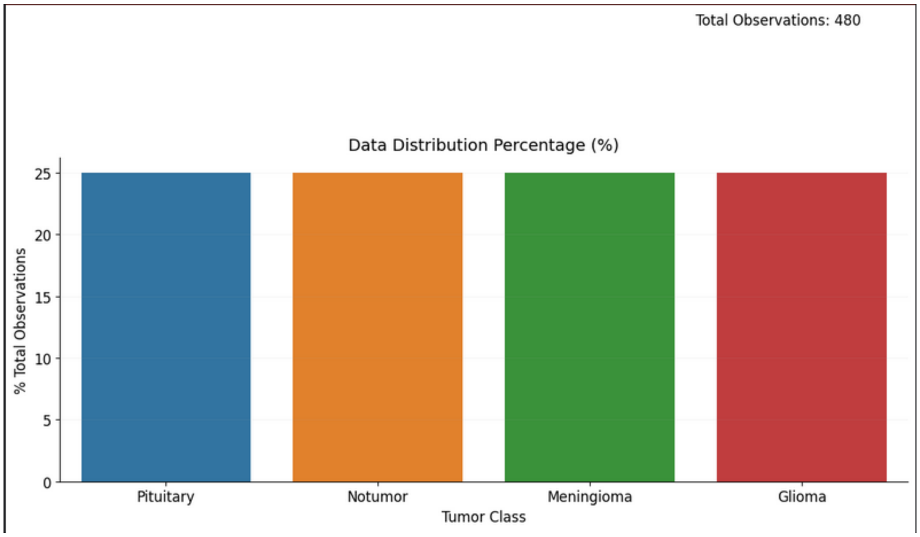

Figure 1: Distribution of images in `dataset_19`.

Overall, `dataset_19` provides a diverse and balanced set of images, essential for training an accurate and reliable deep learning model. The inclusion of different tumor types and multiple views per case enriches the dataset, making it a valuable resource for the task of brain tumor classification.

4.1 Tumor Types

The dataset encompasses four distinct classes of brain tumors, each representing a unique type of pathology. A thorough understanding of these tumor types is vital for developing a model capable of accurately classifying them.

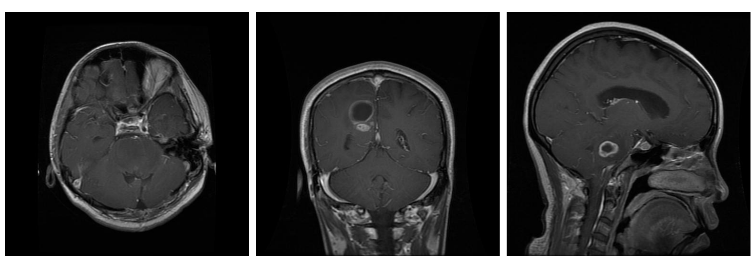

Figure 2: Glioma Tumor: Axial, Coronal, and Sagittal Views.

Gliomas are the most prevalent primary brain tumors, originating in the glial cells of the brain. These tumors can be further classified into subtypes such as astrocytoma, oligodendroglioma, and glioblastoma. Gliomas are characterized by their infiltrative nature and high recurrence rates, often presenting with varying shapes and irregular borders. The complexity and variability in glioma morphology make them particularly challenging to classify, underscoring the importance of incorporating detailed MRI views to capture their diverse appearances [2].

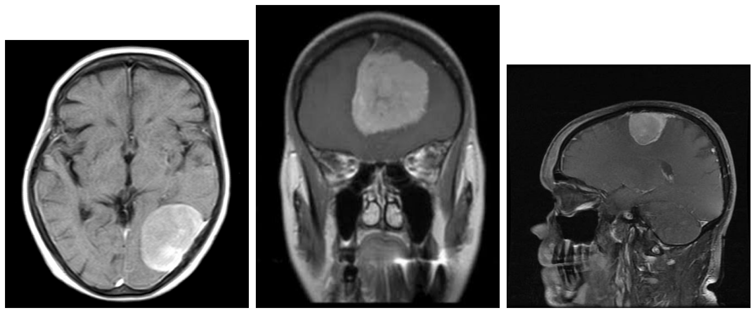

Figure 3: Malignoma Tumor: Axial, Coronal, and Sagittal Views.

Meningiomas, on the other hand, are typically benign tumors arising from the meninges, the protective layers surrounding the brain and spinal cord. These tumors are usually slow-growing and well-defined, which often makes them easier to surgically remove compared to other types. The well-defined nature of meningiomas benefits from clear imaging perspectives, which assist in their precise identification and classification.

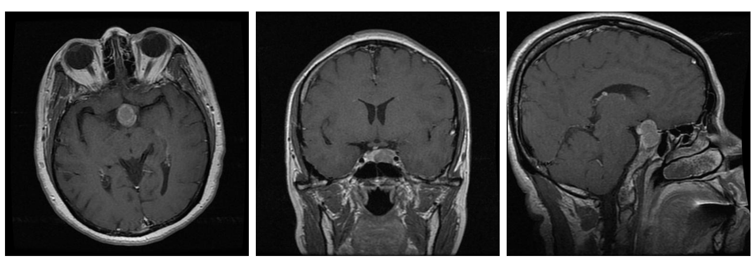

Figure 4: Pituitary Tumor: Axial, Coronal, and Sagittal Views.

Pituitary tumors develop in the pituitary gland, a small but crucial organ located at the base of the brain. These tumors can be either benign or malignant. Given the pituitary gland's critical role in hormone regulation, accurate identification of pituitary tumors is essential. Detailed MRI views help in assessing the tumor's impact on the surrounding brain structures and the gland itself.

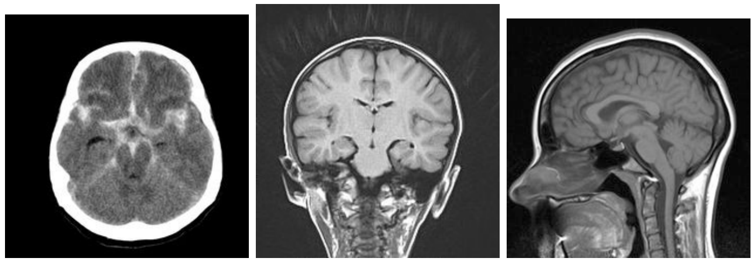

Figure 5: No Tumor: Axial, Coronal, and Sagittal Views.

Lastly, the class labeled ‘No Tumor’ includes images of the brain without any detectable tumors. This class is crucial for training the model to accurately distinguish between pathological and non-pathological images, thereby reducing false positives in diagnoses.

In summary, each tumor type in the dataset presents unique challenges and characteristics that must be considered in model development. The inclusion of diverse MRI views, such as axial, coronal, and sagittal perspectives, provides a comprehensive understanding of the tumor morphology and spatial relationships, thereby enhancing the model’s ability to accurately classify and differentiate between various brain tumor types.

4.2 Image Sizes

The overall average size of the images is approximately $[453.36, 450.83]$ pixels. The smallest image size is $(198, 150)$ pixels, and the largest image size is $(1075, 890)$ pixels. The mean, median, and mode sizes across the dataset are consistent at $[512, 512]$ pixels, suggesting a central tendency around these dimensions.

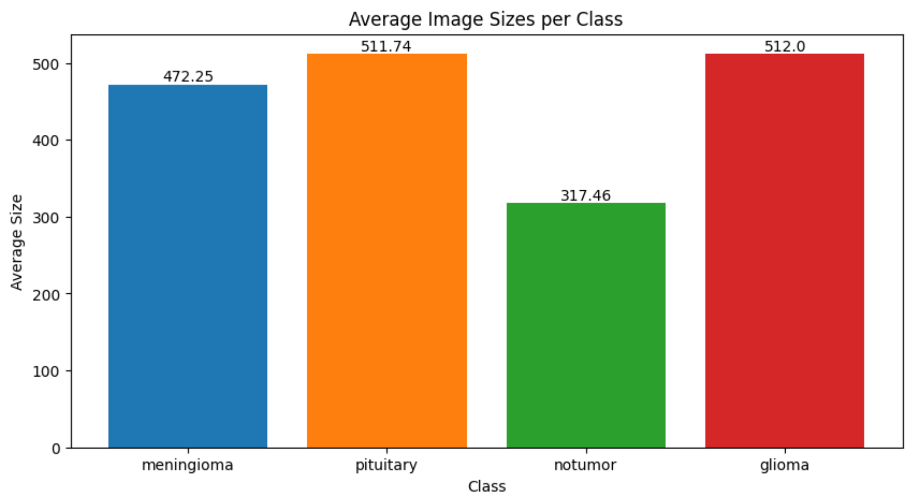

Figure 6: Distribution of brain image sizes in dataset_19.

Table 1: Overall Statistics of Brain Image Sizes

Statistic	X	Y
Mean Size	453.3625	450.83125
Median Size	512	512
Mode Size	512	512
Standard Deviation of Size	124.1067	131.5980
Variance of Size	15402.4644	17318.0236
Smallest Size	198	150
Largest Size	1075	890

Table 2: Class-Specific Statistics of Brain Image Sizes

Statistic	Meningioma	Pituitary	Notumor	Glioma
Mean Size (X)	472.25	511.7417	317.4583	512
Mean Size (Y)	466.4083	510.5417	314.3750	512
Median Size (X)	512	512	236	512
Median Size (Y)	512	512	236	512
Mode Size (X)	512	512	236	512

Statistic	Meningioma	Pituitary	Notumor	Glioma
Mode Size (Y)	512	512	236	512
Standard Deviation of Size (X)	100.7078	43.5696	154.5843	0
Standard Deviation of Size (Y)	108.4743	30.7834	174.3213	0
Variance of Size (X)	10142.0708	1898.3083	23896.3149	0
Variance of Size (Y)	11766.6749	947.6149	30387.9010	0
Smallest Size (X)	223	256	198	512
Smallest Size (Y)	200	256	150	512
Largest Size (X)	650	903	1075	512
Largest Size (Y)	591	721	890	512

Class-specific statistics show variation in image sizes:

- **Meningioma**: Sizes range from $(223, 200)$ to $(650, 591)$ pixels, with a mean size of approximately $[472.25, 466.41]$ pixels.

- **Pituitary**: Sizes range from $(256, 256)$ to $(903, 721)$ pixels, with a mean size of approximately $[511.74, 510.54]$ pixels.

- **Notumor**: Sizes range from $(198, 150)$ to $(1075, 890)$ pixels, with a mean size of approximately $[317.46, 314.38]$ pixels.

- **Glioma**: All images are consistently sized at $[512, 512]$ pixels.

The variability in image sizes across different classes highlights the importance of size normalization during the preprocessing phase. For instance, while the 'glioma' class images are uniformly sized, other classes exhibit significant variation, which could introduce biases or inconsistencies in the training process if not properly addressed.

Proper preprocessing, including size normalization, is vital for several reasons:

- **Uniform Input Size**: Neural networks require inputs of a fixed size. Without resizing, it would be impossible to batch process the images.

- **Consistent Feature Representation**: Ensuring all images are of the same size ensures that features are represented consistently across the dataset, which aids in better model learning.

- **Reduction of Computational Load**: Smaller, consistent image sizes can significantly reduce the computational load and memory requirements, making training more efficient.

- **Enhanced Model Performance**: Properly preprocessed images can lead to improved model convergence and accuracy, as the network can learn from a standardized set of inputs.

In conclusion, the preprocessing step of resizing images to a uniform dimension is an essential consideration in developing a robust and efficient deep learning model for brain tumor classification. It not only facilitates smooth training but also contributes to the overall performance and generalization capability of the model.

5 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.

5.1 Data Splitting and Augmentation

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 7. The training set is used to train the model, while the validation set is used to evaluate its performance.

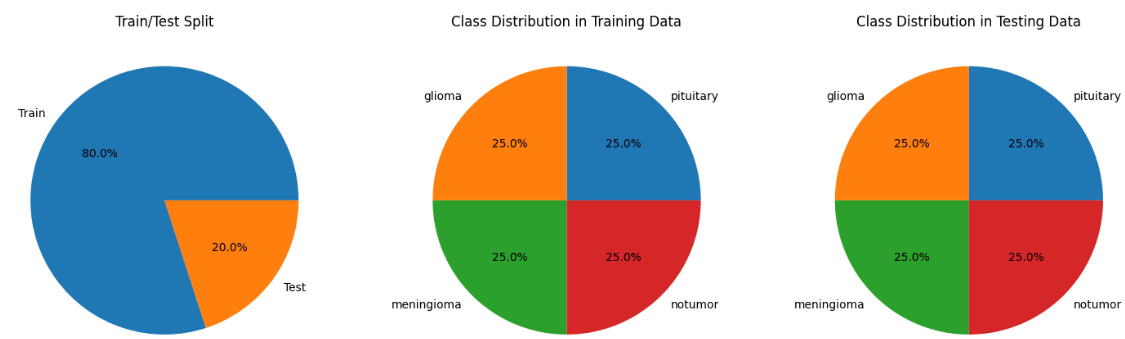

Figure 7: Splitting the dataset into training and validation sets.

Image preprocessing is essential to enable models to focus on the region of interest, namely the brain, while reducing background noise and irrelevant features. This process involves converting images to grayscale, applying Gaussian blur, and performing thresholding and morphological operations to refine image quality. By cropping around the largest contour, which is likely the brain, this step highlights critical anatomical features and enhances model generalization, ultimately leading to more accurate tumor classification.

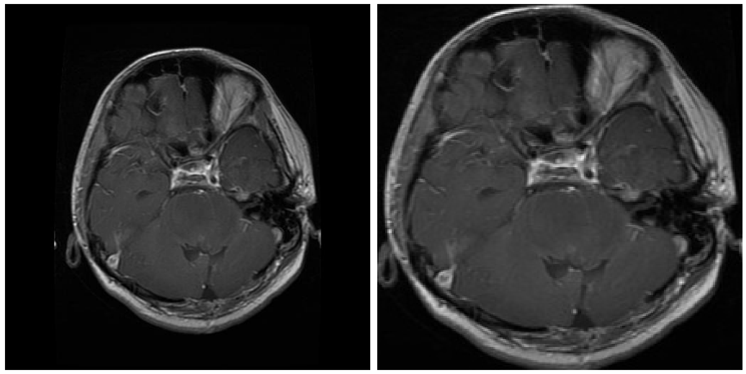

Figure 8: Cropping the MRI image along its contour.

Image augmentation is then 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.

5.2 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 [3]. 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.

6 Data Mining

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

6.1 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.

6.2 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.

6.3 unet

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

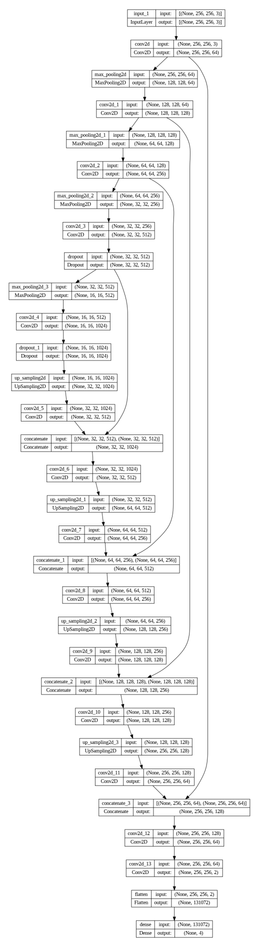

Figure 9: unet Architecture

6.4 VGG16

This is a simple implementation of the VGG16 model

7 Conclusion

8 Future Work

References

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