# Intermediate Project Report:

# Deep Learning for Brain Tumor Classification

Team members:

Chieh Jui Lee(A20523922)

Yi Shi(A20501004)

Xiaoting Zhou(A20503290)

## Introduction and Problem Description

In this intermediate project report, we provide an overview of our ongoing work on using deep learning models for brain tumor classification. The primary objective of this project is to develop a robust classification model that can effectively distinguish between different types of brain tumors based on medical images.

We aim to contribute to the advancement of medical diagnostics and provide a tool that can assist healthcare professionals in making more accurate and timely diagnosis.

Our project utilizes three distinct deep learning models, namely the MobileNet, ResNet, and EfficientNet models. These models have been selected for their suitability in resource-constrained environments, making them ideal candidates for real-world medical applications.

## Description of the Data Used in the Project

The dataset used for this project comprises medical images of brain tumors. The data includes images of different types of tumors, such as glioma, meningioma, pituitary, and others. The dataset is divided into training and validation sets, allowing us to train and evaluate our models effectively. The images are labeled with their corresponding tumor type, enabling supervised learning.

## Work Accomplished So Far

### MobileNet Model

We started by training the MobileNet model using cross-entropy loss and the Adam optimizer. The model was trained with a batch size of 32 for 15 epochs. During training with the training data, the accuracy increased from 65% to 92%, and the loss decreased from 0.92 to 0.21.

Validation data showed an increase in accuracy from 77% to 87%, with a loss reduction from 0.56 to 0.32. The evaluation results revealed an accuracy of 94% for the training data and 87% for the testing data, with a loss of 0.18 and 0.32, respectively. Notably, the MobileNet model achieved the highest accuracy among the three models.

### ResNet Model

The ResNet model was trained using the same setup, with a batch size of 32 for 4 epochs. The accuracy during training with the training data increased from 64% to 83%, while the loss decreased from 0.93 to 0.46.

For the validation data, the accuracy increased from 69% to 79%, with a loss reduction from 0.71 to 0.52. However, the evaluation results were less promising, with an accuracy of 84% for training data and 79% for testing data, along with a loss of 0.41 and 0.52, respectively.

### EfficientNet Model

Similar to the other models, the EfficientNet model was trained with a batch size of 32 for 5 epochs. The accuracy increased from 64% to 85% during training with the training data, and the loss decreased from 0.89 to 0.38. For validation data, the accuracy increased from 73% to 81%, with a loss reduction from 0.64 to 0.46.

The evaluation results showed an accuracy of 86% for the training data and 81% for the testing data, with a loss of 0.36 and 0.46, respectively. The EfficientNet model achieved better accuracy than ResNet but slightly lower than MobileNet.

## What Remains to Be Done

Our project is ongoing, and there are several tasks left to complete:

> Fine-Tuning and Optimization: We plan to further fine-tune and optimize the model hyperparameters to potentially enhance the performance of the ResNet and EfficientNet models.
>
> Addressing Mismatched Data: The observation of mismatches, particularly for glioma and meningioma tumors, suggests the need for further investigation. We will focus on improving the classification accuracy for these specific tumor types.
>
> Model Comparison: We will conduct a detailed comparative analysis of the three models' performance, considering factors such as inference time, model size, and resource utilization.
>
> Reporting and Documentation: We will complete the documentation of our methodology and results, including a comprehensive discussion of model architecture and training procedures.

## Conclusion

In summary, our project has made significant progress in utilizing deep learning models for brain tumor classification. The MobileNet model has shown promising results with the highest accuracy and the lowest loss among the three models.

The discovery of mismatches predominantly occurring in glioma and meningioma tumors provides valuable insights for future model improvement. We plan to address the remaining tasks, fine-tune our models, and further investigate these mismatches to advance our model's accuracy and effectiveness in real-world medical applications.

Our goal is to contribute to improved brain tumor classification and, ultimately, better patient outcomes.