Model Development Phase Template

Date	15 March 2024
Team ID	Team-738168
Project Title	Cognitive Care: Early Intervention for Alzheimer's Disease
Maximum Marks	5 Marks

Model Selection Report

DenseNet169 appears to be a promising candidate for Alzheimer's classification based on medical imaging data, particularly MRI scans. To avoid class imbalance, the sampling should be evenly distributed among the four main MRI image types. Mild demented,moderately demented, non-demented, and very mild demented are the grades assigned by the DenseNet169 algorithm.There is a serious class imbalance issue with the MRI image dataset that was collected through Kaggle. To identify the phases of dementia using MRI, a DenseNet169 algorithm classification is suggested.

Model Selection Report:

Model	Description
DenseNet169	**Why DenseNet169?** **Strong Baseline:** ● Dense connections: DenseNet169's architecture with dense connections between layers improves feature propagation and alleviates the vanishing gradient problem. This can lead to strong baseline performance without complex customizations, making it a good starting point for Alzheimer's classification tasks.

	Transfer Learning: ● Efficiency: DenseNet169's relative efficiency (fewer parameters compared to some architectures) makes it well-suited for transfer learning. Pre-trained models on large image datasets can be fine-tuned for Alzheimer's classification, leveraging their learned features and reducing training time significantly. This is particularly advantageous when dealing with limited medical image datasets for Alzheimer's research. **Adaptability:** ● Feature extraction: DenseNet169's strength in extracting complex features from images translates well to adaptability. It can learn the intricacies of brain scans even with limited Alzheimer's data, potentially allowing for customization to specific datasets. ● Regularization: DenseNet's inherent dense connections act as a regularizer, reducing overfitting. This is crucial when adapting to new datasets, especially in medical imaging where data can be scarce. **Considerations:** ● **Data Dependence:** Like most machine learning models, DenseNet169's effectiveness heavily relies on the quality and size of the training data. If your dataset for Alzheimer's classification is small or lacks quality, the model's performance might be underwhelming. It might require data augmentation techniques to improve performance. ● **Interpretability:** DenseNet169, like many deep learning models, can be challenging to interpret. Understanding exactly how the model arrives at its predictions can be difficult. This is an ongoing area of research in deep learning, and interpretability might be crucial in medical applications. **Computational Cost:** ● **Relative Efficiency:** While DenseNet169 is generally faster to train than some deeper models due to its fewer parameters, training any deep learning model can be computationally expensive. You'll

	need to consider factors like the size of your dataset and the available hardware resources (GPUs) when using DenseNet169. **Alternatives:** ● **Comparison is Key:** It's vital to compare DenseNet169's performance with other deep learning models on your specific Alzheimer's classification dataset. This helps identify the best possible model for your project. Some potential alternatives include: ○ **ResNet models:** Similar to DenseNet, these convolutional neural networks are known for good performance in image classification tasks. ○ **VGG models:** While not the most efficient, VGG models have also shown promise in Alzheimer's classification.