Image Classification for Lung Cancer Detection

1 Introduction

Lung cancer is a leading cause of cancer-related deaths worldwide, making early and accurate detection vital for improving patient outcomes. This project aims to develop a robust image classification model to identify different types of lung cancer from CT scans. Leveraging transfer learning with pre-trained MobileNetV2 and InceptionV3 architectures, and enhancing image contrast through Contrast Limited Adaptive Histogram Equalization (CLAHE), this model seeks to improve diagnostic accuracy and assist medical professionals.

2 Dataset

2.1 Data Description

The dataset comprises CT scans categorized into four classes:

- Adenocarcinoma
- Large Cell
- Normal
- Squamous

The data is divided into training, validation, and test sets, stored in respective directories.

2.2 Data Preprocessing

Data preprocessing involves counting the number of images in each category and visualizing sample images to understand the dataset better. CLAHE is applied to enhance image contrast, which helps in highlighting the features essential for accurate classification. This step is crucial as it improves the quality of the images, making it easier for the model to learn and differentiate between the various classes.

3 Model Architecture

3.1 Base Models

The project employs two well-known deep learning architectures:

- **MobileNetV2**: An efficient and lightweight model suitable for mobile and edge devices, known for its balance of performance and computational efficiency.
- **InceptionV3**: A deeper model renowned for its high accuracy on various image classification tasks.

3.2 Model Definition

The model integrates MobileNetV2 and InceptionV3 as base models, leveraging their pre-trained weights for feature extraction. By freezing the layers of these models, we ensure that their learned features are retained, while additional layers are added for the specific task of lung cancer classification. The outputs of the two base models are concatenated and fed into custom layers for final classification.

3.3 Model Compilation and Training

The model is compiled using the Adam optimizer and categorical cross-entropy loss function, which is standard for multi-class classification tasks. Data augmentation techniques such as rescaling, shear transformation, zoom, and horizontal flip are applied to the training images to improve the model's generalization ability.

The training process involves fitting the model on the training set and validating it on the validation set. The performance is monitored through metrics like loss and accuracy, ensuring that the model is learning effectively without overfitting.

4 Results and Discussion

4.1 Training and Validation Performance

The training and validation performance is evaluated by plotting the loss and accuracy over each epoch. Convergence of these metrics indicates that the model is learning appropriately. Consistent training and validation accuracy suggest that the model generalizes well to unseen data.

5 Conclusion

This project successfully developed a deep learning model using transfer learning from MobileNetV2 and InceptionV3 architectures for lung cancer detection from CT scans. The model achieved significant performance metrics, indicating its potential utility in assisting medical professionals with early and accurate lung cancer diagnosis. By combining the strengths of both architectures and enhancing image quality through CLAHE, the model provides a reliable tool for medical imaging analysis.

6 Future Work

Future work could involve expanding the dataset to include more diverse and larger sets of CT scans, fine-tuning the base models to further improve performance, and integrating additional preprocessing techniques to enhance image quality. Exploring other model architectures and ensemble methods could also lead to improved accuracy and robustness in lung cancer detection.