**Introduction**

This project aims to predict pneumonia from chest X-ray images and generate Class Activation Maps (CAMs) to highlight affected regions. We employed two pre-trained Convolutional Neural Network (CNN) architectures: ResNet50 and DenseNet161, both initially trained on the ImageNet dataset. These CNNs were selected for their feature reuse capabilities and ease of training, facilitated by multiple residual connections. DenseNet161 comprises dense blocks, transition layers, and a classifier layer. Within dense blocks, each convolutional layer receives feature maps from preceding layers, promoting information flow. Transition layers reduce the spatial dimensions of feature maps, decreasing model parameters and mitigating overfitting. The classifier layer maps extracted features to the output classes (Normal and Pneumonia). ResNet50, a 50-layer deep CNN from the ResNet family, utilizes residual connections to enable feature reuse and improve gradient flow during backpropagation. ResNet50 was chosen for CAM generation due to its inherent Global Average Pooling (GAP) layer.

**Dataset (Chest X-ray data from Kaggle)**

* Training set: 5216 images
* Validation set: 16 images
* Test set: 624 images
* Classes: ['NORMAL', 'PNEUMONIA']
* Class mapping: {'NORMAL': 0, 'PNEUMONIA': 1}

**Results**

DenseNet161 achieved a validation accuracy of 93.75%, a validation loss of 0.2636, a test accuracy of 86.54%, and a test loss of 0.4238. ResNet50 obtained a validation accuracy of 81.25%, a validation loss of 0.2552, a test accuracy of 83.97%, and a test loss of 0.6657.

**Conclusion**

Combining transfer learning with progressive unfreezing enhances model learning. The DenseNet architecture outperformed ResNet50, likely due to its dense connectivity pattern.