This submission presents a deep learning model developed for pneumonia classification and heatmap generation from chest X-ray images. The training dataset consisted of X-ray images obtained from two public repositories: the first is the Chest X-Ray Images (Pneumonia) Dataset, available in Kaggle [1]. It contains 5,863 X-ray images (JPEG) divided into two categories: Pneumonia and Normal. These images were selected from retrospective cohorts of pediatric patients aged one to five years from the Guangzhou Women and Children's Medical Center, Guangzhou. The second dataset, named the RSNA Pneumonia Detection Challenge [2], contains 26,684 images with three distinct labels: normal, lung opacity, and no lung opacity/not normal.

The model is built using the Pylon [3] framework and is configured in the PylonConfig class to allow flexibility in architecture selection, number of input/output channels, and other customizable parameters such as pretraining and decoder configurations. Image preprocessing involved resizing to 256x256 pixels, normalization, and conversion to tensor format. The dataset was divided into training and validation sets, with data augmentation applied during training to improve generalization. The PylonCore architecture leverages a backbone (ResNet50) to extract features and a segmentation head to generate heatmaps. The final layer of the model outputs the classification score, which is optimized using a binary cross-entropy loss.

The training process involved 50 epochs with an early stopping mechanism based on the best loss, and the model was implemented on CUDA for GPU acceleration. The best model was saved automatically during training whenever a lower loss was achieved. Heatmaps are generated using the activations from the deeper layers of the model, providing visual explanations of the areas in the chest X-ray images that most contribute to the classification decision. These saliency maps were used for model interpretability. The results achieved by the model demonstrate the effectiveness of the architecture, providing a balance between classification performance and model interpretability. The Pylon framework's modularity and flexibility were key to developing and fine-tuning the model efficiently.

[1] Mooney, P. T. (n.d.). *Chest X-Ray Images (Pneumonia)* [Data set]. Kaggle. Retrieved 10/21/2024, from https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia/data

[2] APA Style: RSNA. (n.d.). RSNA Pneumonia Detection Challenge [Competition]. Kaggle. Retrieved 10/21/2024, from https://www.kaggle.com/c/rsna-pneumonia-detection-challenge

[3] Preechakul, Konpat, et al. "Improved image classification explainability with high-accuracy heatmaps." Iscience 25.3 (2022).