

Domain Background

Pneumonia is a lung infection that causes swelling in the air sacs, which can fill with fluid. It is especially dangerous for young children, older adults, and people with weak immune systems. According to the World Health Organization (WHO), pneumonia is one of the top causes of death in children under five. Detecting pneumonia early and starting treatment can save lives. However, traditional methods like physical exams and X-ray interpretation require skilled doctors, which are not always available.

Chest X-rays (CXRs) are a common and affordable way to diagnose pneumonia, but analyzing them can take time and lead to mistakes. In recent years, artificial intelligence (AI) and deep learning have shown that computers can help doctors by analyzing X-rays more accurately and quickly. Studies like those by Rajpurkar et al. (2017) and Zech et al. (2018) have shown that convolutional neural networks (CNNs) can detect diseases like pneumonia from X-rays.

This project uses deep learning to create a model for detecting pneumonia in chest X-rays. This will make it easier and faster to diagnose pneumonia, especially in areas with few doctors.

Problem Statement

Diagnosing pneumonia using chest X-rays is difficult in places with few trained radiologists. Without proper diagnosis, patients might not get the right treatment, which can lead to serious health problems. There is a need for a reliable and automated tool to analyze X-rays and detect pneumonia accurately.

This project aims to solve this problem by building a deep learning model that can identify pneumonia from X-rays. The solution will be simple, scalable, and useful in both cities and rural areas.

Solution Statement

The solution is to combine two different convolutional neural networks (CNNs) available in PyTorch to improve accuracy. The first model, ResNet-34, will focus on extracting detailed features from the X-rays. The second model, DenseNet-121, will look at fine details and patterns. The predictions from both models will be averaged to get a final result. This combined approach uses the strengths of both models to make better predictions.

By combining these two models, the system can detect pneumonia more accurately than using just one model. This method will be tested against standard benchmarks to ensure its effectiveness and reliability.

Datasets and Inputs

The dataset for this project is "Chest X-Ray Images (Pneumonia)" from Kaggle. It has 5,863 X-ray images divided into three groups: normal,

bacterial pneumonia, and viral pneumonia. The dataset is balanced to ensure fair results.

- **Source:** Published by Kermany et al. (2018) in "Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images."
- **Details:** The images are black-and-white, 1024x1024 pixels, and include patient information like age and diagnosis.
- **Use:** The dataset will be split into training, validation, and testing sets. Techniques like rotating and flipping images will be used to make the training data more diverse.

Benchmark Model

The benchmark model is a pre-trained ResNet-34, which has been fine-tuned to work with the pneumonia dataset. This model uses knowledge from other datasets (like ImageNet) to identify important features in X-rays. The performance of this model will be the baseline to compare with the combined CNN approach.

Metrics like accuracy, precision, recall, and F1-score will be used to measure how well this model works.

Evaluation Metrics

The following metrics will be used to evaluate the models: - **Accuracy:** How often the model predicts correctly. - **Precision:** How many of the positive predictions are actually correct. - **Recall:** How well the model finds all the positive cases. - **F1-Score:** A balance between precision and recall. - **AUC-ROC:** Measures how well the model separates positive and negative cases.

These metrics will show how good the model is at diagnosing pneumonia.

Project Design

The project will follow these steps:

1. Data Collection and Preprocessing:

- Get the chest X-ray dataset.
- Prepare the images (resize, normalize, and augment).

2. Exploratory Data Analysis (EDA):

- Study the data to understand patterns and differences.
- Show sample images and class distributions.

3. Model Development:

- Train a baseline ResNet-34 model.
- Combine ResNet-34 and DenseNet-121 models for the final solution.

Training and Validation:

4.
 - Train models on the training data and validate results on validation data.
 - Adjust settings (like learning rate) to improve performance.

5. Testing and Evaluation:

- Test the models on unseen data.
- Compare the benchmark model and combined model results.

References

1. Rajpurkar, P., Irvin, J., Zhu, K., et al. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv preprint arXiv:1711.05225.
2. Zech, J. R., et al. (2018). Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study. PLoS Medicine, 15(11), e1002683.
3. Kermany, D. S., et al. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell, 172(5), 1122-1131.e9.