Pneumonia Detection

Using Deep Learning Models

Omar yasser saeed   
MSA computer science222575  
Cairo

Abdelrahman Mohammed Rashad  
MSA computer science  
*223795*  
Cairoyoussef Hoassam Anwar  
MSA computer science *222711*  
Giza

Karim Akmal Hussein  
MSA computer science *223309*  
Cairo Khalid Mohammed Gamal  
MSA computer science  
223607 *Giza*

*Abstract*— Pneumonia is a serious lung infection that can be life-threatening. Accurate and timely detection of pneumonia through chest X-ray images is crucial. This project explores the use of various deep learning models, including Convolutional Neural Networks (CNN), VGG16, DenseNet121, MobileNetV2, and ResNet101, to classify chest X-ray images as either normal or pneumonia-infected. We evaluate the models' performance based on metrics such as accuracy, precision, recall, F1 score, and ROC-AUC. A Gradio-based GUI is also developed to facilitate user interaction with the trained models. Our findings indicate that pre-trained models like DenseNet121 and ResNet101 provide superior performance compared to custom CNN architecture Index Terms—Pneumonia detection, deep learning, CNN, VGG16, DenseNet121, MobileNetV2, ResNet101, image classification.

# Introduction

Pneumonia is an infection that inflames the air sacs in one or both lungs, potentially leading to severe health complications or death if not treated promptly. Chest X-ray imaging is a standard diagnostic tool for pneumonia detection, but manual interpretation by radiologists can be time-consuming and subject to human error. Therefore, automated detection using deep learning models has gained significant attention.incorporating the applicable criteria that follow.

## contributions

This paper presents a comprehensive comparison of various deep learning models for pneumonia detection:

1. Custom CNN
2. Pre-trained models (VGG16, DenseNet121, MobileNetV2, ResNet101)
3. A user-friendly interface for model predictions using Gradio

## Roadmap

The paper is organized as follows: Section II reviews related work; Section III describes the dataset and preprocessing steps; Section IV discusses the methodology and models used; Section V presents the results and evaluation metrics; Section VI concludes the paper with insights and future directions.

# Related Work

Several studies have explored deep learning for pneumonia detection:

* Rajpurkar et al. (2017) developed CheXNet, a 121-layer convolutional neural network, achieving radiologist-level performance on pneumonia detection.
* Stephen et al. (2019) compared different pre-trained models for medical image classification, showing the effectiveness of transfer learning.
* Stephen et al. (2019) compared different pre-trained models for medical image classification, showing the effectiveness of transfer learning.

These studies underline the potential of deep learning in medical image analysis, motivating further exploration in this domain.

# Data Desciption and preprocessing

1. *Dataset*

We used the publicly available chest X-ray dataset from the Kaggle competition "Chest X-Ray Images (Pneumonia)" which includes:

* Training set: 5250 images
* Test set: 624 images

1. *Preprocessing*

The images were resized to 150x150 pixels or 224x224(mobileNetv2) and rescaled to [0,1] range. Data augmentation techniques such as rotation, zoom, and horizontal flip were applied to enhance model generalization.

# Methodology/Approach

## Models

We implemented five different models:

1. ***Custom CNN****: A sequential model with convolutional and pooling layers followed by dense layers.*
2. ***VGG16****: A pre-trained model on ImageNet, used as a feature extractor.*
3. ***DenseNet121****: A dense connectivity model, leveraging features from multiple layers.*
4. ***MobileNetV2****: An efficient model optimized for mobile and resource-constrained environments.*
5. ***ResNet101****: A deep residual network, allowing training of very deep networks.*

## GUI Application

A Gradio-based GUI was developed to allow users to upload chest X-ray images and select a model for prediction. The interface is simple, providing real-time results based on the model's prediction.

#### V.Results

*A. Experimental Setup*

* *Training epochs: 10*
* *Batch size: 32*
* *Optimizer: Adam with learning rate adjustments for each model*
* *Loss function: Binary cross-entropy*

## B. Evaluation Metics

* Accuracy: Overall correctness of the model.
* Precision: Ratio of true positive predictions to all positive predictions.
* Recall: Ratio of true positive predictions to all actual positives.
* F1 Score: Harmonic mean of precision and recall.
* ROC-AUC: Area under the receiver operating characteristic curve.

## Performance Comparison

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1 Score** | **ROC-AUC** |
| --- | --- | --- | --- | --- | --- |
| Custom CNN | 0.86 | 0.85 | 0.88 | 0.86 | 0.92 |
| VGG16 | 0.91 | 0.90 | 0.93 | 0.91 | 0.96 |
| DenseNet121 | 0.94 | 0.93 | 0.95 | 0.94 | 0.97 |
| MobileNetV2 | 0.92 | 0.91 | 0.94 | 0.92 | 0.96 |
| ResNet101 | 0.95 | 0.94 | 0.96 | 0.95 | 0.98 |

VI.Conclusion

This study demonstrates the feasibility of using deep learning models for pneumonia detection from chest X-ray images. Pre-trained models, especially DenseNet121 and ResNet101, showed high accuracy and robustness. The Gradio-based GUI enhances accessibility, allowing users to interact with the models effortlessly.

##### References

1. A. Rajpurkar, et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," arXiv preprint arXiv:1711.05225, 2017.
2. H. Stephen, et al., "Comparison of Pre-trained Models for Medical Image Classification," in Proc. 2019 Int. Conf. on Advances in Computing, Communications, and Informatics (ICACCI), 2019.
3. R. Albahli, et al., "Using VGG16 and DenseNet121 for Pneumonia Detection from Chest X-Rays," in Int. J. of Advanced Computer Science and Applications, vol. 12, no. 2, 2021.