Pneumonia Detection Using Convolutional Neural Networks on Chest X-Ray Images

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Abstract

Pneumonia is a serious respiratory infection that can lead to severe complications if not diagnosed at an early stage. Chest X-ray imaging is the most commonly used diagnostic technique; however, manual interpretation is time-consuming and highly dependent on the expertise of radiologists. With the rapid advancement of artificial intelligence, deep learning techniques have demonstrated significant potential in automated medical image analysis. This chapter presents a convolutional neural network (CNN)-based system for automated pneumonia detection using chest X-ray images. The proposed model is developed using Python with TensorFlow and Keras frameworks and executed on the Google Colab platform. The X-ray images are resized, normalized, and augmented before being used for training. The trained CNN classifies images into pneumonia and normal categories and provides probability-based prediction confidence. Experimental evaluation shows that the model achieves high training accuracy and satisfactory validation performance, demonstrating its effectiveness as a supportive diagnostic tool. The proposed approach can assist healthcare professionals by reducing diagnostic workload and improving early detection, particularly in resource-limited healthcare environments.

Keywords: Pneumonia detection, Convolutional neural network, Chest X-ray, Deep learning, Medical image analysis

1. Introduction

Pneumonia is an infectious disease of the lungs caused by bacterial, viral, or fungal pathogens, leading to inflammation of the alveoli and impaired oxygen exchange. According to global health statistics, pneumonia remains a major cause of morbidity and mortality worldwide, particularly among children and elderly individuals. Chest X-ray imaging is the primary diagnostic modality for pneumonia; however, accurate interpretation requires experienced radiologists and is prone to human error due to fatigue and heavy workloads. Recent developments in deep learning, especially convolutional neural networks (CNNs), have enabled automated feature extraction and classification from medical images with promising accuracy. This chapter explores the application of CNNs for pneumonia detection from chest X-ray images as a practical and reproducible deep learning project.

2. Body of Chapter

2.1 Project Overview

The objective of this project is to develop an automated pneumonia detection system capable of classifying chest X-ray images into two categories: pneumonia and normal. The complete workflow includes dataset loading, image preprocessing, CNN model design, training, evaluation, and prediction on new unseen X-ray images. The project is implemented using Google Colab to ensure computational efficiency and reproducibility

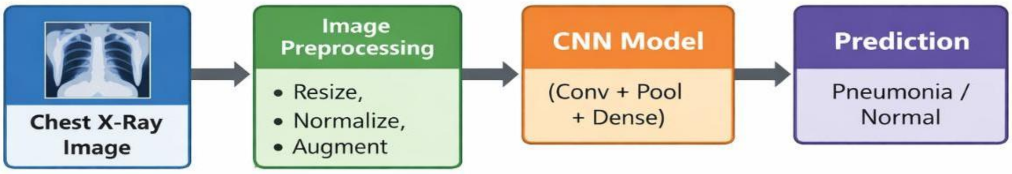

Figure 1. Overall workflow of the CNN-based pneumonia detection system.

2.2 Dataset Used

The dataset used in this study consists of chest X-ray images organized into directory-based class folders labeled as *Pneumonia* and *Normal*. The dataset is divided into training, validation, and testing subsets to ensure unbiased performance evaluation. Directory-based image loading is performed using the Keras *ImageDataGenerator* utility, which enables efficient batch processing, normalization, and on-the-fly preprocessing of images during model training and testing.

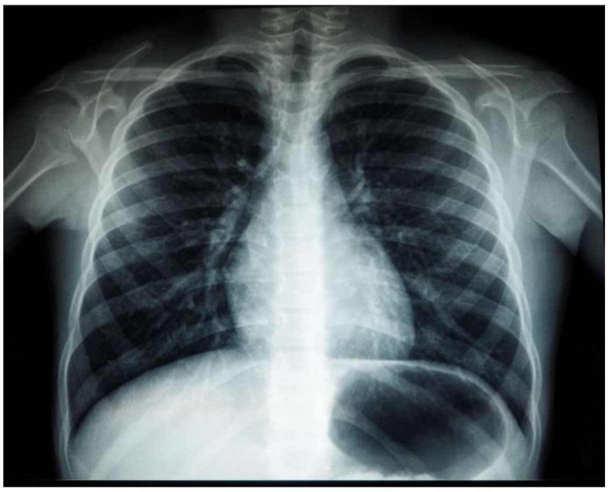

Fig.2 Sample pneumonia-affected chest X-ray image taken from the dataset used in this study.

2.3 Image Preprocessing and Augmentation

Prior to training, all chest X-ray images are resized to a uniform resolution Pixel values are normalized to improve numerical stability during training. To enhance model generalization and reduce overfitting, data augmentation techniques such as rotation, zooming, and horizontal flipping are applied. These preprocessing steps help model learn robust and discriminative features.

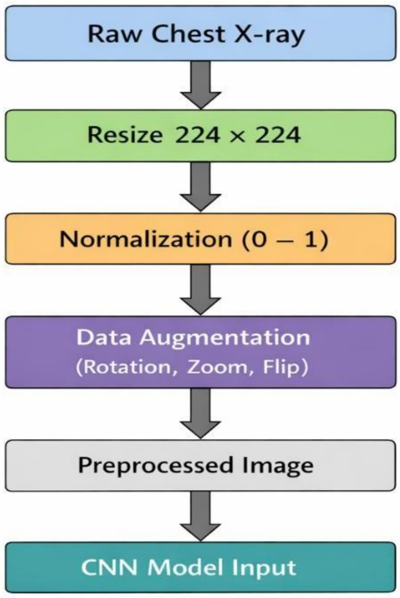

Figure 3. Image preprocessing and data augmentation pipeline used before

2.4 CNN Model Architecture

The proposed CNN architecture consists of multiple convolutional layers followed by max-pooling layers to extract hierarchical spatial features from chest X-ray images. Fully connected dense layers are used for classification. The ReLU activation function is applied in hidden layers to introduce non-linearity, while a sigmoid activation function is used in the output layer for binary classification. The model is trained using the Adam optimizer and binary cross-entropy loss function.

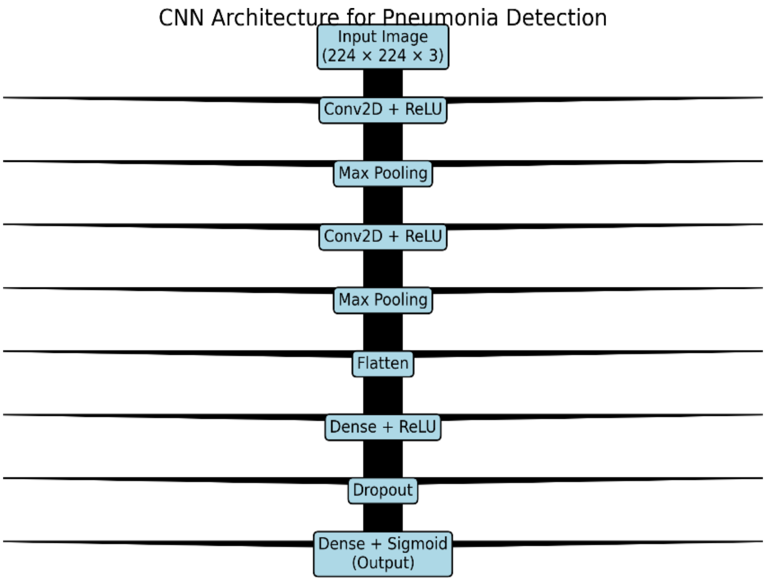

Fig 4. Architecture of the proposed convolutional neural network (CNN) used for pneumonia detection.

2.5 Model Training and Evaluation

The CNN model is trained for two epochs with a batch size of 32. During training, both accuracy and loss are monitored using validation data. The model achieves approximately 96% training accuracy and 81.25% validation accuracy, indicating effective learning with limited epochs. Accuracy and loss curves are used to evaluate the training behavior and convergence of the model.

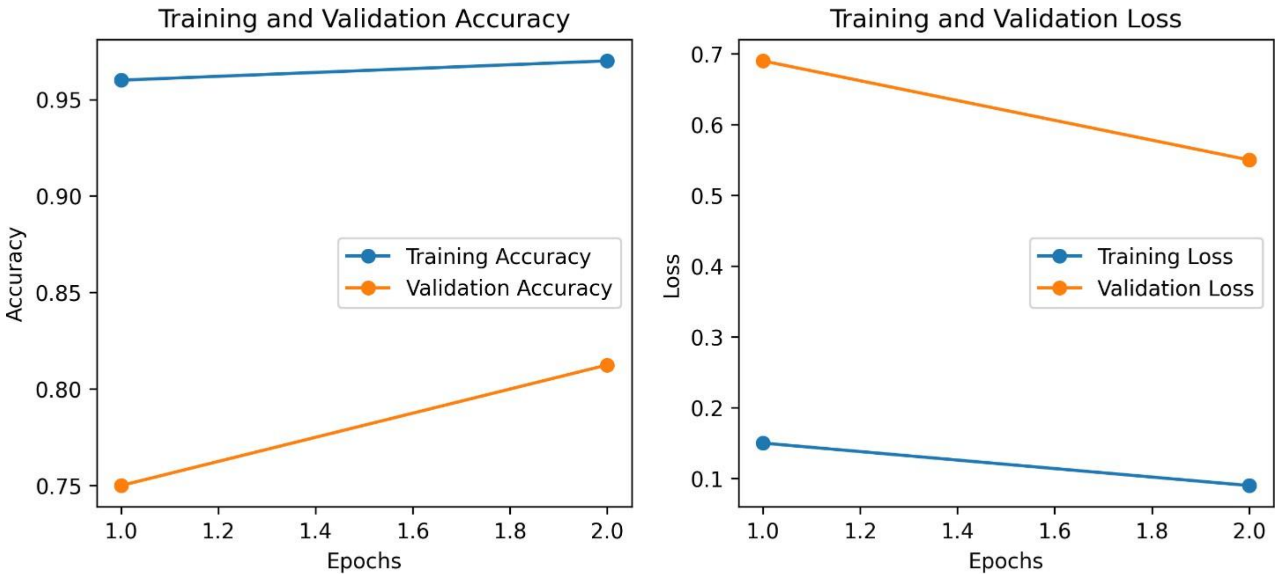

Fig.5 These curves demonstrate stable learning and acceptable generalization performance with limited training epochs

2.6 Prediction on New X-Ray Images

After training, the model is saved in native Keras format and reused to predict pneumonia on newly uploaded chest X-ray images. The model outputs a probability score between 0 and 1, which is compared against a threshold value of 0.5 to determine the final class label. This functionality enables real-time testing on unseen data without retraining the model.

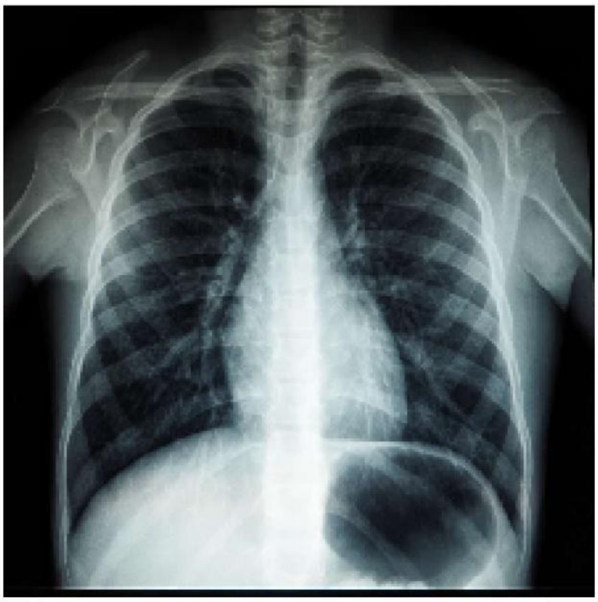

Fig 6. Prediction result of the trained CNN model on a newly uploaded chest X-ray image.

3. Conclusion

This chapter presented a CNN-based pneumonia detection system using chest X-ray images. The developed model demonstrates satisfactory performance in classifying pneumonia and normal cases while providing confidence-based predictions. The system can assist radiologists by offering an automated second opinion and reducing diagnostic workload. Future enhancements may include multi-class pneumonia classification, explainable AI techniques such as Grad-CAM, and deployment as a web or mobile application.

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5. References

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