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# Pneumonia prediction using deep learning in chest X-ray Images

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## Abstract

Pneumonia, a potentially fatal lung disease caused by viral or bacterial infection, poses challenges in diagnosis from chest X-ray images due to similarities with other lung infections. This research aims to develop a computer-aided system for pneumonia detection in children, enhancing diagnostic accuracy. In this paper, five established deep learning models such as VGG-16, VGG-19, ResNet-50, Inception-V3, Xception pre-trained on ImageNet have been used. These models have been applied on the chest X-ray dataset to optimize performance. Xception provides recall, specificity, accuracy and AUC of 97.43%, 91.02%, 95.06% and 94.23%, respectively.

**Keywords:** Lung diseases; X-ray imaging; Deep learning; Pneumonia; Transfer learning; Exception; VGG-16, VGG-19; ResNet-50; Inception-V3.

## 1. Introduction

Pneumonia, typically triggered by bacterial infection, results in inflammation of lung tissues, leading to significant hospitalizations in the USA, with over a million cases annually, and unfortunately, about 50,000 fatalities. Effective management with antibiotics and antivirals is available, underscoring the importance of early detection and treatment to mitigate potentially fatal complications. While chest X-rays remain a primary diagnostic tool for pneumonia, interpreting them accurately poses challenges even for seasoned radiologists. Pneumonia manifestations in X-ray images are often indistinct, resembling other conditions or benign abnormalities, contributing to subjective interpretations and diagnostic variations among radiologists. Consequently, there is a pressing need for computer-assisted diagnostic systems to aid radiologists in pneumonia detection from chest X-ray images [1-7].

Diagnosing pneumonia in chest X-ray images poses a challenge even for experienced radiologists due to similarities with other diseases. Misdiagnosing bacterial or viral pneumonia can lead to incorrect treatment and potentially fatal outcomes for patients. Moreover, distinguishing pneumonia from the novel Coronavirus (Covid-19) is difficult due to their similarities. These factors underscore the urgent need for computer-aided systems (CAD) to assist in pneumonia diagnosis. Deep learning-based CAD approaches, particularly convolutional neural networks (CNNs), have gained traction in the medical field for their ability to rapidly infer and perform complex cognitive tasks. CNNs, inspired by the mammalian visual cortex, can autonomously evaluate numerous attributes, including those previously overlooked by radiologists. They have been successfully applied in various medical imaging tasks, such as skin lesion segmentation,

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skin cancer classification [43-44], diabetic retinopathy detection, early lung cancer detection, arrhythmia detection, and pulmonary tuberculosis classification. [9-19].

## 2. Literature Reviews

The advent of automated pneumonia diagnosis in chest X-ray images represents a significant advancement in recent research. Various studies have explored the application of deep convolutional neural network (CNN) models for pneumonia diagnosis. Rajpurkar et al. [20] introduced CheXNet, a 121-layer CNN model trained on a dataset of 100,000 chest X-ray images containing 14 different diseases. Testing against 420 chest X-ray images revealed that CheXNet outperformed expert radiologists in pneumonia detection. Kermany et al. [21] employed transfer learning to train a CNN model for pneumonia detection in chest X-ray images. Rajaraman et al. [22] utilized a CNN-based system to classify chest X-rays as normal versus pneumonia, bacterial versus viral pneumonia, and normal versus bacterial versus viral pneumonia, focusing on regions of interest (ROIs) containing only the lungs. Stephen et al. [23] proposed a CNN model trained from scratch, achieving remarkable classification performance in distinguishing pneumonia-infected individuals from others. Liang and Zheng [24] developed a CNN model with residual connections and dilated convolution methods for pneumonia detection, highlighting the impact of transfer learning on CNN models for classifying chest X-ray images. In [55], two transfer learning models, namely, VGG 16 and Xception, modified after applying additional layers with the base model. Modified Xception model provided an overall accuracy of 84.82% for Adam optimizer and 78.40% for RMSprop optimizer [55]. Modified VGG 16 model provided an overall accuracy of 84.98% for Adam optimizer and 83.88% for RMSprop optimizer [55].

## 3. Methodology

In this study, our main aim is to develop an effective pneumonia detection system in chest X-ray images by using different deep learning models.

### 3.1. Dataset

The dataset utilized in this study was sourced from Kermany and Goldbaum [28], originating from chest X-ray scans of pediatric patients aged one to five years at the Guangzhou Women and Children's Medical Center. It comprises a total of 5,856 chest X-ray images. Within the training subset, there are images from 5,232 patients, with 3,883 labeled as pneumonia and 1,349 as normal. The test subset comprises images from 624 patients, with 390 labeled as pneumonia and 234 as normal. Furthermore, pneumonia patients are categorized into two types: bacterial and viral. Table 1 presents the numerical distribution of normal, bacterial, and viral samples in the dataset. Additionally, examples of images labeled as pneumonia or normal are illustrated in Fig. 1.

**Table 1** Summary of dataset

| **Class** | **Train** | **Validation** | **Test** |
|---|---|---|---|
| Normal | 1349 | 234 | 234 |
| Pneumonia Viral | 1345 | 148 | 148 |
| Pneumonia Bacterial | 2538 | 242 | 242 |
| Total | 5232 | 624 | 624 |

### 3.2. Data Augmentation and Transfer Learning

Data augmentation is a crucial technique that enhances the generalization ability of models, prevents overfitting, and improves model accuracy [29–31]. In this study, data augmentation was applied both before and during the training phase. Prior to training, it was observed that there were 2,534 fewer normal-labeled images compared to pneumonia-labeled images in the dataset. To address this class imbalance, image processing methods were employed on the normal chest X-ray images. Specifically, 1,349 chest X-ray images in the training dataset underwent random augmentation including rotation (angle range of +10 to -10), zooming (range of 0.8–1.2), and horizontal flipping, resulting in the generation of 2,534 new augmented chest X-ray images. This approach helped achieve class balance in the training dataset.

Another significant technique used to enhance the performance of deep neural networks is transfer learning. Transfer learning involves leveraging knowledge gained from solving one task to address a similar problem [32]. Recently, few researchers have trained CNN networks from scratch. Instead, they have utilized CNN filters pre-trained on ImageNet [33] data, which typically comprises 1.2 million images across 1,000 classes [34]. This approach significantly reduces training time [35].

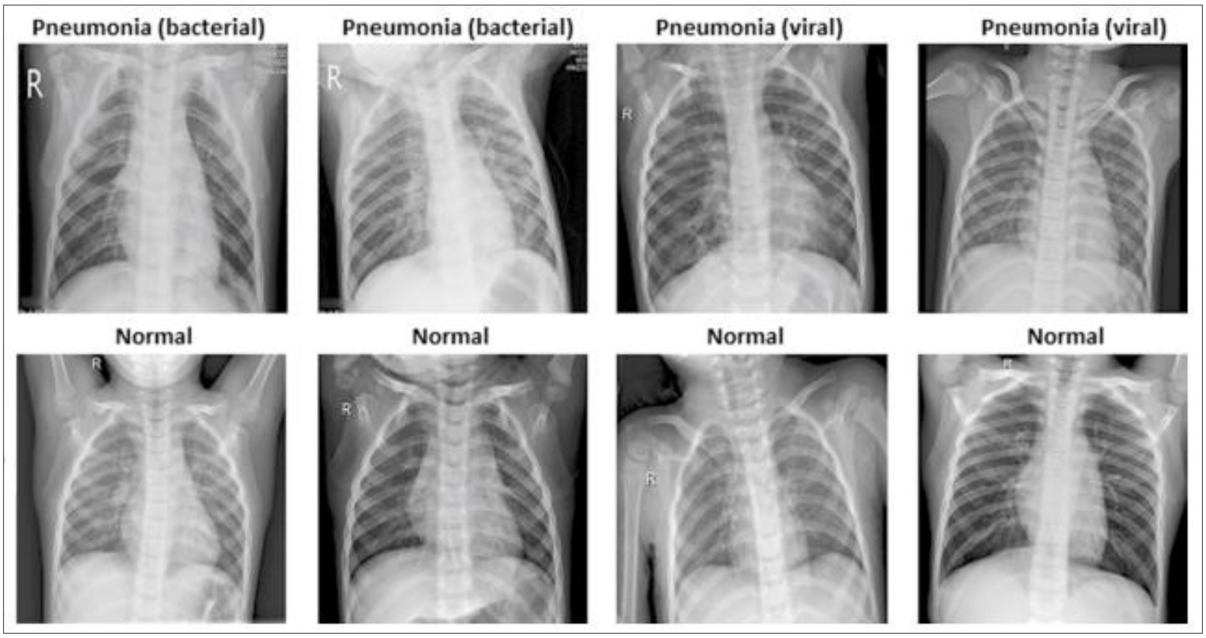


**Figure 1** Images from chest X-ray dataset

## 4. Experimental Results

In the study, five established models have been trained to classify chest X-ray images. During the training process of these well-known models, various transfer learning and fine-tuning strategies have been experimented with, and configurations yielding successful results have adopted for the testing phase. At the training stage, a batch size of 32 and a learning rate of 1e-4 were determined. The Adam optimizer is employed to minimize the categorical cross-entropy loss function. The softmax activation function is utilized in the last layer for classification purposes. To mitigate overfitting, early stopping is implemented. The Python programming language and the Keras deep learning library are utilized.

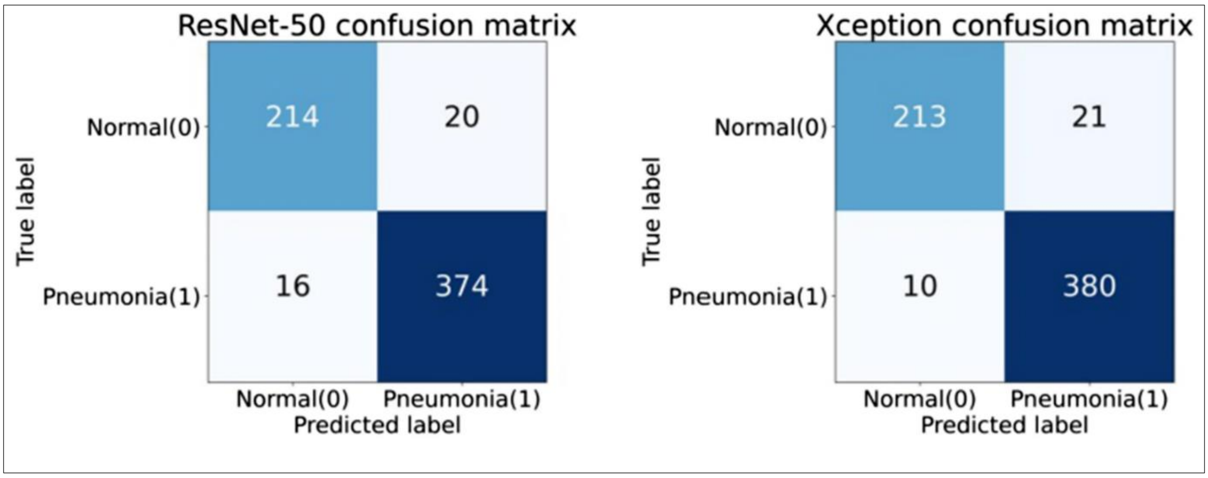


**Figure 2** Confusion matrices ResNet-50, Xception

**Table 2** Classification results (%) of the deep learning models on balanced data

| Models | Recall (%) | Specificity (%) | Accuracy (%) | AUC (%) |
|---|---|---|---|---|
| VGG-16 | 94.25 | 90.79 | 92.44 | 92.58 |
| VGG-19 | 89.85 | 89.11 | 90.82 | 90.48 |
| ResNet-50 | 95.89 | 91.45 | 94.42 | 93.67 |
| InceptionV3 | 96.24 | 89.16 | 93.71 | 92.79 |
| Xception | 97.43 | 91.02 | 95.06 | 94.23 |

Figure 2 shows the confusion matrices of ResNet-50 and Xception. Table 2 shows the classification results of the deep learning models on balanced data. Xception has the highest recall at 97.43%, indicating it correctly identified most positive samples. ResNet-50 has the highest specificity at 91.45%, meaning it correctly identified most negative samples. Xception has the highest accuracy at 95.06%, suggesting it had the highest overall correct predictions. Xception also has the highest AUC at 94.23%, showing the best performance in distinguishing between classes. Overall, Xception appears to be the best-performing model based on the provided metrics.

**Table 3** Comparison of the proposed method with the literature studies

| Ref. | Classes | Model | Accuracy | Recall | Specificity |
|---|---|---|---|---|---|
| [36] | COVID-19, Viral pneumonia, Lung opacity, Normal | RVCNet | 91.27% | 98.30% | 90.48% |
| [37] | COVID-19, Pneumonia, Normal | CoroNet | 89.6% | 89.92% | - |
| [38] | COVID-19, Normal | CO-IRV2 | 94.97% | 93.63% | 96.52% |
| [39] | COVID-19, Normal | ResNet 50 | 76% | 81.10% | 61.50% |
| [40] | COVID-19, Normal | ResNet 18 | 86.70% | 81.50% | - |
| [41] | COVID-19, Normal | NASNet-Mobile | 82.42% | 78.16% | - |
| [42] | Bacterial Pneumonia, Viral Pneumonia | CNN | 80.40% | 77.55% | 92.67% |
| Proposed DL | Normal, Pneumonia | Xception | 95.06% | 97.43% | 91.02% |

Table 3 shows the comparison of the proposed method with the literature studies. The proposed method using the Xception model outperforms the models referenced in the literature [36-42] across several metrics. Specifically, the Xception model achieves the highest accuracy at 95.06%, surpassing the next highest accuracy of 94.97% achieved by the CO-IRV2 model for COVID-19 classification. Additionally, the recall of Xception stands at 97.43%, which is slightly lower than the recall of 98.30% for RVCNet but significantly higher than most other models listed. In terms of specificity, Xception maintains a strong performance at 91.02%, which is comparable to the highest specificity of 96.52% by CO-IRV2 but generally higher than others, such as ResNet 50's 61.50%. Thus, the Xception model demonstrates a balanced and superior performance in identifying both positive and negative samples compared to the other models, making it a robust choice for the classification tasks presented.

## 5. Conclusion

This paper mainly focuses on the application of deep learning models to detect pediatric pneumonia. Comparing the performance metrics of Xception with existing pretrained models confirms that our proposed model demonstrates higher efficiency. Our results indicate that Xception possesses powerful visualization capabilities and a high learning ability, which robustly aids in detecting normal and pneumonia cases. We believe our approach will be highly supportive and reliable for medical professionals. However, the current method has some limitations in multi-label classification, time consumption, and overall efficiency. In the future, we plan to address these issues by adding an additional layer to

Xception or other deep learning models to predict multi-label classes. Additionally, we will enhance the network layers to expand the dataset, aiming for predictions that are more accurate.

## Compliance with ethical standards

*Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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