# Pneumonia Detection From Chest X-Ray Images Using Deep Learning

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## Abstract

*Pneumonia is an interstitial lung disease which is responsible for death of more than 4 millions of people per year. Early detection of pneumonia can facilitate to fast-track the process of recovery and early treatment of patient can prevent millions of death yearly. In this study, we proposed convolutional neural network and ResNet18, a transfer learning-based pre-trained model to accurately detect pneumonia from chest X-rays images. This can be utilized in the real world by medical practitioners to treat pneumonia. Our first model (CNN) achieved an accuracy of 81% whereas our second model (ResNet18) reaches an accuracy of 89.9%. We further compared our two models using sensitivity and specificity metrics and found that even though our transfer learning based model (ResNet18) performed superior than our CNN model in terms of sensitivity (99.49%), our CNN model performed superior than ResNet18 in terms of specificity (77.87%).*

## 1. Introduction

Pneumonia is an interstitial lung disease that is caused by bacteria, fungi, or viruses [5]. It represents a highly ranked cause of death with more than 4 million deaths per year [4]. Early detection of pneumonia and timely diagnosis can help prevent thousands of deaths per year of children. Pneumonia is often diagnosed by chest X-ray or computed tomography (CT) scans, the former being the most commonly used technique due to its reduced costs and ease of availability.

Computer vision, one of the branches of artificial intelligence (AI), has proven to be fruitful in the medical image diagnosis with the aid of another application of AI known as deep learning. In particular, the COVID-19 pandemic caused a new wave in the development of such diagnosis procedures [6]. Computer-aided automated diagnosis of Pneumonia can help healthcare experts and medical practitioners in establishing the diagnosis of pneumonia efficiently with high accuracy rate as the signs of pneumonia in the X-ray images are not always visible or legible to the human eye. Researchers have proposed several computer-aided solutions for early detection of pneumonia using computer vision techniques and deep learning approaches such as Convolutional Neural Netwrok [3][6] and transfer-based learning models such as VGG-16, VGG-19, ResNet50, Inception-V3, and DenseNet-201 [3][2].

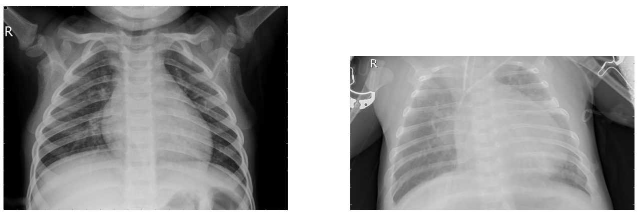
In this study, we have proposed two deep learning-based models for automatically detect Pneumonia from chest X-ray images which can be utilized in the real world by medical practitioners to treat pneumonia. We have built our models, one using CNN from scratch and another using transfer learning to classify chest X-ray images into normal and pneumonia category for the early detection of pneumonia. We then evaluated and compared their performances based on overall accuracy, sensitivity, and specificity. The main contributions of our study are as follow:

- We collected a dataset of chest X-ray images that consists of consists of 5216 training images and 624 test images.
- We performed data preprocessing on our training images by resizing them to 224x224 and normalizing them.
- We utilized data augmentation technique such as Random Horizontal Flip, Random Rotation, Color Jitter. and Random Affine on our training images.
- We built our first model using Convolutional Neural Network (CNN) architecture and built our second model ResNet18 leveraging the power of transfer-based learning image classification model.
- Finally, we evaluated both of our model and compared their performances using evaluation metrics such as accuracy, sensitivity, and specificity.

## 2. Methodology

For building our pneumonia classification model for automatic detection of pneumonia from chest X-ray images, we first collected our dataset. Then we applied data preprocessing and data augmentation technique on our training images and trained both of our model using our training images. Finally, we evaluated our model and compared the performance between a CNN model built from scratch and a transfer-based pre-trained model such as ResNet18. The overall pipeline of our study is shown in figure 1.


Figure 1. Overall Pipeline of Building Our Proposed Automated Pneumonia Detection



(a) Normal X-ray

(b) Pneumonia X-ray

Figure 2. Normal X-Ray (left) and Pneumonia X-Rays (right) Images

## 2.1. Data Collection

For our study, we have collected our dataset of chest x-ray images for pneumonia detection from Kaggle [1]. This is the same dataset as used in the research study of Szepesi et al. for automatic pneumonia detection using CNN [6]. Our dataset consists of 5216 training images and 624 test images. For training dataset, we have 1341 images that belongs to 'NORMAL' category and 3875 images that belongs to 'PNEUMONIA' category. For our test dataset, we have 234 images that belongs to 'NORMAL' category and 390 images that belongs to 'PNEUMONIA' category.

Figure 2 demonstrates example of normal chest x-ray and pneumonia chest x-ray images from our dataset.

## 2.2. Data Preprocessing

We performed data preprocessing by resizing our images into 224x224 pixel size similar to [6]. We further normalized all pixel values of our chest x-ray images to [0, 1] range.

## 2.3. Data Augmentation

After data preprocessing, we performed data augmentation on our training images as our training images is limited to 5216 chest x-ray images. We used four different techniques to perform data augmentation namely:

- Random Horizontal Flip
- Random Rotation
- Color Jitter
- Random Affine

## 2.4. Model Training

In this study, we have built two deep learning based models for automatic pneumonia detection from chest x-ray images. In the following section, we described the in-detail architecture of both of our models (CNN and ResNet18) and the hyperparameter and optimization techniques used for these two models.

### 2.4.1 Convolutional Neural Network (CNN)

Convolutional neural network is a class of deep learning methods which has become dominant in various computer vision tasks such as image classification. CNN is composed of multiple building blocks, such as convolution layers, pooling layers, and fully connected layers, and is designed to automatically and adaptively learn spatial hierarchies of features through a backpropagation algorithm. It is designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers [7].

For our study, we built a CNN model from scratch using multiple building blocks and layers. Below we described the architecture of our CNN model:

- Our model consists of 8 convolutional layers with increasing filters (32, 64, 128, and 256).
- Batch-normalization and ReLU activation followed each of our convolutional layer to stabilize learning and introduce non-linearity.
- We added maxpooling layer to reduce spatial dimensions.
- Dropout layer (40%) was added to prevent overfitting in our model.
- Finally, we added Fully connected layers with softmax activation function to flatten the feature maps and classify our chest X-ray images into either "NORMAL" or "PNEUMONIA" classes.

The following hyperparameter was used to train our CNN model:

- **Loss Function:** Cross Entropy Loss
- **Optimizer:** Adam
- **Number of Epochs:** 10
- **Learning Rate:** 1e-4
- **Batch Size:** 128

### 2.4.2 Residual Network (ResNet18)

In this study, we leveraged ResNet18, a pre-trained transfer learning-based model for our pneumonia classification task. A residual neural network is a deep learning architecture in which the layers learn residual functions with reference to the layer inputs. ResNet18 is a variant of the Residual Network (ResNet) architecture which was designed to tackle the issue of vanishing gradients in deep neural networks. It is a robust and efficient model for image classification tasks. The architecture of ResNet18 consists of several well-designed components that work together to extract hierarchical features from input images which facilitates accurate classification. Its unique architecture uses residual connections to mitigate the vanishing gradient problem, thus enabling the network to train efficiently on deeper layers. This feature can be particularly useful for medical imaging tasks such as pneumonia detection, where subtle differences in X-ray images must be identified.

Our ResNet18 model is composed of the following components :

1. **Input Layer:** Input our preprocessed images (resized to $224 \times 224 \times 3$) for compatibility with the pre-trained model.
2. **Convolutional and Pooling Layers:**
   - Initial 7x7 convolutional layer with stride 2, followed by batch normalization and ReLU activation.
   - A max-pooling layer reduces spatial dimensions while retaining significant features.
3. **Residual Blocks:**
   - Core building blocks of our ResNet18, each containing two convolutional layers with identity (shortcut) connections.
   - Batch normalization was introduced after each convolution layers to stabilize training, while ReLU activation function introduced non-linearity.
4. **Global Average Pooling Layer:**
   - Replaces traditional fully connected layers to prevent overfitting.
5. **Fully Connected Layer:**
   - Customized classification head with:
     – Dropout (50%) for regularization.
     – A linear layer for binary classification (normal vs. pneumonia).

The following hyperparameter and optimization technique was used to train our ResNet18 model:

- **Loss Function:** Cross-Entropy Loss, ideal for binary classification.
- **Optimizer:** Adam, chosen for its adaptive learning rate capabilities.
- **Learning Rate:** $1 \times 10^{-4}$, enabling smooth convergence.
- **Number of Epochs:** 10 epochs to balance training duration and performance.
- **Batch Size:** Optimized during training for efficient GPU utilization.

## 3. Results

We have evaluated our models based on three metrics: accuracy, sensitivity, and specificity. All of these metrics can be determined from our generated confusion matrix.

The confusion matrix of our CNN model can be found in Table 1 and the confusion matrix of our ResNet18n model can be found in Table 2. We have also demonstrated the performance of our two models in Table 3 in terms of accuracy, sensitivity, and specificity.

| CNN Model | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual positive | 126 (TP) | 108 (FN) |
| Actual negative | 10 (FP) | 380 (TN) |

Table 1. Confusion Matrix of CNN Model

| ResNet18 Model | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual positive | 173 (TP) | 61 (FN) |
| Actual negative | 2 (FP) | 388 (TN) |

Table 2. Confusion Matrix of ResNet18 Model

| Model | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| CNN | 81% | 92.65% | 77.87% |
| ResNet18 | 89.90% | 99.49% | 73.93% |

Table 3. Comparison Between CNN & ResNet18 Model Performance for Pneumonia Detection

## 4. Discussion

After comparing our two models' performance, we have observed that our pre-trained transfer-based model ResNet18 surpassed the accuracy and sensitivity rate of our CNN model that we built by ourselves with an accuracy rate of 89.9% and sensitivity rate of 99.49%. This suggests that our ResNet18 model is better at detecting true positive case (e.g., detecting penumonia from chest x-ray images). On the contrary, our CNN model surpassed our ResNet18 model in terms of specificity (77.87%) which suggests that our CNN model is better than our ResNet18 model at correctly detecting true negative cases (e.g., detecting normal patients' chest x-ray images who do not have pneumonia). But both of our models showed promising results at automatically detecting penumonia from chest x-ray images which was the main goal of our study.

## 5. Limitation & Future Work

Our study is limited to exploring two models (CNN & ResNet18) for detecting pneumonia from chest x-ray images. Our future work will be continuing experimenting with other transfer learning based models such as VGG-16, Inception-V3 to experiment whether we can achieve better accuracy, sensitivity, and specificity using these models. Also, in our future work, we plan to develop a desktop based application and integrate our best performing model in the system to detect penumonia from chest x-ray images in real-time.

## 6. Conclusion

In this study, we have built two deep learning based models (CNN & ResNet18) to automatically detect penumonia from chest x-ray images. To built our models, we first collected our dataset. Then we performed data preprocessing and data augmentation on our images to prepare our data for training our models. After training our CNN and ResNet18 models, we evaluated them using three metrics: accuracy, sensitivity, and specificity and then compared their performance. We found that our transfer learning-based model ResNet18 surpassed our CNN model in terms of accuracy (89.9%) and sensitivity rate (99.49%) whereas our CNN model surpassed our ResNet18 model in terms of specificity (77.87%).

## References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