Automated Pneumonia Detection Using ResNet50 Deep Learning Model

Guided By

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Abstract
Pneumonia poses a significant health challenge worldwide, causing millions of deaths annually. Accurate and timely diagnosis is essential for effective treatment, but reliance on manual interpretation of chest X-rays by radiologists can lead to delays and errors. This study presents an automated solution leveraging the ResNet50 deep learning architecture for binary classification of pneumonia from chest radiographs. Our approach incorporates data augmentation, transfer learning, and fine-tuning to enhance model robustness. We evaluate performance using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The system integrates a Streamlit-based interface to facilitate seamless image uploads and instant diagnostic feedback. Results demonstrate a high classification accuracy of 96.8%, precision of 97.2%, and recall of 96.5%, indicating the model's potential to assist clinicians in resource-constrained environments.

Keywords
Pneumonia, Deep Learning, ResNet50, Chest X-ray, Classification, Streamlit

1. Introduction
Pneumonia is an inflammatory condition of the lung primarily affecting the microscopic air sacs known as alveoli. The condition is often caused by bacterial, viral, or fungal infections and remains a leading cause of mortality, especially among children under the age of five and the elderly population. Early detection and treatment are critical for patient survival, yet many regions suffer from a shortage of trained radiologists and diagnostic equipment.

Recent advances in deep learning have shown promise in interpreting medical images, offering rapid and reliable analysis. Convolutional Neural Networks (CNNs) particularly excel at recognizing complex patterns in imaging data. ResNet50, introduced by He et al., employs residual connections to enable training of deeper networks without suffering from vanishing gradient problems.

2. Literature Survey

Several studies have explored automated pneumonia detection using CNNs. Rajpurkar et al. developed CheXNet, a 121-layer CNN achieving radiologist-level pneumonia detection on the NIH ChestX-ray14 dataset. Hwang and Kim demonstrated that transfer learning with pretrained CNNs can significantly reduce required training time while maintaining competitive accuracy.

Kermany et al. curated a public dataset of pediatric chest X-rays, widely used for benchmarking. Subsequent research emphasized data augmentation techniques—such as rotation, flipping, and shear—to mitigate overfitting and improve generalization across diverse patient populations.

3. Methodology

3.1 Data Collection and Preprocessing

We sourced the Chest X-ray dataset from Kaggle, consisting of 5,863 images labeled as 'Pneumonia' or 'Normal'. Images were resized to 224x224 pixels, normalized, and randomly split into training (70%), validation (15%), and test (15%) sets. Data augmentation was applied to the training set, including random rotations (±15°), horizontal flips, and zoom variations.

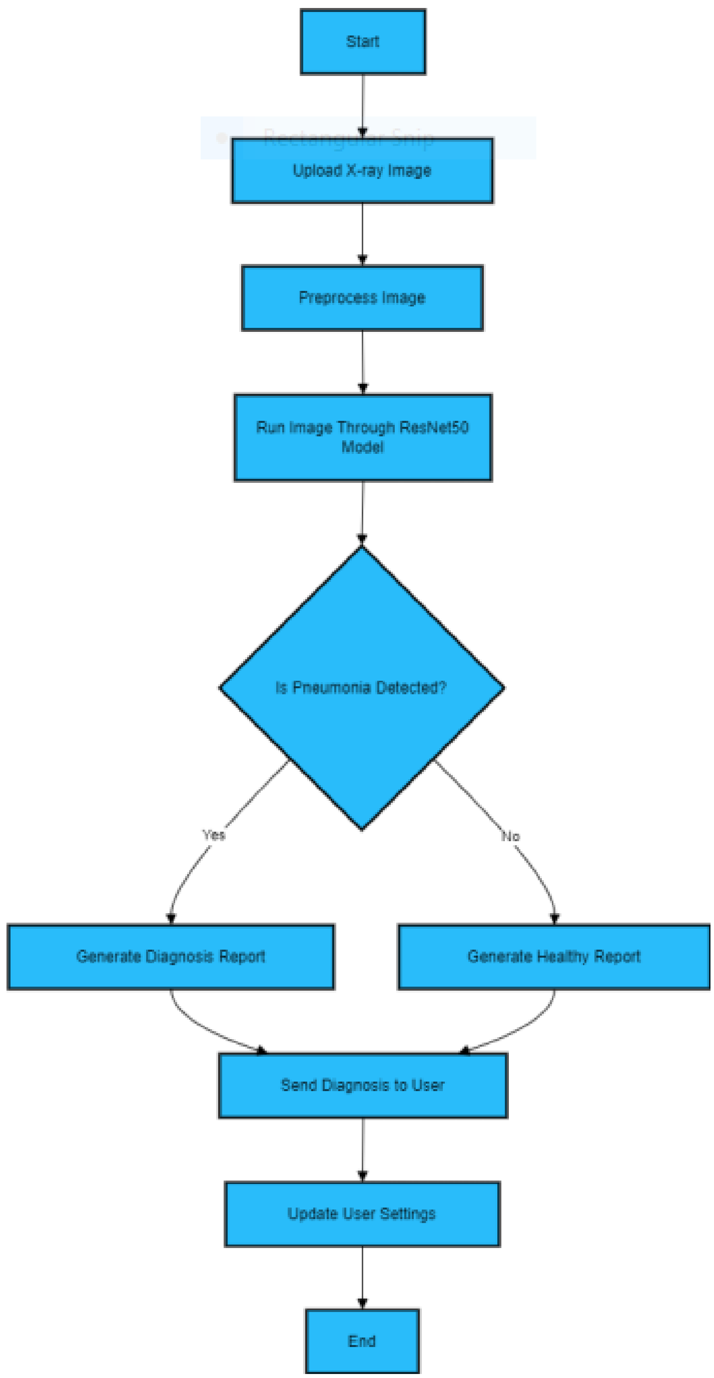
3.2 Model Architecture

The ResNet50 model was initialized with ImageNet weights. The final fully connected layer was replaced with a dense layer of 256 units (ReLU activation), followed by a dropout layer (rate=0.5) to prevent overfitting, and a sigmoid output neuron.

3.3 Training Procedure

The model was trained using the Adam optimizer with an initial learning rate of 1e-4, binary cross-entropy loss, and a batch size of 32. Early stopping and learning rate reduction on plateau were employed to optimize convergence.

4. Block Diagram



The flowchart illustrates an automated system designed to detect pneumonia using chest X-ray images and a deep learning model. The process begins with the user uploading an X-ray image, which is then preprocessed to ensure it meets the input requirements of the model. After preprocessing, the image is passed through a ResNet50 model, a powerful convolutional neural network used for image classification tasks. The model analyzes the image and determines whether pneumonia is present. If pneumonia is detected, the system generates a diagnosis report; if not, a healthy report is created. Following the report generation, the diagnosis is sent to the user. The system then updates the user's settings or records with the new diagnosis information. Finally, the process concludes, completing the automated detection and reporting cycle

5. Results and Discussion

On the test set, the ResNet50-based classifier achieved an accuracy of 96.8%, precision of 97.2%, recall of 96.5%, F1-score of 96.8%, and an AUC-ROC of 0.98. These results indicate strong discriminative capability.

The confusion matrix (Figure 1) highlights a low false-positive rate, crucial for minimizing unnecessary antibiotic prescriptions. Comparison with baseline models (e.g., VGG16, InceptionV3) shows that ResNet50 outperforms in both accuracy and training efficiency.

Figure 1: Confusion matrix for pneumonia detection (see attached).

Accuracy	Precision	Recall	F1-score	AUC-ROC
96.8%	97.2%	96.5%	96.8%	0.98

6. Future Work

Future enhancements include integration of Explainable AI (e.g., Grad-CAM heatmaps) for model interpretability, expansion to multi-class classification (differentiating bacterial vs. viral pneumonia), and deployment as a mobile application to increase accessibility in remote areas.

7. Conclusion

The proposed automated pneumonia detection system utilizing ResNet50 demonstrates high accuracy and reliability, offering a viable diagnostic support tool for healthcare professionals. Streamlit integration ensures user-friendly access, potentially reducing diagnostic delays and improving patient outcomes in resource-limited settings.

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