JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Deep Learning Approaches for Automated Pneumonia Diagnosis in Chest X-rays: A Comparative Study

[1] Pratham R , [2] Gowthami Bhandarkar , [3] Rindiya N , [4] Praveen Bagali , [5] Nithya BP

[1,2,3,4]Student, [5]Assistant professor
[1,2,3,4,5]Artificial Intelligence and Machine Learning,
[1,2,3,4,5]Srinivas Institute of Technology, Mangalore, India

Abstract : Artificial intelligence (AI) integration into medical imaging has revolutionized diagnosis, especially in the detection of lung conditions like pneumonia. In this work, the effectiveness of deep transfer learning models VGG16, ResNet50, InceptionNet-v3, and EfficientNet is assessed in classifying pneumonia from chest X-rays. These models were trained on the RSNA Pneumonia Detection Challenge dataset (32,227 images) and evaluated using validation accuracy and AUC-ROC scores. VGG16 showed better classification performance (88% accuracy, 91.8% AUC-ROC), whereas EfficientNet was 99% confident in localizing lung inflammation. Our results highlight the promise of AI- based diagnostics to complement clinical decision-making in limited-resource environments.

Keywords: **Deep learning, convolutional neural networks, medical image analysis, screening for pneumonia, transfer learning, X-ray classification**

I. INTRODUCTION

Pneumonia, an acute lung alveoli infection, is one of the most common causes of death worldwide, especially in low - resource countries where diagnostic facilities are scarce. The classical diagnosis is based on chest X-ray interpretation, which is prone to inter-observer variability. AI-based technologies, particularly deep learning (DL), provide a potential remedy through the reproducible automated analysis of images. Convolutional Neural Networks (CNNs) perform well for medical image classification but need large labeled data sets—a problem in healthcare. Transfer learning alleviates this by fine-tuning pre-trained models (e.g., ImageNet) to medical applications. This work compares four CNN architectures for the detection of pneumonia based on classification accuracy and localization of pathology.

II. LITERATURE REVIEW

Recent developments in DL have made it possible to achieve breakthroughs in medical imaging, ranging from tumor identification to screening for pneumonia. Experiments by Kallianos et al. (2019) illustrated the capabilities of CNNs in minimizing diagnostic mistakes in chest radiography. Model effectiveness, though, relies on architectural choice and dataset quality.

Pneumonia subtypes (bacterial, viral, fungal) exhibit distinct radiological features, complicating automated detection. Prior works (e.g., Rajpurkar et al., 2017) used CheXNet for pneumonia classification but lacked localization precision. Our work extends these efforts by integrating bounding box prediction for inflammation sites.

III. METHODOLOGY

A. Dataset

- The RSNA Pneumonia Detection Challenge dataset was utilized, comprising:
- 26,684 training images (annotated with bounding boxes for opacity regions)

- 3,000 validation images
- 3,543 test images
- Classes were: "Normal," "Lung Opacity," and "No Opacity/Not Normal."

B. Preprocessing

- Image Augmentation: Used rotation (±15°), zoom (20%), and shear (0.1) to avoid overfitting.
- Normalization: Rescaled pixel values to [0, 1] for the model to converge.
- Resizing: Uniformly resized images to 224×224 pixels (VGG16/EfficientNet) and 299×299 (InceptionNet - v3).

C. Model Architectures

- VGG16: 13 convolutional + 3 dense layers; optimized using Adam (lr=0.001).
- ResNet50: Utilized residual blocks using batch normalization.
- InceptionNet-v3: Used factorized convolutions for computational efficiency.
- EfficientNet: Utilized compound scaling (depth/width/resolution).

D. Evaluation Metrics

- Classification: Precision, recall, F1-score, AUC-ROC.
- Localization: Mean Average Precision (mAP) at IoU threshold 0.5.

IV. RESULTS

Model.Val. Accuracy.AUC-ROC.mAP (IoU=0.5)

- VGG16.88%.91.8%.0.76
- ResNet50.73%.80.9%.0.68
- InceptionNet-v3.79%.87%.0.72
- EfficientNet.85%.90.2%.0.89

VGG16 had the best classification accuracy, and EfficientNet performed best in lesion localization (99% confidence).

V. FUTURE DIRECTIONS

The better performance of VGG16 is consistent with the deep architecture's ability to extract features. EfficientNet's localization accuracy results from its scaled-up approach that is optimized. Problems were false positives in "Not Normal" instances, indicating the necessity of multi-pathology training data.

Comparative Analysis

- **Training Time**: Factorized convolutions made InceptionNet-v3 1.5× faster compared to VGG16.
- **Hardware Efficiency**: EfficientNet consumed 40% less FLOPs compared to ResNet50.

VI. CONCLUSION

This research illustrates that transfer learning improves detection of pneumonia in X-rays, with VGG16 and EfficientNet providing complementary strengths. Future research directions are:

- Hybrid models uniting classification and localization.
- Federated learning for multi-institutional databases.
- Real-time implementation on telemedicine platforms

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