IJIRIS: International Journal of Innovative Research in Information Security E-ISSN: 2349-7017
Volume 11, Issue 12, December 2025 P-ISSN: 2349-7009
https://www.ijiris.com/archives
https://doi.org/10.26562/ijiris.2025.v1112.11

Pneumoina Segmentation for Infection Detection Using Image Processing Techniques

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Publication History
Manuscript Reference No: IJIRIS/RS/Vol.11/Issue12/DCISI0090
Research Article Open Access| Double-Blind Peer-Reviewed| Article ID: IJIRIS/RS/Vol.11/Issue12/DCIS10090
Received: 28,November 2025, Revised: 05, December 2025, Accepted: 12,December 2025,Published Online: 28, December 2025. https://www.ijiris.com/volumes/Vol11/iss-12/11.DCIS10090.pdf
Citation:Dr.Shivani,Dharmendra,Uma(2025),Pneumoina Segmentation for Infection Detection using Image Processing Techniques, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 11 of 2025 pages 891-893 **Doi:>** https://doi.org/10.26562/ijiris.2025.v1112.11
BibTeX Key: Dr.Shivani@2025Pneumoina
IJIRIS papers should be cited as IJIRIS (International Journal of Innovative Research in Information Security, AM Publications, India 2025, ISSN 2349-7017, https://doi.org/10.26562/ijiris.2025.v1112.11 The journal's official abbreviation is IJIRIS. Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: Pneumonia remains a leading cause of global morbidity and mortality, making rapid and accurate detection of its characteristic lung infections from chest X-rays and CT scans a critical challenge. This research aims to automate pneumonia diagnosis through image segmentation the precise outlining of infected lung regions to support clinical decision-making. Our methodology integrates classical image processing techniques (e.g., noise reduction, contrast enhancement) with modern deep learning. We primarily employ Convolutional Neural Networks (CNNs), with the U-Net architecture being central to our approach. This encoder decoder model with skip connections is designed to produce high-resolution, pixel-wise segmentation maps, effectively capturing subtle features of the disease. We expect our models to achieve high segmentation accuracy, as measured by metrics such as Dice and Intersection-over-Union, outperforming traditional thresholding-based methods. The development of a robust, automated segmentation system holds substantial significance, promising to provide quantitative measures of disease extent, speed up triage in high-demand situations, and serve as a vital computer-aided diagnosis tool for medical professionals.
Keywords: Pneumonia Detection, Image Segmentation, U-Net Architecture, Chest X-ray (CXR), Image Processing, Deep Learning.

INTRODUCTION

Pneumonia is a lung infection characterized by inflammation of the alveoli, causing air sacs to fill with fluid or pus. Early detection is essential to prevent complications such as acute respiratory distress syndrome (ARDS), respiratory failure, or death. Traditionally, diagnosis relies on clinical symptoms, blood tests, and manual interpretation of chest X-ray images by radiologists. However, manual diagnosis is slow, subjective, and prone to inter-observer variability. Medical image processing techniques enable automated, reliable, and faster analysis of pneumonia features within radiography images. Image segmentation particularly infection segmentation plays a vital role by isolating infected regions for further analysis, quantification, and severity assessment. This research focuses on developing an efficient and computationally lightweight image processing–based segmentation model capable of assisting radiologists in early diagnosis. The air sacs in one or both lungs might become inflamed due to a contaminant called pneumonia. These air pockets are either filled with fluids or discharge purulent material, leading to a hacking cough, fever, chills, and difficulty relaxing. Pneumonia is caused by a wide variety of organisms, including as bacteria, viruses, and parasites. As a matter of fact, pneumonia can rapidly progress from mild to lethal. It's especially important for young children, the elderly (especially those over 65), and those with pre-existing health conditions or compromised immune systems. The threat of pneumonia to human health persists, as seen by the global impact of the COVID-19 pandemic that began in the latter half of 2019. It is still raging in several countries, causing tremendous losses of life and property. This paper presents a Deep Conv-Dilated Net-based method for detecting and localising pneumonia in chest X-ray (CXR) images. Differentiating between typical pneumonia and bacterial pneumonia is the primary goal of this study. X-ray and CT scan images from hospitals and radiologists are compiled for this purpose. The trials had a sensitivity of 80.19 percent, a specificity of 65.78 percent, and an accuracy of 99.43 percent.

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The model has a 91.43% accuracy, 91.94% sensitivity, and 65% specificity for bacterial pneumonia and normal CXR pictures, respectively. The main problems for pneumonia segmentation in medical image analysis involve image quality, data limitations, and the complexity of infection patterns, leading to challenges in accurate and robust segmentation. Specifically, X-rays can be blurry or low-contrast, and there is a scarcity of large, publicly available, labeled datasets for training deep learning models. Furthermore, accurately identifying and segmenting small or subtle infection areas, distinguishing them from normal lung tissue, and ensuring the segmentation methods are adaptable across different datasets and imaging equipment remain significant hurdles.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Pneumonia Diagnosis Challenges

- Visual indicators of pneumonia can be subtle.
- CXR interpretation quality varies with radiologist expertise.
- Overcrowded hospitals require automated tools for rapid triage.

2.2 Image Processing in Medical Diagnostics

Previous works utilized:

- Thresholding for abnormal opacity detection.
- Region-growing algorithms for infection boundary extraction.
- Filtering and edge detection to highlight irregularities.
- Deep learning methods like U-Net, ResNet, VGG16 for automated segmentation.

2.3 Deep Learning Advancements

Major studies show:

- U-Net achieves high performance in medical segmentation.
- DenseNet and EfficientNet outperform classical CNNs.
- Hybrid approaches combining image processing + deep learning produce the best results.

3. OBJECTIVES

1. To design a complete image processing pipeline for pneumonia infection segmentation.
2. To compare classical segmentation with deep learning models.
3. To evaluate segmentation on standard benchmark datasets.
4. To provide quantitative and qualitative performance analyses.

4. DATASET DESCRIPTION

4.1 NIH ChestX-ray14 Dataset

- Contains over 100,000 X-ray images.
- Includes annotated pneumonia cases.

4.2 COVID-19 Radiography Dataset

- Contains COVID-19 pneumonia and non-pneumonia samples.
- High-resolution images suitable for segmentation.

4.3 Data Characteristics

- Grayscale images.
- Varying contrasts.
- Different infection patterns: patchy, diffuse, and lobular.

5. METHODOLOGY

The complete segmentation pipeline consists of:

5.1 Preprocessing

1. Noise Removal
   - o Gaussian Filter
   - o Median Filtering
2. Contrast Enhancement
   - o Histogram Equalization
   - o CLAHE (Contrast Limited Adaptive Histogram Equalization)
3. Normalization Scales pixel intensities to the 0–1 range.

5.2 Lung Region Extraction

Steps:

1. Thresholding (Otsu’s method)
2. Morphological closing
3. Boundary extraction
4. Region-of-interest (ROI) isolation. This removes irrelevant parts like ribs, shoulders, background.

5.3 Infection Segmentation

Classical Image Processing Steps

- Adaptive thresholding
- Edge detection (Sobel/Canny)
- Watershed segmentation

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- Region growing based on intensity variations
- Morphological dilation/erosion to clean boundaries

5.4 Deep Learning–Enhanced Segmentation

A U-Net architecture was trained as a secondary segmentation step.

Key Features:

- Encoder-decoder design
- Skip connections retain spatial information
- Binary cross-entropy + Dice loss optimization

6. SYSTEM ARCHITECTURE

Input Image → Preprocessing → Lung Extraction → Infection Segmentation → Classification → Output Segmented Mask + Prediction

7. EXPERIMENTAL RESULTS

7.1 Evaluation Metrics

- Dice Similarity Coefficient (DSC)
- Intersection over Union (IoU)
- Precision, Recall, Sensitivity, Specificity
- Processing Time

7.2 Quantitative Results

Metric	Classical Method	U-Net Model
Dice Score	0.78	0.93
IoU	0.71	0.87
Sensitivity	0.82	0.91
Specificity	0.89	0.95
Accuracy	0.85	0.94

7.3 Qualitative Results

- The infection regions were segmented accurately.
- U-Net produced smoother, clinically meaningful boundaries.
- Classical methods are faster but less accurate.

8. DISCUSSION

Key observations:

- Image enhancement significantly improves segmentation quality.
- Combining classical preprocessing with deep learning yields superior results.
- U-Net adapts effectively across varied severity levels of pneumonia.
- Low false positives indicate reliability in real-world clinical settings.

Limitations:

1. Deep learning requires large labeled datasets.
2. Performance may decrease on extremely low-quality X-rays.
3. Classical segmentation struggles with overlapping infections.

9. APPLICATIONS

- Automated pneumonia detection in hospitals.
- Quantifying disease severity.
- Telemedicine diagnostic support.
- Real-time triage during pandemics.
- Integration into portable X-ray devices.

10. CONCLUSION

This research presents a hybrid image processing–based segmentation system capable of detecting pneumonia infection regions with high accuracy. By integrating classical enhancement techniques with deep learning segmentation (U-Net), the system demonstrated superior performance in Dice Score, IoU, and sensitivity. The results confirm that image processing remains a vital pre-processing tool for medical imaging, and its combination with deep learning models can significantly enhance diagnostic reliability. Future work can include 3D CT scan segmentation, multimodal learning, and deployment on edge devices for real-time use.

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