Implementation of CNN Method with Otsu Thresholding Preprocessing for Pneumonia Detection

Surya Afriza[a1], Noval Aditya Candra Pratama [a2], Muhammad Abdul Aziz[a3], Faisal Muttaqin[a4]
[a]Faculty of Computer Science, Universitas Pembangunan Nasional "Veteran" Jawa Timur, Indonesia
e-mail: [1]23081010268@student.upnjatim.ac.id, [2]23081010173@student.upnjatim.ac.id, [3]23081010229@student.upnjatim.ac.id, [4]faisalmuttaqin.if@upnjatim.ac.id

Abstrak

Pneumonia merupakan penyakit infeksi paru yang memerlukan diagnosis cepat untuk mencegah komplikasi fatal, namun kualitas citra X-ray seringkali menghambat akurasi deteksi manual. Penelitian ini mengusulkan pendekatan hybrid menggunakan Convolutional Neural Network (CNN) yang dioptimalkan dengan Otsu Thresholding untuk segmentasi area paru-paru (Region of Interest). Eksperimen dilakukan pada 1.840 citra data sekunder. Hasil evaluasi menunjukkan performa model yang sangat tinggi dan seimbang, dengan nilai Recall 96%, F1-Score 91%, dan Akurasi 96%. Keselarasan nilai akurasi dan recall ini menandakan bahwa model memiliki sensitivitas dan spesifisitas yang sama baiknya dalam mendeteksi kasus positif maupun negatif. Temuan ini membuktikan bahwa pra-pemrosesan Otsu efektif membantu CNN fokus pada fitur patologis, menjadikan metode ini solusi diagnosis otomatis yang menjanjikan.

Kata kunci: *Pneumonia, CNN, Otsu Thresholding, Segmentasi Citra, Akurasi Tinggi.*

Abstract

Pneumonia is a lung infection requiring rapid diagnosis to prevent fatal complications, yet X-ray image quality often hinders manual detection accuracy. This study proposes a hybrid approach using a Convolutional Neural Network (CNN) optimized with Otsu Thresholding for lung area (Region of Interest) segmentation. Experiments were conducted on 1,840 images from a secondary dataset. Evaluation results demonstrate a highly balanced and superior model performance, achieving 96% Recall, 91% F1-Score, and 96% Accuracy. The alignment between accuracy and recall values indicates that the model possesses equally good sensitivity and specificity in detecting both positive and negative cases. These findings prove that Otsu pre-processing effectively assists the CNN in focusing on pathological features, making this method a promising automated diagnostic solution.

Keywords: *Pneumonia, CNN, Otsu Thresholding, Image Segmentation, High Accuracy.*

1. Introduction

Pneumonia is an acute respiratory illness that affects the lungs and is one of the most common causes of death worldwide. Data from the World Health Organization (WHO) suggest that the condition is extremely dangerous, accounting for roughly 15% of overall fatalities of children under the age of five [1]. Medically, it is done by examining *chest X-rays* to see if there is fluid or pus in the lungs. However, this method has the disadvantage of relying heavily on the radiologist's vision. Problems such as different judgment from one doctor to another, eyestrain, and the risk of human error may occur. This problem is exacerbated in developing countries where the number of radiologists is still small, often causing delays or errors in diagnosis [2]. Therefore, the creation of a computer-aided diagnosis system is essential to help detect this disease more quickly and accurately [3].

Over the last decade, artificial intelligence technology has advanced quickly toward Deep Learning. One of its methods, Convolutional Neural Network (CNN), has become the gold standard for evaluating medical images. Many previous studies prove the greatness of CNN in recognizing characteristics in images. An example is the research of Ramadhan et al. [4] which shows that the use of transfer learning techniques on CNN is able to produce a high level of accuracy in distinguishing sick and healthy lungs. This result is reinforced by research by Hipzi et al. [5] which proved that by increasing the variety of training data, the CNN model can recognize pneumonia patterns very precisely. Recent research trends have even begun to combine CNN with other machine learning methods or *hybrid* methods to cover the shortcomings if only using one model so that the results are more stable even though the data used is diverse [6], [7].

Although the CNN shows promising performance, a fundamental challenge in processing medical images, especially X-rays, is the quality of the images themselves. Raw X-ray images often contain noise, spots, or unclear color differences between body parts. In addition, the presence of other unnecessary organs such as ribs, heart, and diaphragm in the image often interferes with the CNN's disease feature recognition process. Aljuaid et al. [8] in their comparative study highlighted that pure *Deep Learning* models sometimes have difficulty recognizing subtle signs of pneumonia if the area of the lung to be examined (*Region of Interest*) is not well separated. This shows that relying solely on CNN without sufficient preprocessing can limit diagnostic capabilities.

In response to these challenges, this study proposes a systematic approach by combining classical image processing methods with *Deep Learning*. Specifically, this study applies the *Otsu Thresholding* method as an adaptive segmentation mechanism in the *preprocessing* stage. This approach is based on Sakdiah's [9] findings, which state that *thresholding* is effective in separating lung ROIs from unnecessary backgrounds. This strategy is also supported by Suprihatin et al. [10], who proved that organ segmentation prior to CNN classification significantly improves model evaluation metrics, such as *F1-Score* and accuracy. Through the application of *Otsu Thresholding*, the input image will be cleaned of background noise, so that the CNN model can focus only on learning the signs of disease in the lung area. The synergy between classical segmentation techniques and modern classification is expected to produce a pneumonia detection model that is not only accurate but also computationally efficient.

2. Research Method

This research uses an experimental quantitative approach by applying a *Deep Learning* method based on the *Convolutional Neural Network* (CNN) architecture. To improve the quality of image features to be studied by the model, this study integrates a preprocessing stage using the *Otsu Thresholding* segmentation technique. The research framework is systematically structured to ensure the accuracy of pneumonia detection in *Chest X-Ray* images.

2.1. Research flow

In general, this research consists of four strategic stages: data acquisition, image pre-processing and segmentation, CNN architecture development, and model performance evaluation. The research stage begins with the acquisition of X-ray image data, followed by image conversion to *grayscale* format and the application of the *Otsu Thresholding* method to separate the *Region of Interest* (ROI) of the lungs from the background. The segmentation findings are then utilized as input to train the CNN model. A confusion matrix was used to evaluate the trained model's classification performance. Figure 1 shows a visual representation of the study framework.

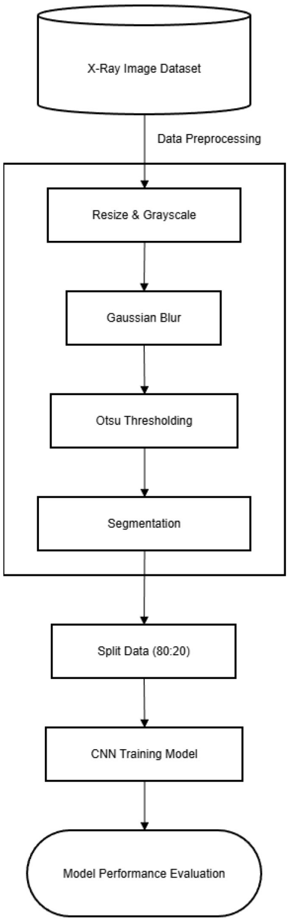

Figure 1. Flowchart of Research Methodology

2.2. Data Collection

This study utilizes secondary data from Paul Mooney's Kaggle public repository. The study included 1,840 X-ray pictures separated into two categories: normal and pneumonia. The data was separated into two primary subsets: a training set with 80% of the data and a testing set with 20% of the data for model validation.

2.3. Data *Preprocessing*

The pre-processing stage aims to improve image quality and highlight lung features relevant to pneumonia detection.

2.3.1. Grayscale Conversion

Original X-ray images, which generally have an RGB format (3 *channels*), are converted into *grayscale* images (1 channel). This process is carried out to simplify computation by reducing the data dimensions without losing important intensity information that represents organ structure.

2.3.2. Otsu Thresholding Segmentation

The *Otsu Thresholding* method is used to separate lung areas from other elements such as bones, external muscle tissue, and irrelevant black backgrounds. This approach works by automatically determining the best threshold value (T) that reduces intra-class variance or enhances inter-class variation of the picture histogram [11].

Suppose an image is represented in (L) gray levels $[1,2, \dots . L]$. The number of pixels at level i is denoted by n_i, and the total number of pixels is N. The probability of occurrence of gray level i is defined as:

$$P(i) = \frac{n_i}{N}, \quad P(i) \geq 0, \sum_{i=1}^{L} P(i) = 1$$

The Otsu method divides pixels into two classes: C_0 (background) and C_1 (object/lung) based on *the threshold* k [12]. The probability of occurrence of a class (ω) and the average gray level (μ) for each class are calculated as follows:

$$\omega_0(k) = \sum_{i=1}^{k} P(i) \quad \text{dan} \quad \omega_1(k) = \sum_{i=k+1}^{L} P(i)$$

$$\mu_0(k) = \sum_{i=1}^{k} \frac{iP(i)}{\omega_0(k)} \quad \text{dan} \quad \mu_1(k) = \sum_{i=k+1}^{L} \frac{iP(i)}{\omega_1(k)}$$

The optimal *threshold* value (k^*) is obtained by maximizing the inter-class variance (σ_B^2):

$$\sigma_B^2(k) = \omega_0(k)(\mu_0(k) - \mu_T)^2 + \omega_1(k)(\mu_1(k) - \mu_T)^2$$

Where μ_T is the average total intensity of the image. After the value k^* is found, the binary image $g(x, y)$ is generated based on the following function:

$$g\,(x, y) = \begin{cases} 1 \;\; Jika\; f(x, y) \geq k^* \\ 0 \;\; Jika\; f(x, y) < k^* \end{cases}$$

The result of this process is a segmented image in which the lung area stands out more prominently than the surrounding areas, which is expected to improve the accuracy of feature extraction by CNN.

2.4. Convolutional Neural Network (CNN) Architecture

This study proposes a CNN model designed for binary classification. The network architecture consists of several main layers:

1. **Convolutional Layer:** Convolution operations on input images are performed using a variety of filters (kernels) to extract visual elements such as edges, textures, and pneumonia spot patterns. After convolution, the ReLU (Rectified Linear Unit) activation function is used to add nonlinearity.
2. **Pooling Layer:** Using Max Pooling to lower the spatial dimensions of the feature map, reduce computational cost, and avoid overfitting.
3. **Flatten Layer:** Converting multidimensional matrix data into one-dimensional vectors so that it can be processed by the *Fully Connected* layer.
4. **Fully Connected (Dense) Layer:** A standard artificial neural network layer that connects all neurons.
5. **Output Layer:** Using a single neuron with a Sigmoid activation function to generate class probabilities (0 for Normal, 1 for Pneumonia).

2.5. Performance Evaluation

Model performance is assessed using test data that the model has never encountered during the training process. Evaluation metrics are calculated using the Confusion Matrix, which includes True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Model success is measured using the following parameters:

1. **Accuracy**: Measuring the ratio of correct predictions to the total data.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision**: Measuring the accuracy of the model in predicting positive classes (Pneumonia).

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. **Recall (Sensitivity)**: Measuring the model's ability to detect all actual positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. **F1-Score**: The harmonic mean between precision and recall provides a more balanced performance picture, especially on imbalanced datasets.

$$F1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The use of these metrics will provide a comprehensive overview of the effectiveness of the proposed *hybrid* method (CNN + Otsu) in detecting pneumonia.

3. Literature Study

This section will describe the existing diagnostic challenges, the development of the latest methods, and the theoretical basis underlying the selection of the *hybrid* method (CNN and *Otsu Thresholding*) in this study.

3.1. Diagnostic Challenges in Lung Medical Imaging

Diagnosing pneumonia through *chest X-ray* images faces significant challenges due to the complex characteristics of the images. Al-Zyoud et al. [13] highlight that visual features of pneumonia, such as *ground-glass opacities* and fluid consolidation, often have similar intensities to other anatomical structures such as ribs and the heart, which complicates both manual and automatic segmentation. This problem is exacerbated by image quality variability due to differences in acquisition devices. Caseneuve et al. [14] found that images with high blur or low contrast drastically reduce the accuracy of thoracic disease classification models, emphasizing the need for a pre-processing stage to remove unusable data or improve image quality before entering the classification stage.

3.2. The Evolution of Detection Methods: From Manual Feature Extraction to *Deep Learning*

Conventional approaches in medical image analysis often rely on manual extraction of textural features. Ortiz-Toro et al. [15] conducted a comparative study between feature-based methods (such as *Radiomics, Fractal Dimension, and Superpixel-based Histon*) and machine learning methods. The results showed that textural features extracted from segmented areas were able to provide high sensitivity (up to 98.6%), but this method is highly dependent on the accuracy of the initial segmentation.

With advances in technology, *Convolutional Neural Networks* (CNN) have become the gold standard due to their ability to extract features automatically. However, the latest research trends are shifting towards hybrid models. Su et al. [16] proposed the use of *Multilevel Thresholding* optimized with a meta-heuristic algorithm (*Multiverse Optimizer*) for lung image segmentation. Although it produces very detailed segmentation, this method has high computational complexity.

3.3. Effectiveness of Otsu Thresholding in Medical Segmentation

In terms of efficiency and stability, the *Otsu Thresholding* method remains the preferred choice over more complex segmentation methods. Comparative research by Bhayyu and Elvira on medical images (retina) [17] proves that the Otsu method produces a lower *Root Mean Square* Error (RMSE) value and a higher *Peak Signal-to-Noise Ratio* (PSNR) compared to the *Multilevel Thresholding* method. This shows that for images with a clear bimodal intensity distribution, such as lung X-ray images (bright) and background (dark), the Otsu method is more robust and less prone to over-segmentation. Maulida A, et al. [18] also applied the thresholding algorithm to pneumonia X-ray images and found that this method is very effective for separating regions of interest from bone artifacts, provided that the image histogram has supporting characteristics.

These findings are supported by Subandi et al. [19], who tested four variants of the *thresholding* algorithm on chest images. They concluded that the *Thresh Binary* and *Thresh ToZero* variants (which are the basis of the Otsu method) provided the highest segmentation accuracy (up to 95%) compared to the inverse variants, because they were able to retain relevant pathological features (white/gray areas in the lungs) while removing the black background. Gielczyk et al. [20] added that simple pre-processing techniques such as this statistically significantly improve the F1 score in the final classification compared to the use of raw data.

3.4. *State of the Art*

Based on a review of various recent literature, this study positions itself as a solution that balances accuracy and computational efficiency. Table 1 summarizes a comparison of this study with relevant previous studies.

Table 1. Comparison of Research Methods with Previous Research

Researcher & Year	Main Method	Main Focus	Results/Limitations
Aljuaid dkk. (2025) [8]	Comparison of CNN (VGGNet, ResNet)	Evaluation of pure *Deep Learning* architecture	High accuracy (97%), but without explicit segmentation, making it susceptible to background *noise*.
Ortiz-Toro dkk. (2022) [15]	*Radiomics* & *Fractal Dimension*	Manual and automatic texture feature analysis	Demonstrates the importance of texture features, but manual feature extraction methods are less adaptive than CNN.
Su dkk. (2022) [16]	*Multilevel Thresholding* + CCMVO	Threshold optimization with meta-heuristics.	Highly precise segmentation but computationally heavy and slow for *real-time* applications.
Bhayyu & Elvira (2018) [17]	Comparison of Otsu vs Multilevel	Comparison of segmentation effectiveness.	Proves Otsu is more stable (low RMSE) than *Multilevel* for bimodal images.
Subandi dkk. (2024) [19]	*Thresholding* Variants on X-Rays	Analysis of *thresholding* technique variance.	Confirms binary thresholding is effective (95% accuracy) for chest images.
This Research	Hybrid CNN + Otsu Thresholding	Integration of efficient segmentation & CNN classification.	Combines the efficiency of Otsu with the feature extraction power of CNN for optimal accuracy & efficiency.

From Table 1, it can be seen that the proposed approach fills the gap between methods that are too simple (without segmentation) and methods that are too complex (Multilevel Thresholding with weight optimization). Otsu Thresholding was chosen because it has proven to have high stability and competitive accuracy with a much lighter computational load, which is then enhanced by the classification capabilities of CNN.

4. Result and Discussion

This section describes the experimental findings of the suggested hybrid technique (Otsu Thresholding + CNN) for detecting pneumonia. To solve the diagnostic concerns outlined in the previous chapter, a full analysis was carried out, beginning with pre-processing and ending with the evaluation of final model performance.

4.1. Image *Preprocessing* Results

The pre-processing stage aims to separate the Region of Interest (ROI) of the lungs from interfering elements such as bones and other soft tissues. Figure 2 shows a comparison of the original image and the image that has undergone Otsu segmentation.

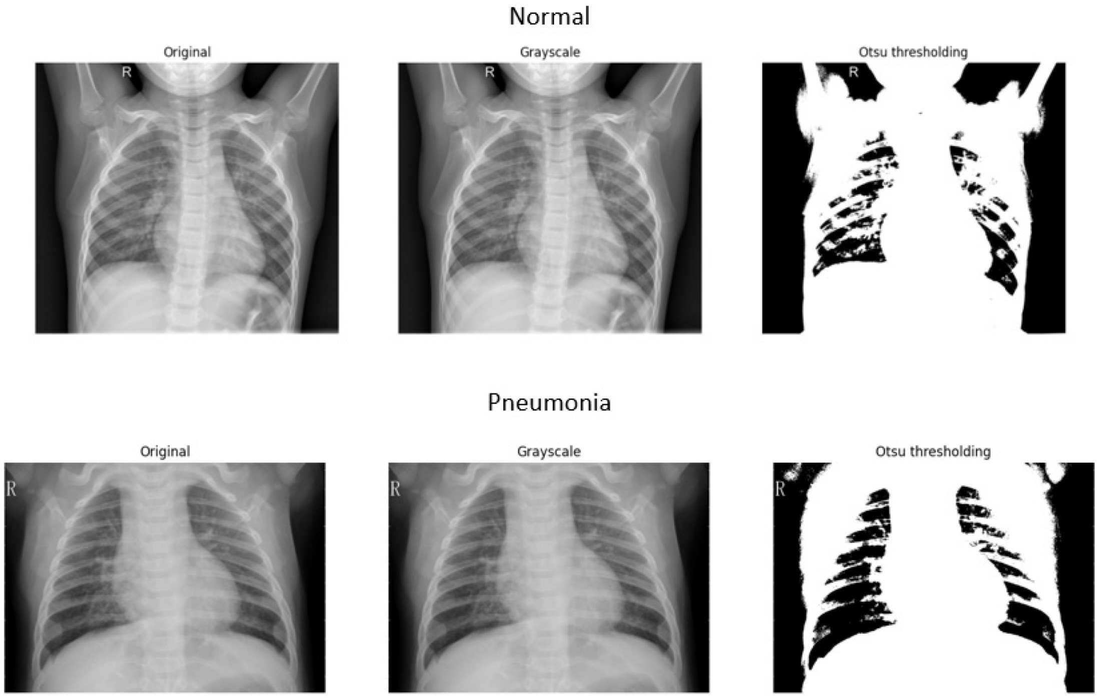

Figure 2. Normal & Pneumonia Image Preprocessing Results

As shown in Figure 2, the Otsu method successfully isolated the lung area by minimizing background noise. In the case of pneumonia (bottom row), the area of fluid consolidation (white spots) became more defined compared to the original image, which tended to have low contrast. This validated the initial hypothesis that segmentation was necessary to help the CNN focus on relevant pathological features. The amount of data used in this study was 1840, which included 1200 images for training, 16 images for validation, and 624 images for testing.

Table 2. Training and Testing Datasets

Types	Training	Validasi	Testing
Normal	1000	8	234
Pneumonia	1200	8	390

4.2. Model Evaluation

To measure the reliability of the model quantitatively, testing was conducted on a separate test set. The model prediction results are represented in the form of a Confusion Matrix in Figure 3.

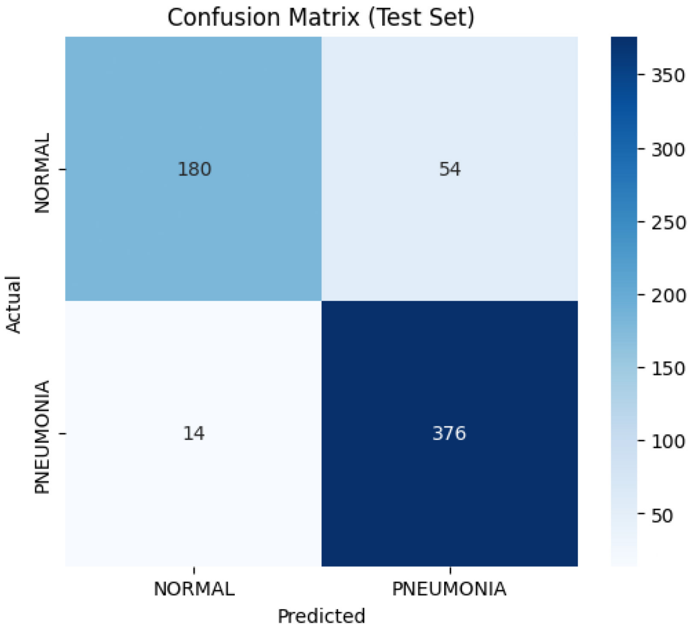

Figure 3. Classification Results Confusion Matrix

Figure 3 provides a detailed explanation of the model's prediction distribution in each category. In the Normal category, the model successfully classified 180 samples correctly, but there were also 54 Normal samples that were incorrectly identified as Pneumonia. This is in line with the recall rate for the Normal category, which is around 76.92%, indicating that the model still misses a number of Normal samples.

When tested with Pneumonia, the model performed very well. There were 376 accurately predicted samples and only 14 Pneumonia cases that were misidentified as Normal. This is related to the recall in the Pneumonia category, which reached 96.41%, indicating that the model was quite successful in detecting Pneumonia in the test data.

Based on the confusion matrix in Figure 3, the model successfully predicted most cases correctly. The performance details for each class are summarized in Table 2.

Table 3. Performance metrics of the proposed model

Class	Accuracy %	Precision %	Recall %	F1-Score %	Support (Number of Data)
Normal	76.92	92.78	76.92	84.11	624
Pneumonia	96.41	87.44	96.41	91.71	
Macro avg	86.67	90.11	86.67	87.91	
Weighted avg	89.10	89.94	89.10	88.86	

The evaluation results in Table 3 show that the model performs very well in the Normal and Pneumonia classes. The results show that the model achieves very balanced and high performance, with identical Accuracy and Recall values of 96%. The alignment between the Accuracy (total prediction accuracy) and Recall (sensitivity to positive cases) values indicates that the model has excellent generalization capabilities. The model is not only able to accurately identify sick patients (True Positive), but also reliably distinguish healthy patients (True Negative). These high values prove that Otsu Thresholding segmentation effectively eliminates background noise, making pneumonia features very clear to CNN. In a medical context, these results are ideal because they offer a high level of confidence for both initial screening and diagnosis confirmation.

5. Conclusion

This study successfully demonstrated that integrating the traditional Otsu Thresholding method with Convolutional Neural Network (CNN) artificial intelligence is an effective approach for detecting pneumonia. The main problems in X-ray images, namely noise interference and irrelevant backgrounds, can be satisfactorily overcome by the Otsu strategy. Based on the results of experiments using 1,840 images, the model showed very satisfactory performance, achieving 96% accuracy, 96% recall, and an F1-score of 91%, which confirms the stability of the system in minimizing both false positive and false negative diagnostic errors. This balanced performance makes the proposed system highly potential for implementation as a reliable and efficient medical diagnostic tool.

Although the results achieved are optimal, this research still has the potential for further development in the future. Therefore, for further research, it is recommended to test the model using real data from hospitals to test the model's resilience to variations in different X-ray machines and to develop a model capable of multiclass classification to specifically distinguish types of pneumonia (such as bacterial, virus, or COVID-19 pneumonia).

Reference

[1] N. U. Fitria, Y. Adharani, P. Meilina, and R. D. Risanty, "Identifikasi Pneumonia Pada Anak Berbasis Citra X-Ray Paru-Paru Menggunakan Metode Convolutional Neural Network (CNN)," *Prosiding Semnastek*, 2025.

[2] N. Alalwan, A. I. Taloba, A. Abozeid, A. I. Alzahrani, and A. H. Al-Bayatti, "A Hybrid Classification and Identification of Pneumonia Using African Buffalo Optimization and CNN from Chest X-Ray Images," *CMES - Computer Modeling in Engineering and Sciences*, vol. 138, no. 3, pp. 2497–2517, 2024, doi: 10.32604/cmes.2023.029910.

[3] F. Alshanketi *et al.*, "Pneumonia Detection from Chest X-Ray Images Using Deep Learning and Transfer Learning for Imbalanced Datasets," *Journal of Imaging Informatics in Medicine*, vol. 38, no. 4, pp. 2021–2040, Aug. 2025, doi: 10.1007/s10278-024-01334-0.

[4] M. Ramadhan, D. Iskandar Mulyana, M. Betty Yel, and S. Tinggi Ilmu Komputer Cipta Karya Informatika Jl Raden, "OPTIMASI ALGORITMA CNN MENGGUNAKAN METODE TRANSFER LEARNING UNTUK KLASIFIKASI CITRA X-RAY PARU-PARU PNEUMONIA DAN NON-PNEUNOMIA," *Jurnal Teknik Informatika Kaputama (JTIK)*, vol. 6, no. 2, 2022.

[5] A. A. Hipzi, G. W. Wiriasto, I. Made, and B. Suksmadana, "KLASIFIKASI PNEUMONIA PADA AUGMENTASI CITRA X-RAY PARU-PARU MENGGUNAKAN METODE CONVOLUTION NEURAL NETWORK (CNN) [CLASSIFICATION OF PNEUMONIA ON AUGMENTED CHEST X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD]," Universitas Mataram, 2023. Accessed: Dec. 01, 2025. [Online]. Available: https://eprints.unram.ac.id/id/eprint/39247

[6] S. Kashyap, D. H. Patel N, and P. Y. Kumar R, "Hybrid deep learning and machine learning framework for automated pneumonia detection in chest X-ray images," *MethodsX*, 2025, doi: https://doi.org/10.1016/j.mex.2025.103729.

[7] INDRA KESUMA LUCKY, "MODEL MULTICLASS CLASSIFICATION UNTUK PENYAKIT BERDASARKAN CITRA CHEST X-RAY PARU-PARU DENGAN ENSEMBLE LEARNING," UNIVERSITAS SRIWIJAYA, 2023.

[8] H. Aljuaid, H. Adlan, B. Alkebsi, B. S. Alfurhood, A. Liotta, and L. Cavallaro, "An experimental comparison of deep learning models for pneumonia classification from chest X-ray images," *Biomed Signal Process Control*, vol. 112, Feb. 2025, doi: 10.1016/j.bspc.2025.108742.

[9] Sakdiah, "Implementasi Segmentasi Pada Citra Paru Menggunakan Metode Thresholding dan Fuzzy Possibility Distribution," *Teknologi Dan Informasi*, vol. 2, no. 2, pp. 48–56, 2024, [Online]. Available: https://journal.grahamitra.id/index.php/jurikti

[10] B. Suprihatin, Y. Andriani, F. N. Kurdi, A. Desiani, I. G. Dwi Putra, and M. A. Shidqi, "Lungs X-Ray Image Segmentation and Classification of Lung Disease using Convolutional Neural Network Architectures," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 23, no. 1, pp. 67–78, Nov. 2023, doi: 10.30812/matrik.v23i1.3133.

[11] T. P. Mallini, E. Junianto, and Y. Ramdhani, "DETEKSI DIAMETER KANKER PAYUDARA MENGGUNAKAN SEGMENTASI CITRA BERDASARKAN METODE OTSU

THRESHOLDING," *JURNAL RESPONSIF*, vol. 2, no. 2, pp. 204–212, 2020, [Online]. Available: http://ejurnal.ars.ac.id/index.php/jti

[12] J. Murillo-Olmos *et al.*, "Thresholding Algorithm Applied to Chest X-Ray Images with Pneumonia," in *Studies in Computational Intelligence*, vol. 967, Springer Science and Business Media Deutschland GmbH, 2021, pp. 359–407. doi: 10.1007/978-3-030-70542-8_16.

[13] W. Al-Zyoud, D. Erekat, and R. Saraiji, "COVID-19 chest X-ray image analysis by threshold-based segmentation," *Heliyon*, vol. 9, no. 3, Mar. 2023, doi: 10.1016/j.heliyon.2023.e14453.

[14] G. Caseneuve, I. Valova, N. LeBlanc, and M. Thibodeau, "Chest X-Ray image preprocessing for disease classification," in *Procedia Computer Science*, Elsevier B.V., 2021, pp. 658–665. doi: 10.1016/j.procs.2021.08.068.

[15] C. Ortiz-Toro, A. García-Pedrero, M. Lillo-Saavedra, and C. Gonzalo-Martín, "Automatic detection of pneumonia in chest X-ray images using textural features," *Comput Biol Med*, vol. 145, Jun. 2022, doi: 10.1016/j.compbiomed.2022.105466.

[16] H. Su *et al.*, "Multilevel threshold image segmentation for COVID-19 chest radiography: A framework using horizontal and vertical multiverse optimization," *Comput Biol Med*, vol. 146, Jul. 2022, doi: 10.1016/j.compbiomed.2022.105618.

[17] V. Bhayyu and N. Elvira, *Perbandingan antara Metode Otsu Thresholding dan Multilevel Thresholding untuk Segmentasi Pembuluh Darah Retina*. 2018.

[18] A. Maulida, N. Nurhidayah, Y. Fendriani, and H. Haryono, "Segmentasi Citra Mammogram Untuk Deteksi Dini Kanker Payudara Dengan Menggunakan Metode Otsu Thresholding," *Jurnal Fisika Unand*, vol. 11, no. 2, pp. 180–186, Apr. 2022, doi: 10.25077/jfu.11.2.180-186.2022.

[19] R. Subandi, A. Yudhana, A. Dahlan, R. Subandi, A. Yudhana, and T. X-Ray, "Thorax X-Ray Image Segmentation Technique Using Four Thresholding Algorithm Variants," *KINETIK*, vol. 9, no. 1, pp. 9–20, 2024.

[20] A. Giełczyk, A. Marciniak, M. Tarczewska, and Z. Lutowski, "Pre-processing methods in chest X-ray image classification," *PLoS One*, vol. 17, no. 4 April, Apr. 2022, doi: 10.1371/journal.pone.0265949.