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Identification of Bacterial Pneumonia on Chest X-Ray Images Using InceptionV3 Feature Extraction and K-Nearest Neighbor (K-NN)

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Abstract: Bacterial pneumonia is a type of respiratory tract infection that can lead to serious complications if not promptly detected and properly treated. This study develops a bacterial pneumonia identification model using chest X-ray images by combining the InceptionV3 feature extraction method with the K-Nearest Neighbor (K-NN) classification algorithm. The process begins with image preprocessing to enhance visual quality, followed by feature extraction using InceptionV3 to capture texture and shape characteristics of the lung area. The extracted features are then classified using the K-NN algorithm. Based on the experiments, the highest classification accuracy was obtained at K = 3, reaching 0.84. Model consistency was further evaluated using a cross-validation scheme with odd K values ranging from 1 to 20, and the best result was achieved at K = 3 with an accuracy of 0.9455. The experimental results indicate that the combination of InceptionV3 and K-NN is effective and promising as an automatic diagnostic tool for detecting bacterial pneumonia through chest X-ray images.

Keywords: Bacterial Pneumonia; InceptionV3; K-NN; Image Classification; Cross-Validation.

INTRODUCTION

Pneumonia is a respiratory tract infection that remains one of the leading causes of morbidity and mortality, particularly among vulnerable age groups such as children and the elderly. A study published in the Journal of Natural Sciences and Mathematics Research by Istianah and Sumarti (2020) emphasized that pneumonia whether caused by bacteria, viruses, or fungi continues to be a serious public health problem requiring sustained attention due to its significant impact on community health (Istianah & Sumarti, 2020). In Indonesia, the urgency to improve early diagnosis of pneumonia has gained increasing attention, along with the growing number of studies utilizing medical imaging as the basis for analysis.

A study published in the Indonesian Journal on Computing by Ahnafi et al. (2020) demonstrated that the use of a Residual Neural Network architecture was capable of classifying pneumonia with a sensitivity level of up to 95% (Hafidh, #1, Arifianto, Nur,

& #3, 2020). This finding highlights the potential of deep learning–based methods in supporting diagnostic processes. Furthermore, research reported in Phi: Jurnal Pendidikan Fisika dan Terapan by Rachman et al. (2021) developed an approach based on Histogram of Oriented Gradients (HOG) feature extraction combined with Local Binary Pattern (LBP) in an ensemble learning system, achieving a classification accuracy of 97.50% (Rachmadany Rachman, Dewang, Dewi Astuti, & Juarlin, 2025).

In addition, another study that utilized the InceptionV3 architecture as a feature extraction method for chest X-ray images also showed promising results, achieving classification accuracy of more than 90% in detecting COVID-19 pneumonia (Baltazar et al., 2021). Other studies have applied various Convolutional Neural Network (CNN) architectures such as ResNet50, InceptionV3, and VGG16 for pneumonia detection. Among these, the InceptionV3 architecture achieved the highest accuracy and recall values, 99.29% and 99.73%, respectively (Mujahid et al., 2022). These results provide strong evidence that image processing and machine learning technologies can enhance pneumonia detection effectiveness while opening broader opportunities for application in healthcare services. Another study performed pneumonia classification using Sobel edge detection and moment invariant feature extraction. The K-Nearest Neighbor (K-NN) method was also employed for pneumonia classification, with K values ranging from 2 to 900. The best performance was achieved at K = 3, with an accuracy rate of 96% (Ainun, Halim, & Anraeni, 2021).

In the context of clinical practice in Indonesia, the diagnosis of pneumonia through chest X-ray interpretation still faces several limitations. One major challenge is the limited number of radiologists, which leads to a high workload and may affect the consistency of diagnostic results. Moreover, manual image interpretation often depends on the subjective judgment of medical personnel, resulting in inter-observer variability. The advancement of digital technology particularly the application of machine learning methods offers a great opportunity to support the diagnostic process. This approach enables more objective and rapid image analysis, reducing potential bias and improving the efficiency of disease detection, while still maintaining the essential role of medical experts in final decision-making.

RESEARCH METHOD

This study focuses on developing a classification model aimed at distinguishing chest X-ray images between normal and bacterial pneumonia conditions. The primary algorithm applied is the K-Nearest Neighbor (K-NN), while the feature extraction process is carried out using the feature extraction capability of the pre-trained InceptionV3 architecture. The research workflow is designed through several essential stages, including data acquisition, image preprocessing and feature extraction, model construction, and classification performance evaluation. A summary of the methodological stages used in this study is illustrated in Figure 1.

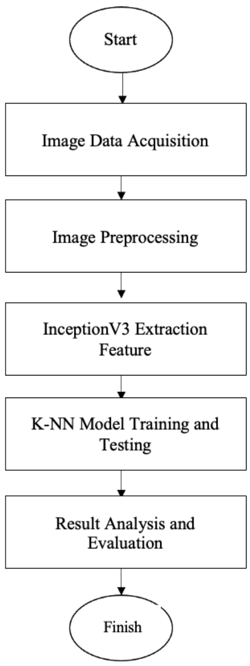


Image Data Acquisition

The chest X-ray dataset used in this study was obtained from an open-source repository available on the Kaggle platform, which has been widely utilized in previous studies related to lung disease classification. The dataset consists of two main classes, namely Normal and Pneumonia, with a total of 1,320 chest X-ray images. Labeling was performed automatically using the code 0 for Normal images and 1 for Pneumonia images. Subsequently, the dataset was divided into two subsets: training for model learning and testing for evaluation purposes, thereby supporting a structured classification performance assessment. Examples of chest X-ray images used for both Normal and Pneumonia classes are shown in Figure 2.

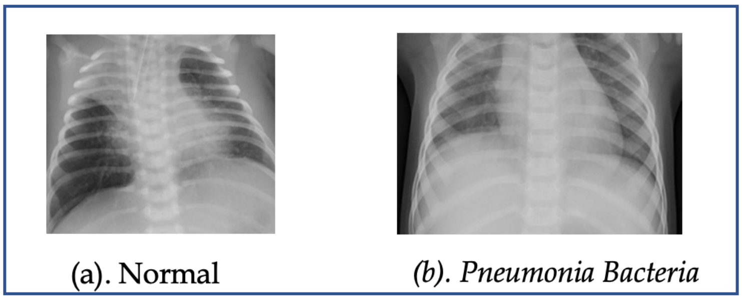


Figure 2. Examples of Normal and Bacterial Pneumonia Chest X-Ray Images

Image Preprocessing

The chest X-ray image preprocessing stage consists of two main steps. The first step involves converting the X-ray images from the RGB (Red, Green, Blue) format into grayscale, followed by contrast enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization). The second step is image resizing. Since the acquired X-ray images vary in dimensions, it is necessary to standardize their size to 299 × 299 pixels for each chest X-ray image (Farin, Islam Prottasha, & Reza, 2023; Samir, Mwanahija, Soumia, Özkaya, & Oran, 2023; Yothapakdee, Pugtao, Charoenkhum, Boonnuk, & Tamee, 2025). The preprocessing stages of chest X-ray image data are illustrated in Figure 3.

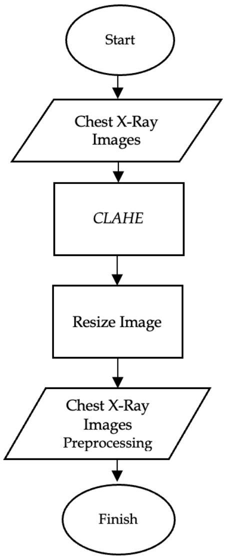


Figure 3. Chest X-Ray Image Preprocessing Stages

The preprocessing stage begins with the use of raw chest X-ray images obtained from data acquisition, which remain in their original condition without any prior modification or transformation. The images, initially in RGB format, are converted into grayscale to simplify visual representation by retaining only pixel intensity information. This conversion reduces computational complexity while preserving essential anatomical details.

The image contrast is then enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method. CLAHE has been proven effective in improving the visual quality of radiographic images by clarifying anatomical structures (Gonca, Sazak, & Gündoğdu, 2024). Studies on lateral cephalometric radiographs have demonstrated that CLAHE facilitates the identification of landmark points, although automated systems such as WebCeph still require additional adjustments (Yoon et al., 2023).

Furthermore, since the acquired chest X-ray images have non-uniform resolutions, image normalization is performed to ensure consistent dimensions across all images, specifically 299 × 299 pixels. This resizing step is crucial for maintaining compatibility with the InceptionV3 architecture and ensuring uniformity during subsequent processing stages. Through grayscale conversion, contrast enhancement, and dimension normalization, the preprocessed chest X-ray images become well-prepared for the feature extraction and classification stages that follow.

Inceptionv3 Feature Extraction

In the feature extraction stage, the InceptionV3 architecture is utilized as the foundation of the feature extraction process. The InceptionV3 model is initialized with pre-trained weights from the ImageNet dataset to leverage previously learned visual representations. The fully connected layer of the model is removed by setting the parameter include_top=False, leaving only the convolutional layers, which function as the feature extractor (Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016).

Subsequently, a new model is constructed that retains the input structure of InceptionV3, while the output is derived from the final convolutional layer. Using this approach, input images with a size of 299 × 299 pixels and three color channels are processed to generate high-dimensional feature representations that are more compact and informative. These feature representations are then used as the foundation for subsequent classification stages, according to the objectives of the study. The InceptionV3 architecture applied in this study is summarized in Table 1.

Table 1. Summary of the InceptionV3 Architecture (without Fully Connected Layer) (Mujahid et al., 2022).

Stage / Block	Layer Type	Output Shape	Description
Input	Input Layer	(299, 299, 3)	RGB input image with a size of 299×299 pixels.
Stem	Conv + Pooling	(35, 35, 192)	Initial feature extraction from the image.
Inception-A (×3)	Inception Module	(35, 35, 288)	Combination of 1×1, 3×3, and 5×5 convolutions to capture multi-scale patterns.
Reduction-A	Conv + Pooling	(17, 17, 768)	Reduces spatial dimensions while increasing feature depth.
Inception-B (×4)	Inception Module	(17, 17, 768)	Feature extraction with a larger receptive field.
Reduction-B	Conv + Pooling	(8, 8, 1280)	Reduces spatial size to 8×8.
Inception-C (×2)	Inception Module	(8, 8, 2048)	Final feature extraction with maximum depth.
Output Feature Map	Tensor	(8, 8, 2048)	Feature representation of the image.
Flatten (optional)	Reshape	(131,072)	1D feature vector used as input for KNN or other classifiers.

Model Training And Testing

In the training stage, this study utilizes the feature representations extracted from the InceptionV3 architecture, which was previously trained on the ImageNet dataset. These feature representations from chest X-ray images are then used as input for the K-Nearest Neighbors (KNN) algorithm in the classification process. Before the main training, an optimization process was conducted to determine the most suitable K parameter by applying 5-fold cross-validation on the training data. The range of K values tested was from 1 to 20, and each model was evaluated based on its average accuracy. The K value with the highest accuracy was selected as the optimal configuration to be used in the final classification stage.

After obtaining the optimal K value, the KNN model was retrained using the entire training dataset and subsequently tested on a separate testing dataset. Additionally, several random predictions from the test data were presented to illustrate the model's ability to distinguish between Normal and Pneumonia categories. This approach enables the classification process to be performed without retraining the convolutional model from scratch. Instead, the system leverages transfer learning by utilizing feature representations that have been proven effective in various computer vision studies. (Szegedy et al., 2016), which serves as a simple yet robust classification method.

Result Analysis And Evaluation

The model performance evaluation was carried out by comparing the predicted results with the actual labels using a confusion matrix and a classification report. Evaluation metrics such as accuracy, precision, recall, and F1-score were calculated as follows (Fahmy Amin & Amin, 2022):

1. **Accuracy:**

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

2. ***Precision*:**

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

3. ***Recall*:**

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

4. **F1-Score:**

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

RESULT AND DISCUSSION

Preprocessing – Clahe Application Results

The CLAHE (Contrast Limited Adaptive Histogram Equalization) technique was applied to enhance image contrast prior to further processing. CLAHE was selected for its ability to emphasize local details within the image particularly in darker regions without causing the overexposure effects commonly observed in conventional histogram equalization. The results of the CLAHE application are presented in Table 2.

Table 2. Example Results of CLAHE Application

Original Image	CLAHE Image

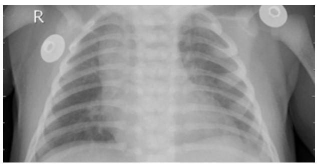
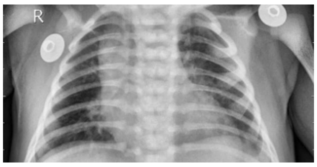
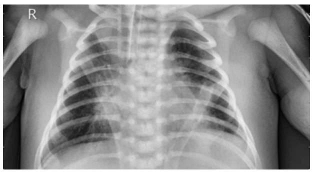
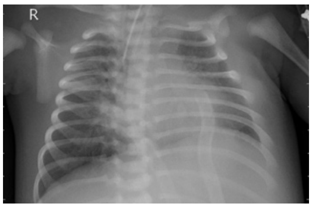
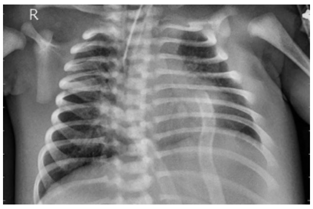

	

Image Size: 728×368 Pixels	Image Size: 728×368 Pixels

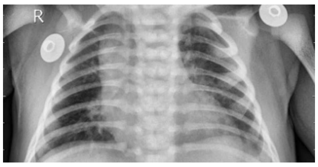
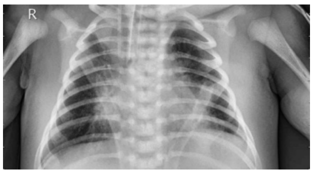
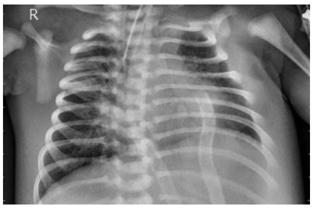
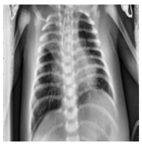
Original Image	CLAHE Image
 Image Size: 864×464 Pixels	 Image Size: 864×464 Pixels
 Image Size: 824×536 Pixels	 Image Size: 824×536 Pixels
 Image Size: 1016×544 Pixels	 Image Size: 1016×544 Pixels

Comparison between the original and CLAHE-enhanced images demonstrates a significant improvement in image contrast, enabling details that were previously hidden in dark regions to become more discernible. In road surface images, fine cracks and texture patterns appear more distinct, while in medical images such as X-rays, organ structures and tissue density variations can be more effectively identified. This enhancement is achieved through the adaptive histogram equalization mechanism applied to each image tile, using a clip limit of 2.0 and a tile grid size of 8×8. The results confirm that CLAHE effectively enhances critical image features without introducing noticeable noise amplification, thereby improving the reliability of subsequent feature extraction and classification processes.

Preprocessing – Dimension Adjustment Results

Table 3 presents the image dimensions before and after the adjustment process. The resizing procedure was performed to standardize all images to a resolution of 299 × 299 pixels.

Table 3. Example of Chest X-ray Image Dimension Adjustment (Resizing) Results

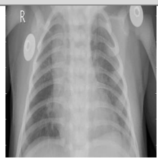
CLAHE Image	Resize Image
 Image Size: 728×368 Pixels	 Image Size: 299×299 Pixels
 Image Size: 864×464 Pixels	 Image Size: 299×299 Pixels
 Image Size: 824×536 Pixels	 Image Size: 299×299 Pixels
 Image Size: 1016×544 Pixels	 Image Size: 299×299 Pixels

The resizing process was carried out to ensure consistency in image dimensions while preserving the aspect ratio and essential visual information. By standardizing the image size, each input can be processed uniformly by the convolutional network, thereby reducing potential errors caused by resolution discrepancies. The target resolution of 299 × 299 pixels was selected to match the default input size of the InceptionV3 architecture, facilitating efficient feature extraction.

Inceptionv3 Feature Extraction Results

During the feature extraction stage, feature vectors with a dimensionality of (1100, 131072) were generated. Table 4 presents an example of the extracted features corresponding to the first image in the chest X-ray dataset.

Table 4. Feature Extraction Process Using the InceptionV3 Feature Extraction Layer

Resize Image	InceptionV3 Feature Extraction
	0.9426459 0.0 0.0 0.6932783 0.0 Etc.
	0.13801526 0.0 0.0 0.013703153 0.0 Etc.
	0.28101578 3.8423474 0.7509474 0.8921213 0.0 Etc.
	0.85384023 0.8287765 0.0 0.0 0.0 Etc.

After the images were processed using the InceptionV3 architecture, numerical representations in the form of feature vectors were obtained. These vectors capture the essential characteristics of each image, including texture patterns, intensity variations, and shape distributions relevant to the classification process. The extracted features are represented as numerical values, such as 0.9426459**,** 0.6932783**,** 0.13801526, and so on. Each value reflects the weight of representation in a specific feature dimension. A value of zero indicates that no significant information was extracted in that dimension. In chest X-ray images, the predominance of black background areas often results in zero-valued features. The inherent contrast between objects and the background in X-ray images facilitates the classification process, as it allows the model to distinguish relevant anatomical structures more effectively (Yoon et al., 2023). Non-zero values, on the other hand, indicate the presence of important characteristics successfully captured by the model.

Model Training and Testing Results

Table 5 presents the cross-validation accuracy results for different values of K in the K-Nearest Neighbors (KNN) model.

K	Cross Validation Accuracy
1	0.9200
2	0.9291
3	0.9455
4	0.9418
5	0.9418
6	0.9400
7	0.9391
8	0.9345
9	0.9355
10	0.9373
11	0.9391
12	0.9400
13	0.9391
14	0.9409
15	0.9373
16	0.9391
17	0.9364
18	0.9373
19	0.9391
20	0.9400

From the obtained results, it can be observed that the highest accuracy of 0.9455 was achieved at K = 3, while other K values produced relatively consistent accuracies ranging from 0.9200 to 0.9418. These findings indicate that the selection of the K parameter influences the model's performance, although the variation in accuracy around the optimal value is not substantial. Based on this analysis, K = 3 can be considered the most appropriate choice for the KNN model on this dataset, as it provides an optimal balance between bias and variance, thereby maximizing the model's classification capability during cross-validation.

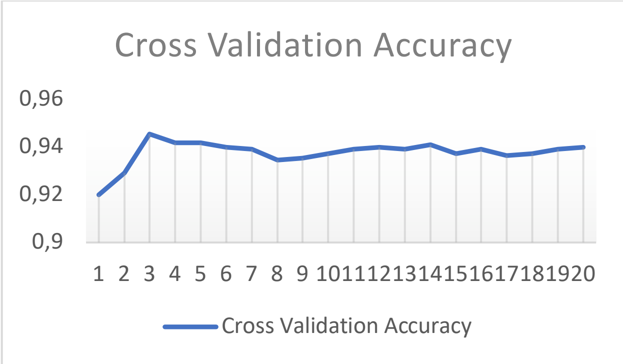


Figure 4. Cross-Validation Accuracy Graph

Figure 4 illustrates the cross-validation accuracy curve for different values of K in the K-Nearest Neighbors (KNN) model. As shown in the graph, the accuracy increases significantly as the value of K rises from 1 to 3, reaching its peak performance at K = 3 with the highest accuracy of 0.9455. Beyond this point, the accuracy tends to stabilize, showing minor fluctuations within the range of 0.92 to 0.94 for larger K values. This trend indicates that the selection of the K parameter plays an important role in determining the model's performance. The value of K = 3 can be considered optimal, as it not only yields the highest accuracy but also maintains model stability during the cross-validation process.

```
Classification Report:
              precision    recall  f1-score   support

      Normal       0.92      0.75      0.82       110
   Pneumonia       0.79      0.94      0.85       110

    accuracy                           0.84       220
   macro avg       0.85      0.84      0.84       220
weighted avg       0.85      0.84      0.84       220
```

Figure 5. Classification Report of the K-NN Model for Bacterial Pneumonia Identification

The classification report presented in Figure 5 demonstrates the performance of the K-Nearest Neighbors (KNN) model in classifying chest X-ray images into two categories: *Normal* and *Pneumonia*. For the *Normal* class, the model achieved a precision of 0.92, recall of 0.75, and F1-score of 0.82. In contrast, for the *Pneumonia* class, the respective precision, recall, and F1-score were 0.79, 0.94, and 0.85. Overall, the model obtained an accuracy of 0.84. Both the macro average and weighted average yielded similar scores of 0.84 for precision, recall, and F1-score. These results indicate that the model demonstrates high sensitivity in detecting *Pneumonia* cases, although its recall performance for the *Normal* class is slightly lower, suggesting a mild tendency toward false-positive predictions.

CONCLUSION

The K-Nearest Neighbors (KNN) model with a parameter setting of K = 3 achieved optimal performance in classifying chest X-ray images into *Normal* and *Bacterial Pneumonia* categories, obtaining the highest cross-validation accuracy of 0**.**9455. Further evaluation using the classification report revealed that the model demonstrated high sensitivity in detecting *Pneumonia* cases (recall = 0.94), although the detection performance for the *Normal* class was slightly lower (recall = 0.75). Overall, the model achieved an accuracy and F1-score of approximately 0.84. These findings highlight the importance of selecting an appropriate K value to maintain model stability and effectiveness. Moreover, they suggest opportunities for further improvement, such as feature optimization or the integration of ensemble methods, to enhance the detection accuracy of the *Normal* class.

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