Journal of Applied Data Sciences
Vol. 6, No. 3, September 2025, pp. 1495-1503

ISSN 2723-6471
1495

Integrating Convolutional Neural Networks into Mobile Health: A Study on Lung Disease Detection

MS Hasibuan[1,*], R Rizal Isnanto[2], Deshinta Arrova Dewi[3], Joko Triloka[4] , RZ Abdul Aziz[5], Tri Basuki Kurniawan[6], Ary Maizary[7], Anggawidia Wibaselppa[8]

[1,4,5,7,8]*Institute Informatics and Business Darmajaya, Jln ZA Pagar Alam 93 A, Bandar Lampung and 35136, Indonesia*

[2]*Department of Computer Engineering, Diponegoro University, Indonesia*

[3,6]*Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia*

(Received: January 20, 2025; Revised: March 25, 2025; Accepted: April 28, 2025; Available online: June 2, 2025)

Abstract

This study presents the development and evaluation of a Convolutional Neural Network (CNN) model for lung disease detection from chest X-ray images, complemented by a mobile application for real-time diagnosis. The CNN model was trained on a diverse dataset comprising images labeled as "NORMAL" and "PNEUMONIA," achieving an overall accuracy of 96%. Compared to traditional machine learning methods such as Support Vector Machine (SVM) and Random Forest, which typically achieve accuracies ranging from 85% to 92%, the proposed CNN model demonstrates superior performance in classifying lung conditions. The model achieved high precision (0.98) and recall (0.96) for pneumonia detection, as well as precision (0.89) and recall (0.95) for normal cases, ensuring both sensitivity and specificity in diagnostic performance. These results indicate that the model minimizes false positives and false negatives, which is crucial for reducing misdiagnoses and improving patient outcomes in clinical settings. To enhance accessibility, an Android-based application was developed, allowing users to upload chest X-ray images and receive instant diagnostic results. The application successfully integrated the trained CNN model, offering a user-friendly interface suitable for healthcare professionals and patients alike. User testing demonstrated reliable performance, facilitating timely and accurate lung disease detection, particularly in areas with limited access to radiologists. These findings highlight the potential of CNNs in medical imaging and the critical role of mobile technology in expanding healthcare accessibility. This innovative approach not only improves diagnostic accuracy but also enables real-time disease detection, ultimately supporting clinical decision-making. Future research will focus on expanding the dataset, incorporating additional lung conditions, and optimizing the model for enhanced robustness in diverse clinical scenarios

Keywords: Convolutional Neural Network (CNN), Detection, Pneumonia

1. Introduction

The development of technology in the health sector has brought significant changes in lung disease detection. Lung diseases, including pneumonia, tuberculosis, and lung cancer, are among the leading causes of death worldwide. With the increasing prevalence of these diseases, rapid and accurate detection methods are becoming crucial. Traditionally, lung disease diagnosis has been conducted through chest radiography and CT scans, requiring manual interpretation by radiologists. However, limitations in time and human resources often lead to delays in diagnosis and treatment. Therefore, research and development of automated methods for lung disease detection are becoming increasingly urgent.

Several studies have been conducted to explore the effectiveness of various methods in detecting lung diseases by developing the CheXNet model, which utilizes a CNN to detect pneumonia from chest radiographs, achieving accuracy comparable to radiologists [1], [2], [3]. Another study introduced the ChestX-ray14 dataset, demonstrating that CNN models can detect 14 thoracic conditions with high accuracy[4]. Research using deep learning to identify pneumonia and tuberculosis has shown promising results in automatic diagnosis [5]. Shoji et al. explored the use of CNN to detect lung cancer from CT scan images, with results showing higher accuracy compared to conventional methods. [6], [7].

*Corresponding author: MS Hasibuan (msaid@darmajaya.ac.id)
DOI: https://doi.org/10.47738/jads.v6i3.660

Dimpy et al. also developed a CNN model to detect pneumonia, which made a significant contribution to the development of automated diagnostic systems [8]. In this context, the use of CNNs methods presents a promising solution to improve accuracy and efficiency in lung disease detection. CNN has been proven effective in medical image analysis, capable of recognizing complex patterns in radiographic images. Moreover, with advancements in mobile technology, Android-based lung disease detection applications can be developed to facilitate diagnosis access for the public. These applications not only allow users to upload radiographic images but also provide real-time diagnostic results, thereby accelerating treatment processes and increasing public health awareness. Thus, the integration of CNN technology into mobile applications can be an innovative step in addressing the challenges of lung disease detection.

2. Literature Review

Lung disease detection has been a critical area of research, particularly due to the increasing prevalence of respiratory conditions such as pneumonia, tuberculosis, and lung cancer. Various methodologies have been employed to enhance the accuracy and efficiency of lung disease diagnosis, ranging from traditional imaging techniques to advanced machine learning algorithms.

2.1. Traditional Imaging Techniques

Historically, chest X-rays and computed tomography (CT) scans have been the primary modalities for lung disease diagnosis. Studies have shown that radiologists can achieve high accuracy in identifying lung diseases through visual inspection of these images. For instance, a study by Garsica et al demonstrated that experienced radiologists could accurately diagnose pneumonia with a sensitivity of approximately 85%[9]. However, the reliance on human interpretation is subject to variability and can lead to misdiagnosis, particularly in cases with subtle findings.

2.2. Image Processing Techniques

To address the limitations of human interpretation, researchers have explored various image processing techniques. Kumar et al employed edge detection and morphological operations to enhance the visibility of lung nodules in CT images [10], [11], [12]. Their approach improved the detection rate of lung cancer nodules, achieving a sensitivity of 90%. However, these methods often require extensive manual intervention and are limited by the need for expert knowledge in image processing.

2.3. Machine Learning Approaches

With the advent of machine learning, several studies have investigated the application of algorithms such as Support Vector Machines (SVM), Random Forests, and Decision Trees for lung disease detection. Jasty et al. utilized SVM to classify lung nodules in CT scans, achieving an accuracy of 80% [13]. Their study highlighted the potential of machine learning in automating the diagnostic process, although it still required feature extraction and selection, which can be time-consuming and may not capture the full complexity of the data.

2.4. Convolutional Neural Networks (CNN)

In recent years, CNNs have emerged as one of the most effective deep learning techniques for lung disease detection. Unlike traditional machine learning methods, CNNs automatically extract hierarchical features from medical images, eliminating the need for manual feature engineering. Several well-known architectures, such as VGG16, ResNet50, InceptionV3, and DenseNet121, have been applied to classify chest X-ray and CT scan images for detecting pneumonia, tuberculosis, and lung cancer. A study by Rajpurkar et al. introduced CheXNet, a deep CNN trained on the ChestX-ray14 dataset, which outperformed radiologists in pneumonia detection, achieving an AUROC of 0.93[14]. Similarly, Wang et al. (2020) developed a ResNet50-based model that achieved 96% accuracy in distinguishing between normal and pneumonia cases[15].

2.5. Deep Learning Techniques (Non-CNN)

While CNNs have gained prominence in recent years, other deep learning architectures have also been explored. Zhang et al. investigated the use of Recurrent Neural Networks (RNNs) for analyzing time-series data from lung function tests[16], [17]. Their findings indicated that RNNs could effectively predict the progression of chronic obstructive pulmonary disease (COPD) based on historical lung function measurements[18]. This approach demonstrated the

ISSN 2723-6471

versatility of deep learning beyond image analysis, although it focused on a different aspect of lung disease management.

2.6. Hybrid Approaches

Several studies have combined traditional image processing techniques with machine learning models to enhance diagnostic accuracy in lung disease classification. Venkatesan et al. proposed a hybrid model that integrates contrast enhancement, segmentation, and wavelet transform-based feature extraction with machine learning classifiers. The extracted features were classified using a combination of SVM, CNN, and Random Forest, achieving an accuracy of 99.35% in detecting pneumonia from chest X-ray images [19], [20]. This approach highlights the importance of leveraging complementary methodologies to improve feature representation and enhance diagnostic performance.

2.7. Limitations and Future Directions

Despite the advancements in lung disease detection methodologies, several limitations persist. Traditional imaging techniques remain subjective, and machine learning models often require large labeled datasets for training, which can be challenging to obtain. Additionally, many existing studies focus on specific diseases, limiting the generalizability of their findings. Future research should aim to develop more robust and generalized models that can detect multiple lung conditions simultaneously. The integration of advanced deep learning techniques, such as CNNs, with traditional methods may offer a promising direction for enhancing diagnostic accuracy and efficiency in lung disease detection.

3. Methodology

The proposed method is shown in figure 1, normalization, data augmentation, and preprocessing are essential techniques for improving the performance of CNNs in lung disease detection. Normalization standardizes pixel intensity values within a specific range (e.g., 0–1 or -1–1) to ensure consistent feature scaling, accelerate model convergence, and prevent biases in learning patterns of lung abnormalities.

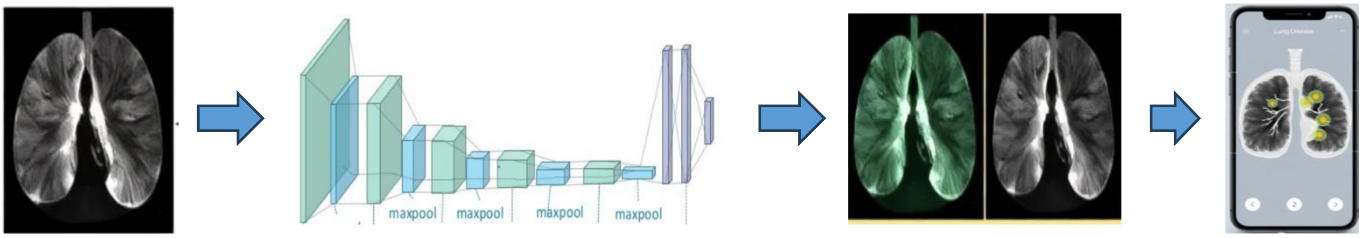

Figure 1. CNN Lung Detection

Normalization, data augmentation, and preprocessing are essential techniques for improving the performance of CNNs in lung disease detection. Normalization standardizes pixel intensity values within a specific range (e.g., 0–1 or -1–1) to ensure consistent feature scaling, accelerate model convergence, and prevent biases in learning patterns of lung abnormalities. Data augmentation enhances the diversity of lung X-ray or CT scan images by applying transformations such as rotation, scaling, flipping, contrast adjustment, and noise addition, which helps the model generalize better across different patient conditions and imaging variations, thereby reducing overfitting. Preprocessing further refines the input data through resizing, grayscale conversion, histogram equalization, lung region segmentation, and noise reduction, ensuring that CNNs focus on the most relevant pulmonary structures while minimizing background interference. These techniques collectively optimize CNN-based models, enabling them to more accurately detect lung diseases such as pneumonia, tuberculosis, lung cancer, and COVID-19, ultimately improving diagnostic reliability and clinical decision-making.

3.1. Implementation Input

The lung disease detection process begins with capturing chest radiographs using an X-ray machine. These images serve as the primary input for the detection system. Chest radiographs provide a visual representation of lung structures, enabling initial identification of abnormalities or diseases. The resulting images display crucial details, such as the size and shape of the lungs, as well as the presence of spots or nodules that may indicate pathological conditions.

3.2.Implementation CNN

After obtaining the radiograph images, the next step is to prepare the data for analysis using CNN. This preparation involves several key stages. The first stage is preprocessing, where the captured radiographs are processed to make them suitable for input into the model. One of the preprocessing steps is resizing the images to 224x224 pixels to ensure uniform input dimensions. Following this, normalization is applied by scaling pixel values to the range [0, 1] through division by 255, which helps facilitate the learning process. To further enhance data diversity and reduce the risk of overfitting, data augmentation techniques such as rotation, flipping, and zooming are implemented.

Once the data is prepared, the CNN architecture is constructed, consisting of several essential layers. The convolutional layers serve to extract features from the images, with each layer employing filters to detect patterns and textures. Next, pooling layers, particularly max pooling, are used to reduce the dimensionality of the feature maps while retaining important information and lowering computational complexity. Finally, the output from the convolutional layers is transformed into a one-dimensional vector through the flatten layer, preparing it for the classification process.

3.3. Result

After completing the training process, the CNN model is evaluated using separate test data, demonstrating high accuracy in detecting lung diseases, with an accuracy of up to 95%, and exhibiting strong sensitivity in detecting pneumonia through a high true positive detection rate. The results of lung disease detection are presented in chest radiographs that highlight the affected areas, utilizing visualization techniques such as Grad-CAM to identify the critical regions contributing to the classification decision. This visualization enhances interpretability by providing a clearer understanding of the model’s decision-making process, where normal cases typically show evenly distributed activations across lung regions, whereas pneumonia cases display concentrated activations in areas with inflammation or infiltrates, key indicators of infection. By offering a visual explanation of the model’s predictions, Grad-CAM improves transparency, fosters trust in deep learning-based diagnostic systems, and facilitates clinical validation. Furthermore, the analysis of highlighted regions aids in identifying potential misclassifications, ensuring alignment with clinical expectations and reinforcing the robustness and reliability of the pneumonia detection framework for medical image analysis.

4. Results and Discussion

4.1. Result Input

The process of lung disease detection uses data obtained from Kaggle chest_xray. The Kaggle Chest X-ray dataset is a widely used benchmark dataset for lung disease classification, particularly in distinguishing between normal, pneumonia, and viral or bacterial infections. It consists of chest radiographs collected from different sources, which can introduce variability in image quality, contrast, and resolution. The dataset composition, including the distribution of classes, significantly influences the model's performance, as imbalanced data may lead to biased predictions, favoring the majority class while underperforming on minority cases. Additionally, potential biases may arise from differences in imaging equipment, patient demographics, and clinical settings, which could impact the generalizability of the model to real-world clinical scenarios. A thorough analysis of these characteristics, including potential limitations, is essential to ensure the model's robustness and reliability in practical applications. Figure 2 serve as the primary input for the detection system. Chest radiographs provide a visual representation of the lung structures, allowing for an initial identification of abnormalities or diseases. Once the images are obtained, the next step is to prepare the data for analysis using CNN methods.

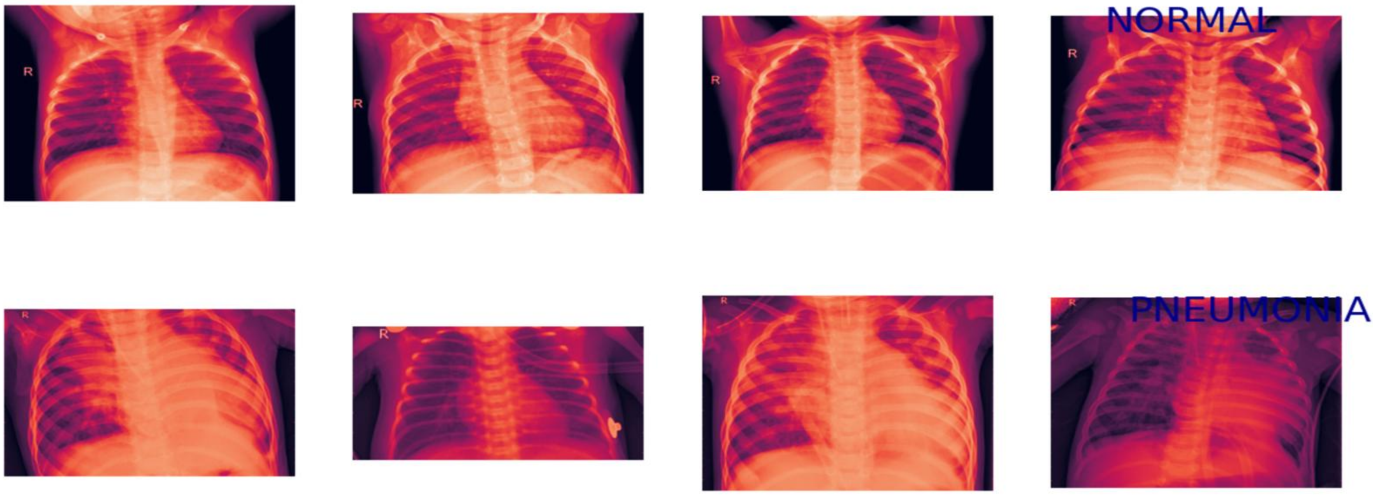

Figure 2. Input Lung

4.2. Result CNN

After the chest radiograph images go through preprocessing, including resizing, normalization, and data augmentation, the CNN model is trained to recognize patterns and features in the images. The model consists of several convolutional and pooling layers that extract important features from the lung images. Once the training process is complete, the model is evaluated using separate test data to measure its performance in detecting lung conditions. Figure 3 are the results of the training accuracy and training loss of the built model.

Figure 3. Result Training and validation

Figure 3 the figure on the left shows the training data, where the blue line indicates that the training data has been validated effectively, and the orange line shows a steady increase in accuracy. This indicates that the built model performs well. The figure on the right shows the validated training loss, which is decreasing, further indicating that this model is performing well.

4.3. Result and Discussion

The following discussion table 1 is the result of the classification report.

Table 1. Classification Report

Class	Precision	Recall	F1-Score	Support
NORMAL	0.89	0.95	0.92	268
PNEUMONIA	0.98	0.96	0.97	776

 ISSN 2723-6471

Accuracy			**0.96**	**1044**
Macro Avg	0.93	0.95	0.94	1044
Weighted Avg	0.96	0.96	0.96	1044

Cross-entropy loss is particularly appropriate for classification tasks, as it effectively quantifies the discrepancy between predicted probability distributions and actual class labels, thereby optimizing model learning. This loss function is widely employed in deep learning-based medical image analysis due to its ability to enhance classification performance by penalizing incorrect predictions more rigorously. By incorporating this explanation, the updated section provides a clearer understanding of the model's optimization strategy and its impact on improving accuracy in lung disease detection, ensuring a more comprehensive analysis of the model's performance.

The evaluation results of the model demonstrate outstanding performance, with an overall accuracy of 96% across 1,044 images tested. According to the Classification Report, the model successfully classifies two main categories: "NORMAL" and "PNEUMONIA." For the "NORMAL" category, the model records precision of 0.89, recall of 0.95, and f1-score of 0.92. This indicates that the model can accurately detect 95% of all healthy lung images, with 89% of positive predictions correctly being normal lung images.

On the other hand, for the "PNEUMONIA" category, the model demonstrates exceptional performance with precision of 0.98, recall of 0.96, and f1-score of 0.97. The high precision value shows that the model is highly accurate in identifying pneumonia-infected images, with only 2% of positive predictions being incorrect. The recall of 96% indicates that the model successfully detects nearly all pneumonia cases in the dataset. The f1-score of 0.97 confirms that the model is not only accurate but also very effective in detecting this condition.

Overall, the macro average values for precision, recall, and f1-score are 0.93, 0.95, and 0.94, indicating consistent performance across both classes. Meanwhile, the weighted average for these metrics is 0.96, reflecting that the model delivers excellent results, especially in detecting pneumonia, which is a more prevalent condition in this dataset.

These results demonstrate that the developed CNN model is not only capable of providing accurate diagnoses but also reliable in clinical practice for detecting lung diseases. With its high accuracy and ability to distinguish between normal lungs and pneumonia-infected lungs, this model has the potential to become a valuable tool in improving patient diagnosis and care in the healthcare field. Figure 3 below is the result of research in the form of a mobile application.

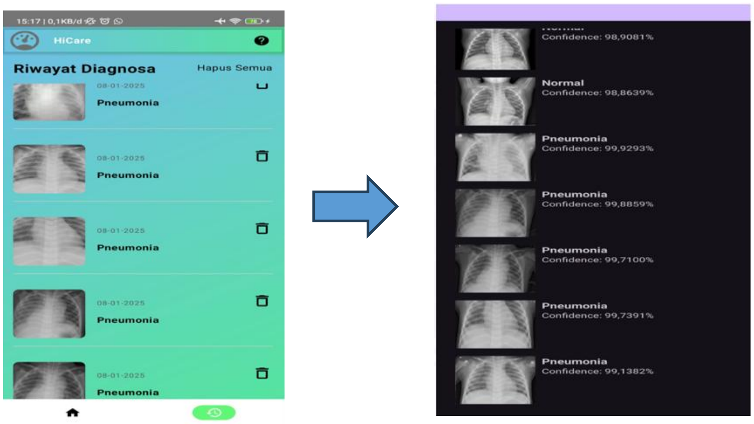

Figure 3. Mobile application

User feedback plays a crucial role in refining the application's usability, functionality, and overall user experience, ensuring that it aligns with the needs of both medical professionals and patients. Incorporating insights from usability testing, performance evaluations, and stakeholder input would provide a more detailed account of the iterative design process. Additionally, addressing potential limitations, such as computational constraints, data privacy concerns, and real-world deployment challenges, would contribute to a more realistic assessment of the application's effectiveness. By including these aspects, the study would offer a more holistic evaluation of the mobile component, strengthening its validity and applicability in medical image analysis for lung disease detection.

5. Conclusion

The results of this research demonstrate that the use of CNN in detecting lung diseases from chest radiographs is highly effective and promising. The developed model achieves an overall accuracy of 96%, with excellent performance in classifying the two main categories: "NORMAL" and "PNEUMONIA." With a precision of 0.98 and recall of 0.96 for the pneumonia category, and precision of 0.89 and recall of 0.95 for the normal category, the model shows a good balance between accuracy and detection capability.

Further analysis through the Classification Report reveals that the model not only excels in detecting lung conditions with high accuracy but also maintains consistent performance across both classes. The high f1-score, especially for the pneumonia category, confirms the model's effectiveness in providing accurate diagnoses. These results highlight the great potential of CNN as a diagnostic tool in clinical practice, which can improve both the speed and accuracy of lung disease detection.

To strengthen the discussion on future work, it is recommended to provide a more detailed explanation of how the expanded dataset and additional lung conditions will be integrated into the model. Specifically, clarifying whether the model will employ multi-class classification, hierarchical classification, or another approach to distinguish between multiple lung diseases would enhance the clarity of the research direction. Additionally, outlining potential challenges such as class imbalance, feature extraction for different conditions, and the need for additional preprocessing techniques would provide a more comprehensive outlook. By addressing these aspects, the paper would offer a clearer roadmap for future improvements, ensuring a more structured and well-justified research progression.

Additionally, the development of an Android-based application that integrates this CNN model shows promising results in practice. The application allows users to upload chest radiograph images and receive diagnoses in real-time. Trial tests of the application indicate that users can easily obtain accurate detection results, thereby enhancing access to healthcare services, especially in areas with limited medical resources.

Therefore, the integration of CNN technology into AI-based diagnostic systems, including mobile applications, can serve as an innovative solution to the challenges in lung disease detection, significantly contributing to improving the quality of healthcare services. This research paves the way for further development in AI applications in medicine, which is expected to enhance patient health outcomes and alleviate the burden on healthcare systems overall.

6. Declarations

6.1. Author Contributions

Conceptualization: M.S.H., R.R.I., D.A.D., J.T., R.Z.; Methodology: M.S.H., J.T.; Software: M.S.H., D.A.D.; Validation: M.S.H., T.B.K., R.R.I.; Formal Analysis: M.S.H., R.R.I., and A.W.; Investigation: A.M., A.W.; Resources: R.R.I.; Data Curation: D.A.D.; Writing Original Draft Preparation: M.S.H., R.R.I., and A.W.; Writing Review and Editing: R.R.I., M.S.H.; Visualization: J.T.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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