Performance Analysis of a Hybrid Deep Learning Framework Integrating CNN, RNN, LSTM, and ResNet50 for Lung Disease Recurrence Prediction Using Chest X-Ray Images and Post-Recovery Clinical Data

Olha Musa
Department of Electrical Engineering, Hasanuddin University, Bontomarannu, Gowa, Indonesia | Department of Information Systems, Faculty of Computer Science, Ichsan University, North Gorontalo, Gorontalo Province, Indonesia
musao22@student.unhas.ac.id

Syafruddin Syarif
Department of Electrical Engineering, Hasanuddin University, Bontomarannu, Gowa, Indonesia
syafruddin.s@eng.unhas.ac.id

Zahir Zainuddin
Department of Electrical Engineering, Hasanuddin University, Bontomarannu, Gowa, Indonesia
zahir@unhas.ac.id (corresponding author)

Received: 21 December 2025 | Revised: 30 January 2026, 17 February 2026, and 20 February 2026 | Accepted: 22 February 2026

 DOI: https://doi.org/10.48084/etasr.17083

ABSTRACT

Post-recovery lung disease recurrence remains a significant clinical challenge, as it can increase morbidity and delay medical treatment. Early detection of recurrence requires an analytical approach capable of comprehensively integrating visual and clinical information. This study aimed to analyze the performance of a hybrid deep learning framework using Convolutional Neural Network (CNN), ResNet50, Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) models to predict lung disease recurrence using post-recovery X-ray images and longitudinal clinical data. The dataset consists of post-recovery chest X-ray images of patients with pneumonia, pleural effusion, and tuberculosis, enriched through augmentation techniques, and longitudinal clinical data representing the dynamics of patient conditions over time. CNN and ResNet50 models are used to extract spatial features from medical images, while clinical-data RNN and LSTM models are utilized to model temporal patterns based on the patient's clinical history. The experimental results show that both CNN and ResNet50 achieved the highest accuracy of 97.78% with an F1-score of 0.978, demonstrating excellent performance in visual classification of lung images. On clinical data, RNN achieved 86% accuracy with an F1-score of 0.85, while LSTM demonstrated more stable performance with 90% accuracy and an F1-score of 0.89 in capturing longitudinal patterns of relapse. These findings confirm that the integration of spatial and temporal modeling within a hybrid deep learning framework can improve the effectiveness of early detection of lung disease relapse. The proposed approach has significant potential as a basis for developing medical decision support systems for more accurate and continuous post-recovery patient monitoring.

Keywords-recurrence; lung disease; clinical data; chest X-ray images; CNN-LSTM; deep learning analysis

I. INTRODUCTION

According to the World Health Organization (WHO), lung disease is one of the leading causes of global morbidity and mortality, ranking third among causes of death worldwide. Every year, millions of individuals are affected by various lung disorders, such as tuberculosis, pneumonia, and other chronic lung diseases [1]. Early detection and appropriate treatment have been shown to significantly reduce mortality and prevent disease progression [2]. The lungs play a vital role in the human respiratory system, capturing oxygen from the air and transferring it to the bloodstream. Therefore, accurate diagnosis of lung conditions is a crucial aspect of healthcare [3, 4]. However, in clinical practice, the risk of lung disease recurrence after a patient is declared cured remains a serious challenge, particularly due to the influence of lifestyle factors, environmental conditions, and seasonal patterns [5]. This situation emphasizes the need for an analytical approach capable of continuously monitoring changes in patient conditions.

Deep learning has opened up significant opportunities in the analysis of medical images and clinical data. Various studies have shown that deep learning models are capable of classifying lung diseases with a high level of accuracy, thus helping medical personnel make clinical decisions quickly and accurately [6]. Hybrid deep learning approaches have also been applied to the diagnosis of pneumonia and other lung diseases with promising results [7, 8]. In addition, deep learning techniques have been used in the classification of lung carcinomas based on chest CT scan images and chest X-ray image analysis to improve diagnostic accuracy [9, 10]. Several recent studies have proposed Convolutional Neural Network (CNN)-based deep learning models for multi-class classification of lung diseases using chest X-ray images, which have demonstrated strong performance, particularly in capturing the spatial characteristics of the images [11, 12]. Efforts to improve model performance have also been made through image preprocessing and data augmentation to increase the diversity of training data [13]. In addition, advanced hybrid models combining multiple network architectures and explainable mechanisms have been reported to improve the robustness and diagnostic performance of lung disease detection systems [14, 15]. Other studies have compared the performance of several popular deep learning architectures, such as CNN, InceptionV3, and ResNet50, in improving diagnostic accuracy for lung malignancies [16, 17].

Table I presents a summary of previous research related to the application of deep learning in the diagnosis of lung disease. Most studies focused on one or two types of data modalities and have not specifically examined the aspect of post-recovery lung disease recurrence. A limitation can be identified in research that simultaneously integrates lung images and longitudinal clinical data to detect the risk of lung disease recurrence after a patient is declared recovered. Furthermore, most previous studies only compare two or three deep learning models and have not comprehensively analyzed post-recovery temporal patterns.

TABLE I. LITERATURE REVIEW

Ref.	Year	Study variables	Method/ Model	Accuracy/Results
[18]	2025	Detecting respiratory diseases from sound	CNN + RNN (including LSTM)	Performance improved over a single model
[19]	2024	Classification of lung cancer from X-ray images	Hybrid CNN + LSTM	Accuracy of ~90.99% on JSRT dataset
[1]	2024	Segmentation and classification of lung diseases	Transformer-CNN + L-MLSTM	Accuracy reached 95% on CT datasets

This study focuses on analyzing the performance of a hybrid deep learning framework that integrates four main approaches: CNN, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and ResNet50. This approach combines post-recovery chest X-ray images and clinical data from the patient to detect the risk of lung disease recurrence earlier and more accurately. The novelty of this research lies in the investigation of spatial and temporal analysis to develop a single hybrid framework to support medical decision support systems and prevent lung disease recurrence.

II. MATERIALS AND METHOD

A. Dataset

The dataset used in this study was collected through formal and ethically approved procedures involving several healthcare institutions in Gorontalo, Indonesia. Research permission was obtained from Prof. Dr. Aloei Saboe Regional Hospital, followed by coordination with pulmonary specialists and primary healthcare centers to identify patients who had completed treatment and were clinically cured, such as tuberculosis patients with a treatment duration of 6 to 9 months. Eligible participants were contacted through healthcare providers and invited to participate voluntarily in the study.

1) Chest X-Ray Images

The chest X-ray image dataset includes patients who had recovered from three types of lung disease: pneumonia, pleural effusion, and tuberculosis. Patients who consented underwent follow-up chest X-ray examinations in partner medical facilities during the 2024–2025 period from two health facilities: the Pratama Mulia Clinic and the Maxima Laboratory Clinic in Gorontalo Province. All examination procedures, including registration and radiographic imaging, were performed under medical supervision, and associated costs were covered by the researchers.

Before data collection, written informed consent was obtained from all participants. To ensure privacy and confidentiality, all personal identifiers were removed, and the dataset was anonymized before analysis. All use of medical images complies with research ethics and patient consent, without violating privacy or data ownership rights. The dataset is categorized as private and non-public, but was obtained legally and ethically for research purposes.

The X-ray images represent post-recovery lung conditions and were used to train CNN and ResNet50 to learn visual patterns that indicate the likelihood of lung disease recurrence. Figures 1–3 show examples of post-recovery patient images with pneumonia, pleural effusion, and tuberculosis.

Fig. 1. X-ray Image of a patient recovering from pneumonia.

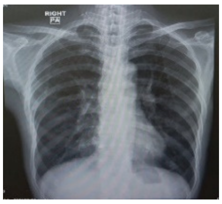

Fig. 2. X-ray image of a patient recovering from pleural effusion.

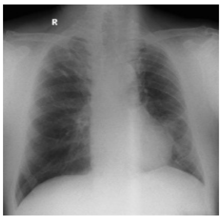

Fig. 3. X-ray image of a patient recovering from tuberculosis.

2) *Clinical Data (Longitudinal Medical Records)*

In addition to medical images, this study utilized longitudinal clinical data derived from patient medical records at Prof. Aloei Saboe Regional General Hospital, Gorontalo. This data was used to train an RNN and an LSTM to model temporal patterns and recurrence tendencies based on patient visit histories. The clinical data included chronological information that enabled time-series analysis, complementing the spatial analysis obtained from chest X-ray images.

3) *Dataset Structure*

Table II shows the structure of the clinical dataset.

TABLE II. DATASET STRUCTURE

Column	Data type	Description
Number	int64	Patient data entry sequence number
Registration_date	datetime	Date the patient registered for a follow-up visit
Medical_record_number	int64	Unique medical record number for each patient
Disease_code	object	Lung disease code (referring to ICD-10)
Disease_name	object	Lung disease name (e.g., pneumonia, pleural effusion, tuberculosis, etc.)
Doctor_name	object	Name of the treating physician
Encoded_doctor_name	object	Numerical encoding of the physician's name for statistical analysis and ML models

4) *Sample Dataset Description*

A longitudinal sample represents a single patient with multiple clinical visits during the observation period. Patients with two or more visits with the same diagnosis at different times were categorized as having potential lung disease recurrence. The data distribution shows a total of 975 patients, with the distribution, shown in Table III, indicating the dominance of tuberculosis cases in the study area, while also highlighting the challenge of class imbalance.

TABLE III. SAMPLE DATASET DESCRIPTION

Disease type	Total records	Unique patients	First_Reg	Last_Reg
Pleural Effusion	37	41	2024-01-08	2024-10-03
Pneumonia	347	357	2024-01-02	2024-12-08
Tuberculosis	519	577	2024-01-08	2024-12-08

B. *Methodology*

This study was designed to detect and analyze lung disease recurrence using a multimodal approach, integrating chest X-ray images and longitudinal clinical data. Figure 4 shows the stages of the study.

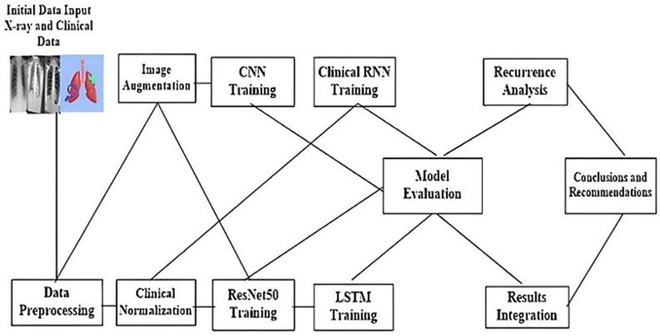

Fig. 4. Hierarchical method followed.

1) *Data Preprocessing*

The initial stage included clinical data cleaning (removal of blank values, standardization of date formats) and selection of suitable X-ray images.

2) *Image Augmentation and Clinical Normalization*

X-ray images were augmented using rotation, flipping, zooming, and contrast adjustment to improve the model's generalizability. The clinical data were normalized using numeric encoding and feature scaling for temporal modeling purposes.

3) *Model Training*

Four models were used:

- A CNN for spatial feature extraction from X-ray images.
- A ResNet50 as a transfer learning model.
- An RNN and an LSTM model for temporal pattern analysis of longitudinal clinical data.

4) *Model Evaluation*

Evaluation was conducted using test data amounting to 15% of the total dataset, with metrics such as accuracy, F1-score, AUC, and performance curves.

5) *Results Integration and Recurrence Analysis*

The results of the image and clinical model evaluations were integrated to analyze the frequency and pattern of lung disease recurrence. CNN and ResNet50 excelled in visual pattern recognition, while RNN and LSTM were effective in predicting temporal patterns.

C. Algorithm

The RNN and LSTM models were used to capture temporal dependencies in clinical data, while CNN and ResNet50 learned the spatial characteristics of lung images. The integration of these four approaches enabled a comprehensive analysis of post-recovery patient outcomes.

1) Convolutional Neural Network (CNN) Model

A CNN was used to classify lung conditions based on post-recovery X-ray images.

$$y_{i,j} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} r_{i+m,j+n} \cdot w_{m,n} + b \quad (1)$$

2) Recurrent Neural Network (RNN) Model

An RNN model was used to analyze changes in the patient's clinical condition over the observation period. However, RNNs have limitations in capturing long-term dependencies due to the vanishing gradient problem.

$$h_t = f(W_h h_{t-1} + W_r r_t + b) \quad (2)$$

3) Long Short-Term Memory (LSTM)

An LSTM was used to capture complex temporal patterns from longitudinal clinical data of patients after recovery from lung disease.

Forget Gate:

$$F_t = \sigma\,(W_t[h_{t-1,} r_t + b_f]) \quad (3)$$

Input Gate:

$$i_t = \sigma(W_i[h_{t-1}, r_t] + b_i) \quad (4)$$

Cell State:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (5)$$

Output Gate:

$$O_t = \sigma(W_0\ [h_{t-1,} r_t] + b_0) \quad (6)$$

Hidden State:

$$h_t = O_t \odot tanh(C_t) \quad (7)$$

4) ResNet50

ResNet50 was used to compare with CNN to improve the spatial feature extraction capability of lung images.

$$y = f\,(r) + r \quad (8)$$

5) Hybrid Model Integration

The proposed hybrid approach integrates image-based models (CNN and ResNet50) with temporal-based models (RNN and LSTM). This integration enables a comprehensive analysis of the spatial features of medical images and the dynamics of a patient's clinical condition over time. This hybrid approach is expected to improve the accuracy of lung disease recurrence detection compared to using either model separately.

III. RESULTS AND DISCUSSION

A. Description of X-Ray Image and Clinical Data Datasets

The research dataset consists of two main components: post-recovery chest X-ray images of patients and longitudinal clinical data. A total of 180 X-ray images were used, consisting of 40 pneumonia images, 20 pleural effusion images, and 120 tuberculosis images, collected from two official clinics in Gorontalo with institutional permission and patient consent.

TABLE IV. DESCRIPTION OF THE COMBINED DATASET

Attribute	Description
Total clinical records (filtered 3 diseases)	975
Unique patients	834
Time range (registrations)	2024-01-02 to 2024-12-08
Disease groups (focus)	Pneumonia, Pleural Effusion, Tuberculosis
Total chest X-ray images	180 images
X-ray images per disease	Pneumonia: 40; Pleural Effusion: 20; Tuberculosis: 120
Image acquisition stage	Post-recovery
Image source	Two authorized clinics in Gorontalo
Image preprocessing	Augmentation (rotation, flip, zoom, contrast adjustment
Longitudinal clinical features	Registration date, disease code (ICD-10), physician ID (encoded)

The longitudinal clinical data included 975 medical records from 834 unique patients in 2024, containing information on visit dates, ICD-10 disease codes, and physician identifiers, which were numerically encoded for temporal modeling purposes.

B. Lung Disease Recurrence Analysis

Longitudinal analysis showed that tuberculosis had the highest recurrence rate compared to pneumonia and pleural effusion. Patients were categorized as having a recurrence if they had more than one visit with the same diagnosis at different times. This variation in recurrence rates reflects differences in disease characteristics and the influence of external factors such as therapy adherence and environmental conditions.

TABLE V. DISTRIBUTION OF PATIENT RECURRENCES BY DISEASE TYPE (2024)

Disease code	Disease name	Total patients	Number of relapses	Relapse rate (%)
J18.9	Pneumonia	347	10	8.11
J90	Pleural Effusion	37	3	2.88
A16.2	Tuberculous	519	48	9.25

Relapse rates in patients after clinical recovery varied across diseases, with tuberculosis showing the highest rates. This variation reflects differences in clinical patterns influenced by external factors such as the environment or adherence to therapy. The graph in Figure 5 shows the highest proportion of relapsed patients in tuberculosis and pleural effusion, indicating a tendency for both diseases to relapse after recovery.

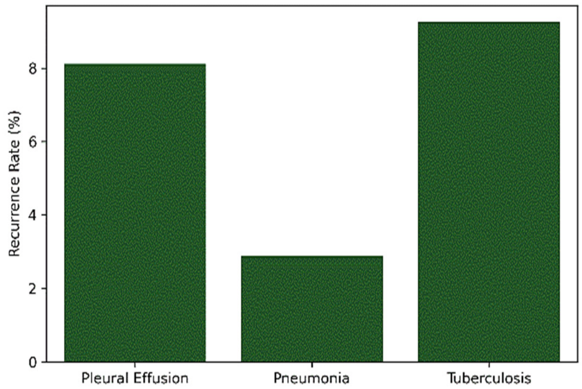

Fig. 5. Graph of recurrence frequency per disease (2024).

C. Deep Learning Model Results

The CNN and ResNet50 were used to analyze spatial patterns in post-recovery X-ray images, while the clinical RNN and LSTM models were applied to longitudinal clinical data to capture temporal patterns of recurrence. All models were trained with a data split of 70% training, 15% validation, and 15% testing. Figure 7 shows the confusion matrices for the CNN and ResNet50 models. The highest proportion was in the tuberculosis class, which helped improve the performance and generalization of the CNN model.

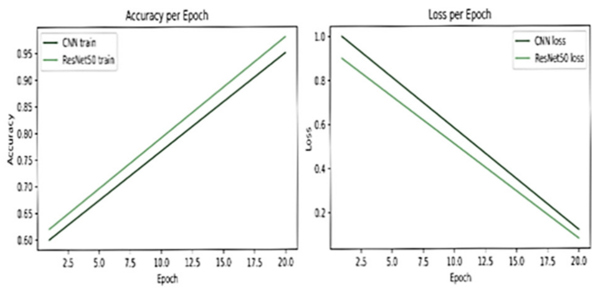

Fig. 6. Accuracy and loss curves of CNN vs ResNet50.

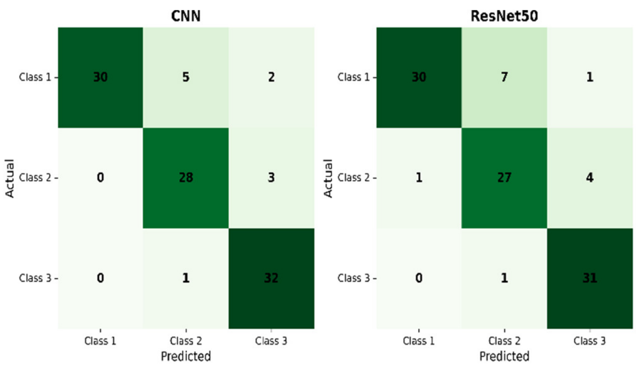

Fig. 7. Confusion matrices for the CNN and ResNet50 models.

The evaluation results show that the image-based models performed very well, with CNN and ResNet50 achieving 97.78% accuracy with an F1-score of 0.978. This confirms the effectiveness of convolutional models in extracting visual lung features despite a relatively limited number of images.

TABLE VI. CNN AND RESNET50 MODEL EVALUATION

Model	**Accuracy**	**F1**
CNN	0.977777778	0.978477267
ResNet50	0.977777778	0.978477267

D. Clinical-Data Model Performance Evaluation

The clinical data-based models exhibited different characteristics. The clinical RNN achieved 86% accuracy but was less than optimal in capturing complex temporal variations. The LSTM model demonstrated more stable performance with 90% accuracy and an F1-score of 0.89, indicating its ability to model long-term dependencies in longitudinal patient data.

TABLE VII. PERFORMANCE OF CLINICAL RNN AND LSTM

Model	**Accuracy**	**F1**	**RMSE**
Clinical RNN	0.86	0.85	0.12
Clinical LSTM	0.9	0.89	0.09

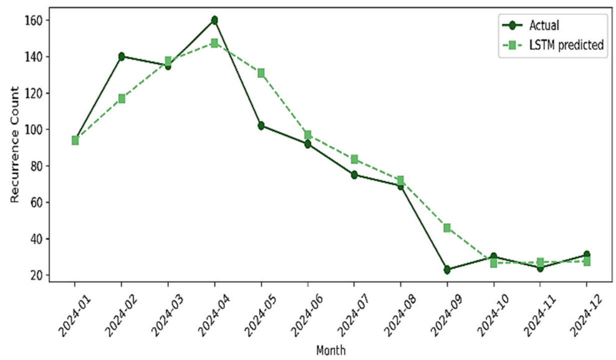

Fig. 8. Visualization of longitudinal recurrence trend (LSTM model).

Figure 9 indicates that the models achieve stable training behavior without notable overfitting, demonstrating a good balance between the training and test data.

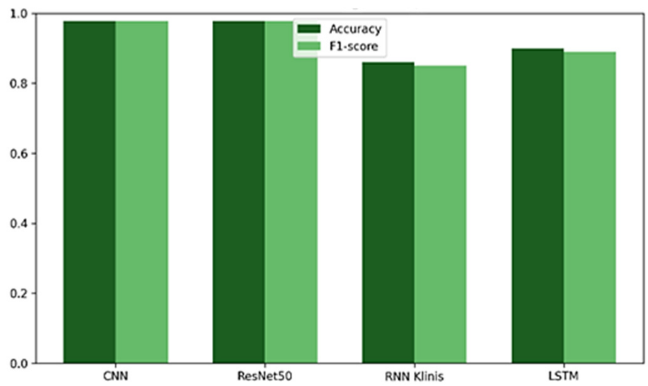

Fig. 9. Model performance comparison.

E. Integrative Model Discussion and Recurrence

Based on the evaluation results, both CNN and ResNet50 demonstrated equally high performance in image classification, while the LSTM model achieved the best performance in longitudinal recurrence prediction. Therefore, the integration of image-based and clinical data approaches is proposed as a hybrid deep learning framework that utilizes spatial and temporal information in a complementary manner.

TABLE VIII. PERFORMANCE COMPARISON OF ALL METHODS

Model	Accuracy	F1
CNN	0.9777778	0.978477267
ResNet50	0.9777778	0.978477267
Clinical RNN	0.86	0.85
Clinical LSTM	0.9	0.89

A multimodal approach combining image models (CNN/ResNet50) and clinical models (LSTM) provides comprehensive analysis for post-recovery patient monitoring and can serve as the basis for developing a medical Decision Support System (DSS). CNN and ResNet50 identified spatial changes in X-ray images, while LSTM predicted the likelihood of recurrence based on the order of patient visits.

The proposed framework compares favorably with recent deep learning studies that report accuracies between 90 and 95% [1, 6, 19]. The CNN and ResNet50 models achieved 97.78% accuracy with an F1 score of 0.978, outperforming comparable approaches, as shown in Table IX. The integration of longitudinal clinical data using RNN and LSTM further enables temporal relapse prediction, demonstrating the superiority of multimodal learning for post-recovery lung disease analysis.

TABLE IX. COMPARISON WITH EXISTING STUDIES

Study	Method	Data	Accuracy	Contribution
[1]	Transformer+ CNN+LSTM	CT images	~95%	Hybrid architecture for classification
[19]	CNN+LSTM	X-ray	90.99%	Hybrid detection model
[6]	Pretrained CNN	X-ray	Competitive	Multi-class classification
This study	CNN+ResNet50+ RNN+LSTM	X-ray+ Clinical data	97.78% (image) / 90% (clinical)	Multimodal recurrence prediction

IV. CONCLUSION AND FUTURE WORK

This study investigated a hybrid deep learning framework for predicting lung disease recurrence using the integration of post-recovery chest X-ray images and longitudinal clinical data. Four primary approaches were evaluated: CNN and ResNet50 for spatial modeling of medical images, and clinical RNN and LSTM for temporal pattern modeling based on patient clinical history. Experimental results showed that the CNN and ResNet50 models achieved very high image classification performance with 97.78% accuracy and an F1-score of 0.978, confirming the effectiveness of the image-based approach in detecting changes in lung condition after recovery. When modeling longitudinal clinical data, RNN achieved 86% accuracy, while LSTM demonstrated more stable performance with 90% accuracy and an F1-score of 0.89, capturing temporal patterns of lung disease recurrence.

These findings indicate that the integration of spatial and temporal modeling within a hybrid deep learning framework can improve the effectiveness of early detection of lung disease recurrence compared to either approach alone. The proposed framework has significant potential as a basis for developing medical decision support systems for continuous post-recovery patient monitoring. Further research could focus on expanding the dataset, validating it on a larger cohort, and integrating the system into a real clinical environment.

ACKNOWLEDGEMENTS

The authors would like to thank the Director of Prof. Aloei Saboe Regional General Hospital, Gorontalo, the Director of the Maxima Laboratory Clinic, Gorontalo Branch, and the Head of Radiology of the Pratama Mulia Gorontalo Clinic, Dr. Elen M. Lukum, Sp. Rad, M. Kes., who provided access to important data for this research, and Dr. Mohammad Zukri Antuke, Sp. P, who provided consultation in this investigation.

REFERENCES

[1] S. M. Shafi and S. K. Chinnappan, "Hybrid transformer-CNN and LSTM model for lung disease segmentation and classification," *PeerJ Computer Science*, vol. 10, Dec. 2024, Art. no. e2444, https://doi.org/10.7717/peerj-cs.2444.

[2] P. Sengodan, K. Srinivasan, R. Pichamuthu, and S. Matheswaran, "Early detection and classification of malignant lung nodules from CT images: An optimal ensemble learning," *Expert Systems with Applications*, vol. 229, Nov. 2023, Art. no. 120361, https://doi.org/10.1016/j.eswa.2023.120361.

[3] M. Jasmine Pemeena Priyadarsini *et al.*, "Lung Diseases Detection Using Various Deep Learning Algorithms," *Journal of Healthcare Engineering*, vol. 2023, no. 1, Jan. 2023, Art. no. 3563696, https://doi.org/10.1155/2023/3563696.

[4] O. R. Musa and A. Alang, "Analisis Penyakit Paru-Paru Menggunakan Algoritma K-Nearest Neighbors Pada Rumah Sakit Aloei Saboe Kota Gorontalo," *ILKOM Jurnal Ilmiah*, vol. 9, no. 3, pp. 348–352, Dec. 2017, https://doi.org/10.33096/ilkom.v9i3.177.348-352.

[5] O. Musa, S. Syarif, and Z. Zainuddin, "Application of Deep Learning Models in Clinical Data Analysis for Lung Disease Diagnosis," in *2025 8th International Conference on Trends in Electronics and Informatics (ICOEI)*, Apr. 2025, pp. 1214–1219, https://doi.org/10.1109/ICOEI65986.2025.11013196.

[6] S. H. Karaddi and L. D. Sharma, "Automated multi-class classification of lung diseases from CXR-images using pre-trained convolutional neural networks," *Expert Systems with Applications*, vol. 211, Jan. 2023, Art. no. 118650, https://doi.org/10.1016/j.eswa.2022.118650.

[7] S. Y. Sourab and M. A. Kabir, "A comparison of hybrid deep learning models for pneumonia diagnosis from chest radiograms," *Sensors International*, vol. 3, 2022, Art. no. 100167, https://doi.org/10.1016/j.sintl.2022.100167.

[8] S. Bharati, P. Podder, and M. R. H. Mondal, "Hybrid deep learning for detecting lung diseases from X-ray images," *Informatics in Medicine Unlocked*, vol. 20, 2020, Art. no. 100391, https://doi.org/10.1016/j.imu.2020.100391.

[9] S. V. S. N. Murthy and P. M. Krishna Prasad, "Adversarial transformer network for classification of lung cancer disease from CT scan images," *Biomedical Signal Processing and Control*, vol. 86, Sept. 2023, Art. no. 105327, https://doi.org/10.1016/j.bspc.2023.105327.

[10] N. Ozcelik, A. E. Ozcelik, N. M. Guner Zirih, I. Selimoglu, and A. Gumus, "Deep learning for diagnosis of malign pleural effusion on computed tomography images," *Clinics*, vol. 78, Jan. 2023, Art. no. 100210, https://doi.org/10.1016/j.clinsp.2023.100210.

[11] K. Gupta and V. Bajaj, "Deep learning models-based CT-scan image classification for automated screening of COVID-19," *Biomedical Signal Processing and Control*, vol. 80, Feb. 2023, Art. no. 104268, https://doi.org/10.1016/j.bspc.2022.104268.

[12] C. H. Tsai *et al.*, "Automatic deep learning-based pleural effusion classification in lung ultrasound images for respiratory pathology diagnosis," *Physica Medica*, vol. 83, pp. 38–45, Mar. 2021, https://doi.org/10.1016/j.ejmp.2021.02.023.

[13] R. Raza *et al.*, "Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images," *Engineering Applications of Artificial Intelligence*, vol. 126, Nov. 2023, Art. no. 106902, https://doi.org/10.1016/j.engappai.2023.106902.

[14] A. G. Taylor, C. Mielke, and J. Mongan, "Automated detection of moderate and large pneumothorax on frontal chest X-rays using deep convolutional neural networks: A retrospective study," *PLOS Medicine*, vol. 15, no. 11, Nov. 2018, Art. no. e1002697, https://doi.org/10.1371/journal.pmed.1002697.

[15] M. K. Islam, M. M. Rahman, M. S. Ali, S. M. Mahim, and M. S. Miah, "Enhancing lung abnormalities diagnosis using hybrid DCNN-ViT-GRU model with explainable AI: A deep learning approach," *Image and Vision Computing*, vol. 142, Feb. 2024, Art. no. 104918, https://doi.org/10.1016/j.imavis.2024.104918.

[16] J. Bokefode, M. P. Rao, and K. G, "Ensemble Deep Learning Models for Lung Cancer Diagnosis in Histopathological Images," *Procedia Computer Science*, vol. 215, pp. 471–482, 2022, https://doi.org/10.1016/j.procs.2022.12.049.

[17] K. Kansal, T. B. Chandra, and A. Singh, "ResNet-50 vs. EfficientNet-B0: Multi-Centric Classification of Various Lung Abnormalities Using Deep Learning," *Procedia Computer Science*, vol. 235, pp. 70–80, 2024, https://doi.org/10.1016/j.procs.2024.04.007.

[18] T. Bikku *et al.*, "Deep Learning-Driven Early Diagnosis of Respiratory Diseases using CNN-RNN Fusion on Lung Sound Data," *Scientific Reports*, vol. 15, no. 1, Nov. 2025, Art. no. 45233, https://doi.org/10.1038/s41598-025-28832-7.

[19] F. A. Badish, A. Elbayoudi, and N. A. Badish, "Hybrid CNN-LSTM Network for Lung Cancer Detection from Chest X-ray Images," *Asian Journal of Mathematics and Computer Research*, vol. 32, no. 3, pp. 133–146, July 2025, https://doi.org/10.56557/ajomcor/2025/v32i39465.