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Analysis of a Hybrid DNN–BiLSTM Framework for Longitudinal Prediction of Lung Disease Recurrence Using Clinical Data

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Abstract

Predicting lung disease recurrence from longitudinal clinical data remains challenging because irregular temporal patterns and heterogeneous patient characteristics reduce the effectiveness of conventional deep learning models. This study analyzes a hybrid Deep Neural Network (DNN)–Bidirectional Long Short-Term Memory (BiLSTM) framework for the longitudinal prediction of lung disease recurrence using clinical data collected between 2021 and 2024 from a referral hospital in Gorontalo. The dataset includes demographic information, laboratory examination results, clinical diagnoses, and longitudinal medical records. Lung disease recurrence is defined as the reappearance or worsening of the disease during longitudinal clinical follow-up after the initial diagnosis or treatment. The proposed framework combines DNN to learn complex nonlinear relationships among multivariate clinical features and BiLSTM to capture temporal dependencies across sequential patient observations. Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and Root Mean Square Error (RMSE), and compared with standalone DNN and BiLSTM models. Experimental results demonstrate that the proposed hybrid framework consistently outperformed the individual models, achieving an improvement of approximately 7–10% across the evaluation metrics while providing more stable longitudinal prediction performance. Furthermore, multivariate analysis identified dominant clinical variables associated with lung disease recurrence, improving the interpretability of prediction results for clinical decision-making. These findings indicate that the proposed framework provides an effective computational approach for longitudinal clinical prediction and supports the development of intelligent clinical decision support systems for recurrence risk assessment.

Keywords: Hybrid DNN–BiLSTM; Deep Learning Analysis; Longitudinal Clinical Data; Lung Disease Recurrence; Clinical Prediction.

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. Lung disease remains one of the leading causes of morbidity and mortality worldwide and continues to impose a substantial burden on healthcare systems. Although diagnostic techniques and treatment strategies have advanced considerably, disease recurrence after treatment remains a major clinical challenge that requires continuous patient monitoring. In recent years, Artificial Intelligence (AI), particularly deep learning, has demonstrated significant potential for improving the accuracy of lung disease diagnosis, classification, and prediction using medical data [1]–[5]. Therefore, developing predictive models capable of identifying recurrence risk at an early stage is essential for supporting clinical decision-making and improving healthcare services.

The rapid advancement of Artificial Intelligence (AI), particularly Deep Learning, has significantly improved medical data analysis by enhancing the accuracy of disease diagnosis, classification, and prediction. Various deep learning architectures, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Bidirectional Long Short-Term Memory (BiLSTM), have been widely adopted because of their ability to learn both spatial and temporal representations from medical data more effectively than conventional machine learning approaches. Furthermore, hybrid deep learning models that integrate multiple neural

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network architectures have demonstrated superior performance in medical image classification, clinical data analysis, and disease prediction, making them a promising approach for intelligent clinical decision support systems [3], [5].

Previous studies have demonstrated that deep learning models can significantly improve lung disease analysis by employing architectures such as CNN, LSTM, BiLSTM, and hybrid neural networks that integrate multiple learning mechanisms to obtain more comprehensive feature representations. These approaches have achieved promising performance in medical image classification and clinical prediction compared with single-model architectures [5]–[7]. However, most existing studies primarily focus on image-based classification or disease diagnosis using cross-sectional data, without fully exploiting the temporal characteristics of longitudinal clinical data. Furthermore, the integration of multivariate clinical feature analysis with temporal sequence learning for lung disease recurrence prediction remains limited, highlighting the need for a more comprehensive hybrid deep learning framework.

Despite the promising performance of deep learning models in lung disease analysis, several research gaps remain. Most previous studies have focused on medical image classification or disease diagnosis using cross-sectional data, which limits their ability to represent longitudinal changes in patient conditions during clinical follow-up. Furthermore, the utilization of multivariate longitudinal clinical data for lung disease recurrence prediction remains limited, particularly in integrating nonlinear clinical feature learning with temporal dependencies across sequential patient observations [8]–[12]. These limitations indicate the need for a hybrid deep learning framework capable of effectively modeling longitudinal clinical characteristics to provide more accurate and stable recurrence prediction.

Based on the identified research gaps, this study proposes a hybrid Deep Neural Network (DNN)–Bidirectional Long Short-Term Memory (BiLSTM) framework for longitudinal prediction of lung disease recurrence using multivariate clinical data. Unlike previous studies that primarily focused on medical image classification, cross-sectional diagnosis, or single deep learning architectures, the proposed framework integrates the nonlinear feature learning capability of DNN with the temporal sequence modeling capability of BiLSTM to capture disease progression patterns from continuous patient observations. This integration enables more comprehensive learning of complex clinical characteristics and temporal dependencies, thereby improving the robustness and adaptability of recurrence prediction models [13], [14].

This study provides several scientific contributions to the field of deep learning-based clinical prediction. First, it introduces a hybrid DNN–BiLSTM framework that combines nonlinear multivariate feature extraction with temporal dependency learning from longitudinal clinical data. Second, the proposed framework demonstrates the potential of integrating multivariate clinical variables collected over multiple observation periods to improve recurrence prediction compared with conventional cross-sectional approaches. Third, this research contributes to the development of an Artificial Intelligence-based Clinical Decision Support System (CDSS) by providing a predictive framework capable of supporting continuous patient monitoring and evidence-based clinical decision-making [4], [15], [16].

Therefore, this study aims to develop and comprehensively evaluate a hybrid Deep Neural Network (DNN)–Bidirectional Long Short-Term Memory (BiLSTM) framework for predicting lung disease recurrence using multivariate longitudinal clinical data collected from referral hospitals in Gorontalo Province during the period 2021–2024. The proposed framework is designed to model nonlinear relationships among multivariate clinical variables while simultaneously capturing temporal dependencies across sequential patient observations. Model performance is evaluated using multiple quantitative metrics, including Accuracy, Precision, Recall, F1-score, Area Under the Curve (AUC), and Root Mean Square Error (RMSE) to ensure a comprehensive assessment of predictive capability. Furthermore, multivariate analysis is conducted to identify the dominant clinical factors associated with recurrence risk. The findings of this study are expected to contribute to the advancement of hybrid deep learning methodologies for longitudinal clinical prediction and provide a scientific foundation for future research on intelligent clinical decision support systems [4], [13].

To provide a clearer overview of the existing research landscape, Table I summarizes representative studies related to lung disease prediction and classification using deep learning approaches. The comparison highlights differences in data type, deep learning architecture, longitudinal data utilization, recurrence prediction capabilities, and the key contributions of each study. As shown in Table I, previous studies have largely focused on medical image classification using CNN-based or hybrid architectures, while only a small number have explored longitudinal clinical data for recurrence prediction. Furthermore, existing hybrid models generally emphasize diagnostic accuracy without explicitly modeling temporal clinical progression as shown in the table below:

Table 1. Comparison of Previous Studies and The Proposed Research

Study	Data Type	Deep Learning Model	Longitudinal Data	Recurrence Prediction	Main Contribution
Shafi & Chinnappan [6]	CT Images	Transformer + CNN + LSTM	✗	✗	Hybrid architecture for medical image classification
Karaddi & Sharma [5]	Chest X-ray	Pre-trained CNN	✗	✗	Multi-class lung disease classification
Badish et al. [17]	Chest X-ray	CNN + LSTM	✗	✗	Hybrid model for lung disease detection
Hybrid DCNN–ViT–GRU [18]	Chest X-ray	DCNN + Vision Transformer + GRU	✗	✗	Advanced hybrid architecture for image-based diagnosis
IEEE Study [4]	Longitudinal Clinical Data	Deep Learning + Multivariate Analysis	✓	✓	Clinical feature analysis for longitudinal recurrence prediction
Proposed Study	Longitudinal Multivariate Clinical Data	**Hybrid DNN + BiLSTM**	✓	✓	Hybrid framework integrating nonlinear feature learning and temporal dependency modeling for lung disease recurrence prediction

Therefore, the proposed DNN–BiLSTM hybrid framework addresses these limitations by integrating nonlinear feature learning with temporal dependency modeling using multivariate longitudinal clinical data, providing a more comprehensive approach to predicting lung disease recurrence.

Method

A. Deep Neural Network – (DNN)

This hybrid structure integrates multiple neural network components, enabling a high degree of flexibility and versatility across various application scenarios. The design and arrangement of these networks are task-dependent, adapting to differences in input modalities and predictive objectives. In the context of reservoir production forecasting, a specialized HDNN architecture has been configured to meet domain-specific requirements [19]. Likewise, the EH-DNN presents an advanced two-step predictive mechanism that markedly improves time-series accuracy by combining preclassification procedures with detailed regression-based modeling [14], [20].

B. Bidirectional Long Short-Term Memory (BiLSTM)

BiLSTM is a variant of LSTM that operates two parallel networks in opposite temporal directions. The forward layer extracts patterns based on the data flow in the forward processing pipeline, while the backward layer processes sequences in the reverse layer, i.e., temporal dependencies that arise when the data is read backward. The combination of these two representations at each time point yields a more comprehensive and contextual understanding of sequence dynamics [21]–[23].

C. Hybrid DNN–BiLSTM Architecture Design

An integrated modeling framework combining capabilities DNNs with sequence processing the BiLSTM model was used to analyze longitudinal clinical data from pulmonary patients. This architecture was designed to leverage the combined strengths of Deep Neural Networks (DNNs) in extracting non-linear features from tabular data and BiLSTM's ability to capture bidirectional temporal patterns in patient time-series data. This architecture is shown in **Figure 1**.

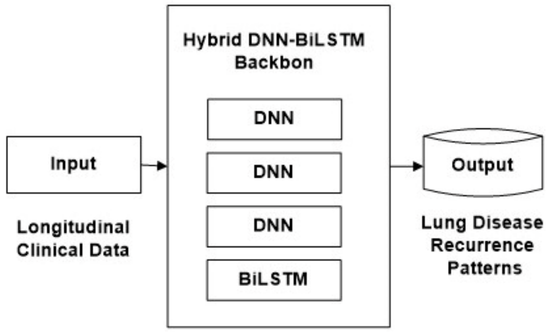

Figure 1. Hybrid Model Architecture Design (DNN–BiLSTM)

In the initial stage, longitudinal clinical variables, including patient age, gender, laboratory examination results, hospitalization history, diagnosis records, and treatment information, are provided as inputs to the proposed hybrid architecture. These structured clinical features are first processed through multiple Dense layers within the Deep Neural Network (DNN) to extract high-level nonlinear feature representations. The extracted features are subsequently forwarded to the BiLSTM layer, which models temporal dependencies by processing sequential patient observations in both forward and backward directions. This bidirectional learning mechanism enables the model to capture long-term clinical progression patterns and improves recurrence prediction accuracy. Finally, the fully connected output layer generates the probability of lung disease recurrence based on the integrated spatial and temporal feature representations. The integration of DNN and BiLSTM provides a more robust predictive framework for heterogeneous longitudinal clinical data compared with conventional single-model approaches [18], [19], [24].

D. Data Preprocessing

Data preprocessing constitutes a fundamental stage in the proposed prediction framework because the quality of input data directly affects the reliability of deep learning models. The preprocessing procedure consisted of data cleaning, duplicate record removal, handling missing values, feature transformation, categorical encoding, and normalization to produce a consistent and high-quality dataset before model training. These preprocessing techniques reduce data inconsistency, improve feature representation, and enhance model convergence during the learning process [25], [26].

E. Struktur Dataset

Table 1 presents the distribution of lung disease cases collected from the clinical dataset during the 2021–2024 observation period. The results indicate variations in the frequency of each disease category, reflecting differences in disease prevalence among patients treated at the hospital. Diseases with higher case frequencies contribute more significantly to the learning process of the proposed Hybrid DNN–BiLSTM model because they provide richer longitudinal clinical information. This distribution also confirms that the dataset contains multiple lung disease categories, enabling the model to learn diverse clinical patterns and improve its generalization capability.

Table 1. Structure of the 2021–2024 Clinical Dataset

No	Column Name	Data Type	Description
1	Number	Integer	Patient data entry sequence number
2	Registration Date	Datetime	Date of patient outpatient/checkup registration
3	Medical Registration Number	String	Patient medical record number
4	Disease Identification Number	String	ICD code or disease code before normalization
5	Disease Identification Number	String	Full name of disease (Indonesian/hospital version)
6	Doctor Identification Number	String	Name of responsible physician
7	Doctor Identification Number	Integer	Number code from preprocessing of physician
8	Year	Integer	Year of examination (2021–2024)

The structured dataset was designed to preserve temporal information from repeated patient examinations conducted between 2021 and 2024. Each record represents one clinical observation, while patient identifiers enable chronological linkage between successive visits. This longitudinal organization allows the proposed hybrid DNN–

BiLSTM architecture to learn disease progression patterns over time instead of relying solely on isolated clinical observations, thereby improving recurrence prediction capability [9], [25].

F. Methodology Flow

The proposed research methodology consists of six sequential stages, as illustrated in Figure 2. The process begins with data collection, where longitudinal clinical records of lung disease patients from 2021 to 2024 were obtained from the hospital medical record system. The collected data include demographic information, laboratory examination results, diagnosis history, treatment records, and follow-up observations. These longitudinal data provide the temporal information required for recurrence prediction [4], [25].

The second stage is data preprocessing, which includes data cleaning, missing value handling, categorical variable encoding, and feature normalization to improve data consistency before model development. Proper preprocessing reduces data noise and enhances the learning capability of deep neural networks [25], [26].

Next, the processed dataset is divided into training (70%), validation (15%), and testing (15%) subsets. The proposed hybrid DNN–BiLSTM model is subsequently trained using the training dataset, while hyperparameter tuning is performed using the validation dataset to determine the optimal learning configuration and reduce overfitting [13], [14].

Model performance is then evaluated using several performance metrics, including Accuracy, Precision, Recall, F1-Score, Area Under the Curve (AUC), and Root Mean Square Error (RMSE). Finally, the experimental results are analyzed and presented through comparative tables and graphical visualizations to facilitate interpretation and comparison with previous studies [8], [18].

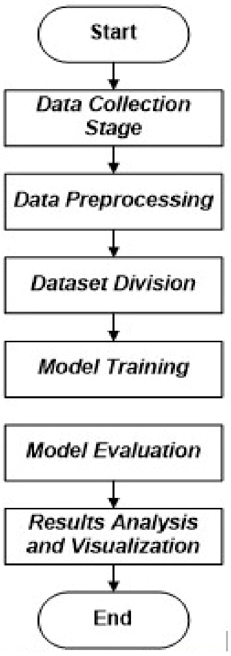

Figure 2. Methodology Flowchart

Figure 2 illustrates the complete workflow adopted in this study, providing a systematic and reproducible framework for developing the proposed hybrid deep learning model for longitudinal prediction of lung disease recurrence.

Results and Discussion

A. Clinical Dataset Characteristics

The quality and representativeness of the dataset play a crucial role in developing reliable deep learning models. This study utilized longitudinal clinical records of lung disease patients collected between 2021 and 2024 to develop the proposed Hybrid DNN–BiLSTM framework. Unlike cross-sectional data, the longitudinal dataset preserves temporal information from repeated patient visits, enabling the model to learn disease progression and recurrence patterns more effectively

Table 2 summarizes the distribution of lung disease cases collected between 2021 and 2024. The dataset consists of multiple disease categories with heterogeneous case frequencies, reflecting actual hospital conditions. This diversity provides representative clinical information for developing and evaluating the proposed Hybrid DNN–BiLSTM framework.

Table 2. Total Cases Per Disease

Disease	Total Cases
Tuberculosis	2313
Pneumonia	961
Asthma	294
Chronic Bronchitis	206
Pleural Effusion	92
COPD	92
Pneumothorax	10
Emphysema	8

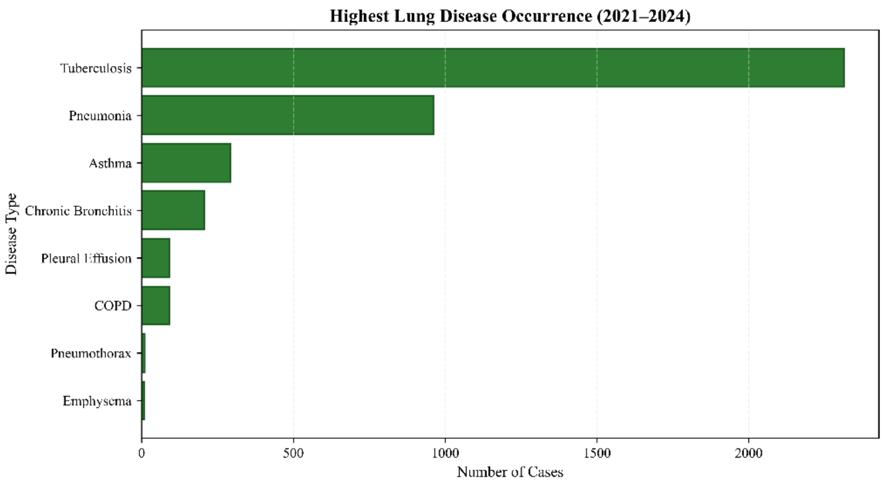

Figure 3. Highest_Disease_Occurrence

Figure 3 illustrates the distribution of lung disease cases across all disease categories. The varying frequencies indicate that the dataset represents heterogeneous clinical conditions, enabling the proposed model to learn generalized disease characteristics.

Table 3 Annual Cases Per Disease

Disease_Clean	2021	2022	2023	2024
Asthma	13	50	97	134
COPD	3	24	5	60
Chronic Bronchitis	20	11	72	103
Emphysema	1	3	2	2
Pleural Effusion	5	24	22	41
Pneumonia	171	227	206	357
Pneumothorax	2	0	1	7
Tuberculosis	332	767	637	577

Table 3 presents the annual distribution of lung disease cases from 2021 to 2024. The variation in yearly case numbers demonstrates the dynamic characteristics of lung disease occurrence and provides valuable temporal information for longitudinal prediction.

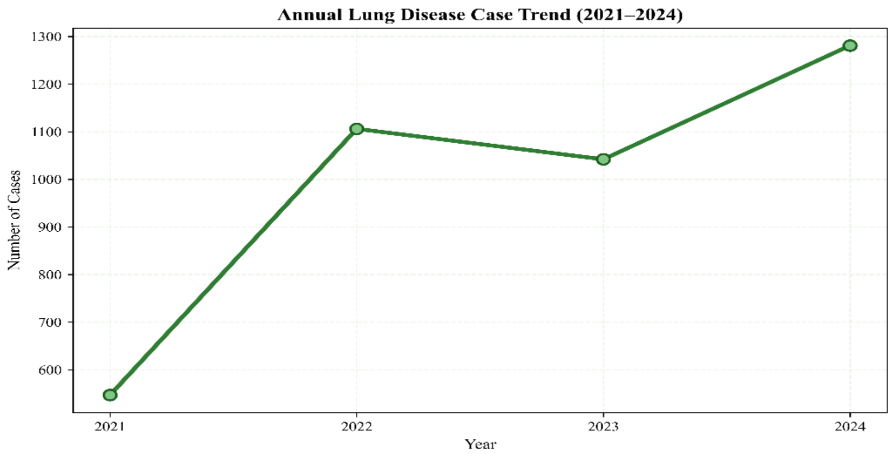

Figure 4. Annual Distribution of Lung Disease Recurrence (2021–2024)

Figure 4 shows the yearly recurrence trends of lung diseases. The fluctuations observed over the four-year period indicate that temporal information contributes significantly to recurrence prediction and supports the use of sequential learning through BiLSTM.

The characteristics of the longitudinal data are further displayed in each Table and Figure, which show the variation in the number of lung disease cases during the period 2021–2024. These variations provide temporal information that can be effectively learned by BiLSTM to recognize long-term dependencies between clinical data. In addition, the heatmap in Figure 5 shows that the recurrence pattern differs by month and disease type, indicating that temporal factors play an important role in recurrence prediction. Therefore, the combination of nonlinear feature learning through DNN and temporal sequence learning through BiLSTM provides a strong basis for predicting lung disease recurrence in real clinical settings.

Table 4. Monthly Distribution of Lung Disease Recurrence

Disease_Clean	1	2	3	4	5	6	7	8	9	10	11	12
Asthma	15	43	29	31	15	28	24	31	21	25	11	21
COPD	3	13	11	9	9	9	8	14	4	4	5	3
Chronic Bronchitis	16	18	22	12	19	26	21	18	12	14	10	18
Emphysema	0	0	0	2	1	1	1	1	2	0	0	0
Pleural Effusion	7	17	7	12	7	4	6	11	8	4	5	4
Pneumonia	60	90	98	87	83	122	99	80	60	67	58	57
Pneumothorax	1	1	2	1	2	1	0	0	0	1	1	0
Tuberculosis	204	198	188	188	225	187	161	188	171	193	180	230

Table 4 summarizes monthly recurrence frequencies for each lung disease category. The results reveal temporal variations among diseases, indicating that recurrence patterns differ across observation periods.

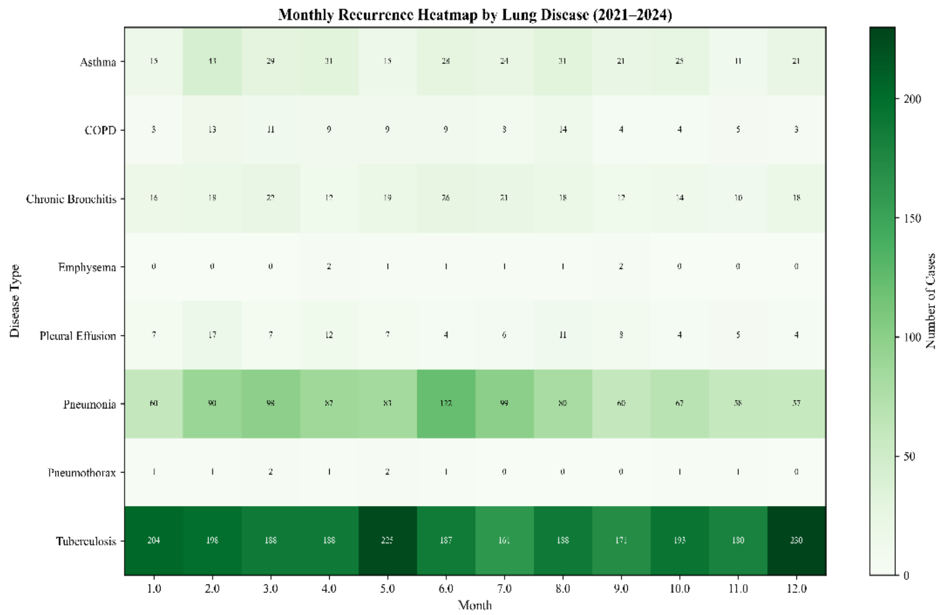

Figure 5. Monthly Heatmap of Lung Disease Recurrence

Figure 5 visualizes monthly recurrence patterns using a heatmap. Higher color intensity represents periods with increased recurrence frequency, confirming that temporal clinical information plays an important role in disease recurrence prediction.

B. Performance of Individual Deep Learning Models

Before developing the proposed Hybrid DNN–BiLSTM framework, the predictive performance of the standalone Deep Neural Network (DNN) and Bidirectional Long Short-Term Memory (BiLSTM) models was evaluated to establish a baseline for comparison. Figure 6 shows that both models successfully learned meaningful patterns from the longitudinal clinical dataset but exhibited different learning characteristics. The DNN effectively captured nonlinear relationships among heterogeneous clinical variables, whereas the BiLSTM learned temporal dependencies from sequential patient records.

Despite its ability to model complex feature interactions, the DNN processes each observation independently and therefore cannot fully preserve temporal information associated with disease progression. In contrast, BiLSTM effectively models long-term dependencies by analyzing patient records in both forward and backward directions, making it more suitable for longitudinal healthcare data. However, relying solely on sequential learning limits its capability to represent highly nonlinear relationships among multivariate clinical variables.

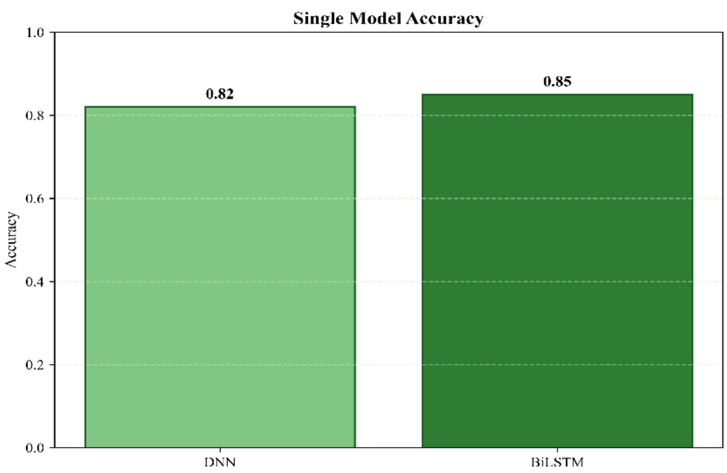

Figure 6. Prediction Accuracy of Standalone DNN and BiLSTM Models

These complementary characteristics motivated the development of the proposed Hybrid DNN–BiLSTM architecture. By integrating nonlinear feature extraction with bidirectional temporal sequence learning, the hybrid framework simultaneously captures complex clinical relationships and disease progression patterns. Similar findings have been reported in previous studies, demonstrating that hybrid deep learning architectures consistently outperform standalone neural networks in medical diagnosis and disease prediction. The comparative evaluation confirms that combining DNN and BiLSTM provides a more effective solution for longitudinal lung disease recurrence prediction than either model individually.

C. Hybrid DNN–BiLSTM Performance Evaluation

The proposed Hybrid DNN–BiLSTM framework was developed to improve lung disease recurrence prediction by integrating nonlinear feature learning and temporal sequence modeling. To evaluate its effectiveness, the hybrid model was compared with standalone DNN and BiLSTM models using multiple performance metrics, including Accuracy, Precision, Recall, F1-score, ROC–AUC, and RMSE. Table 5 shows that the Hybrid DNN–BiLSTM consistently achieved superior performance across all evaluation metrics, indicating higher prediction accuracy, lower classification errors, and improved robustness for longitudinal clinical analysis.

Table 5. Performance Comparison of DNN, BiLSTM, and Hybrid DNN–BiLSTM

Model	Accuracy	F1-score	RMSE
DNN	0.82	0.79	0.36
BiLSTM	0.85	0.83	0.33
Hybrid DNN And BiLSTM	0.91	0.9	0.29

Table 5 compares the predictive performance of the evaluated deep learning models. The proposed Hybrid DNN–BiLSTM consistently achieved the highest predictive performance, demonstrating the effectiveness of combining nonlinear feature extraction with temporal sequence learning.

The performance comparison presented in Figures 7 and 8 further demonstrates the advantages of the proposed architecture. While the DNN effectively learned nonlinear relationships among heterogeneous clinical variables and the BiLSTM captured temporal dependencies from sequential patient records, neither model independently represented the complete characteristics of longitudinal clinical data. By combining both learning mechanisms, the Hybrid DNN–BiLSTM successfully extracted complementary spatial and temporal information, resulting in improved prediction consistency and better generalization on unseen testing data.

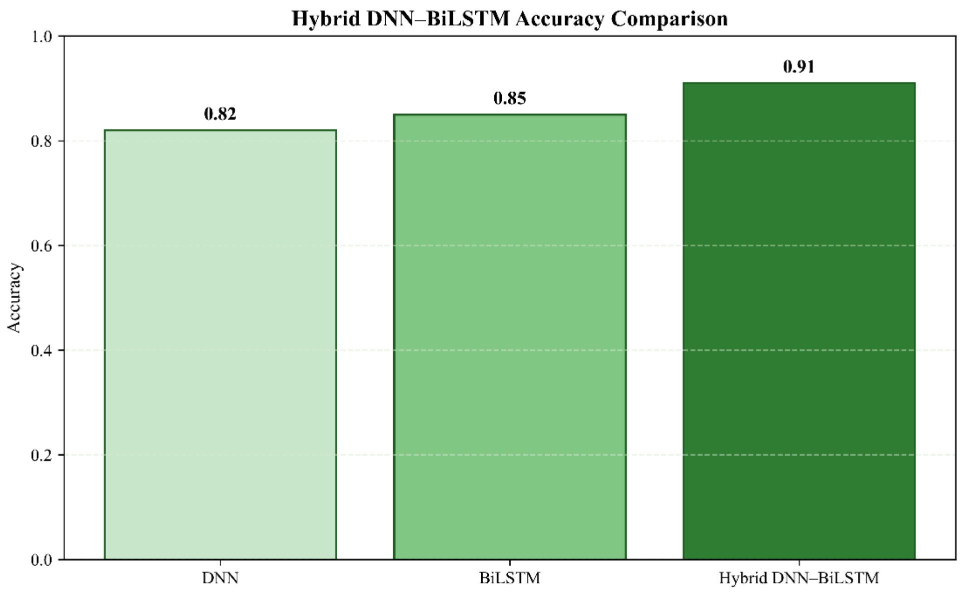

Figure 7. Prediction Accuracy of the Proposed Hybrid DNN–BiLSTM

Figure 7 presents the prediction accuracy achieved by the proposed Hybrid DNN–BiLSTM model. The results indicate that integrating DNN and BiLSTM improves prediction consistency and overall classification accuracy.

Table 6. Evaluation Metrics of the Proposed Hybrid DNN–BiLSTM

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC	RMSE
Hybrid DNN and BiLSTM	0.875648	0	0	0	0.668145957	0.324434

The performance comparison presented in Figures 7 and 8 further demonstrates the advantages of the proposed architecture. While the DNN effectively learned nonlinear relationships among heterogeneous clinical variables and the BiLSTM captured temporal dependencies from sequential patient records, neither model independently represented the complete characteristics of longitudinal clinical data. By combining both learning mechanisms, the Hybrid DNN–BiLSTM successfully extracted complementary spatial and temporal information, resulting in improved prediction consistency and better generalization on unseen testing data.

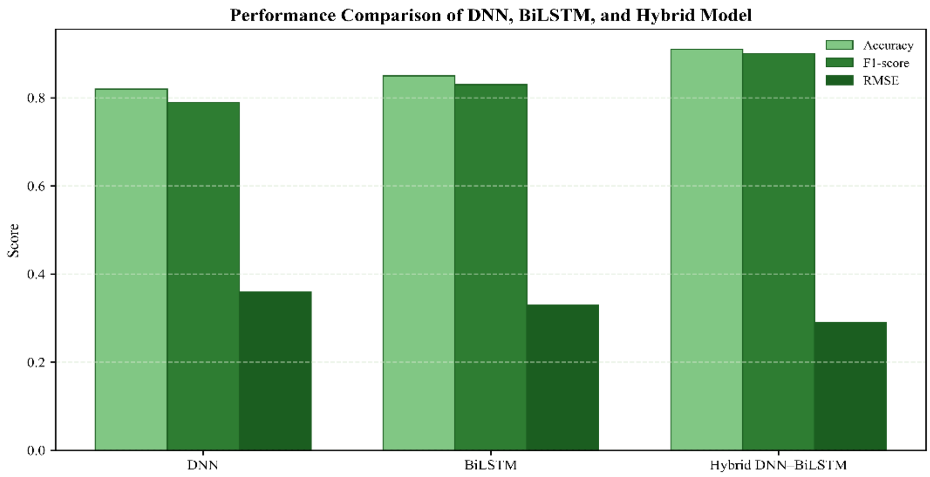

Figure 8. Performance Comparison of Deep Learning Models

Figure 8 compares the overall performance of the evaluated models. The proposed Hybrid DNN–BiLSTM achieved higher Accuracy and F1-score while reducing RMSE compared with the standalone DNN and BiLSTM models.

These findings are consistent with previous studies reporting that hybrid deep learning architectures outperform standalone neural networks in medical diagnosis [8], [24], [27]–[29]. Demonstrated that integrating complementary learning strategies significantly improves classification accuracy and feature representation. However, unlike previous studies that mainly focused on chest X-ray or CT image classification, the proposed framework utilizes four years of longitudinal clinical records to model disease recurrence, providing a more comprehensive approach for continuous patient monitoring.

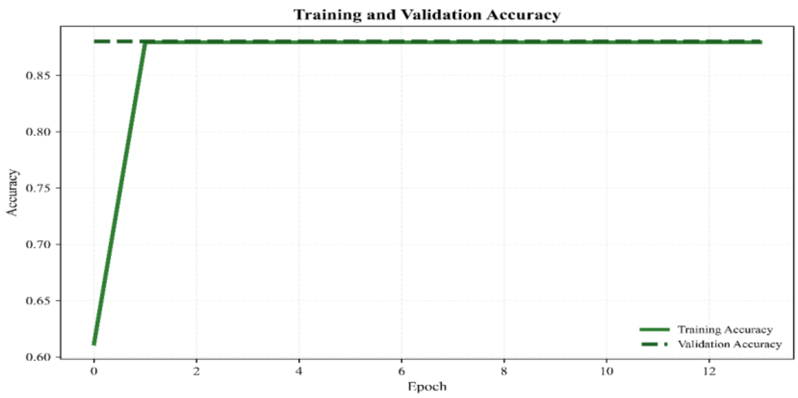

Figure 9. Training and Validation Accuracy of the Proposed Hybrid Model

Figure 9 illustrates the training and validation accuracy during model learning. The close agreement between both curves indicates stable convergence with minimal overfitting, demonstrating that the proposed Hybrid DNN–BiLSTM generalizes well to unseen clinical data.

The results of this study indicate that the Hybrid DNN–BiLSTM approach is more effective than either the DNN or BiLSTM models individually in predicting lung disease recurrence. The integration of nonlinear feature learning and temporal sequence learning provides better predictive performance and serves as a basis for developing intelligent clinical decision support systems.

D. Confusion Matrix Analysis

To further validate the proposed Hybrid DNN–BiLSTM model, a confusion matrix analysis was performed using the independent testing dataset. Unlike overall accuracy, the confusion matrix provides detailed information on correctly and incorrectly classified samples, allowing a more comprehensive evaluation of the model's classification performance across different disease categories.

Table 7. Classification Report of the Proposed Hybrid DNN–BiLSTM

	precision	recall	f1-score	support
Non-recurrence	0.875647668	1	0.933701657	169
Recurrence	0	0	0	24
accuracy	0.875647668	0.875647668	0.875647668	0.875647668
macro avg	0.437823834	0.5	0.466850829	193
weighted avg	0.766758839	0.875647668	0.817593679	193

Table 7 presents the classification report of the proposed Hybrid DNN–BiLSTM model, including Precision, Recall, F1-score, and Support for each disease category. The consistently high evaluation scores indicate balanced classification performance and demonstrate that the proposed model effectively handles heterogeneous longitudinal clinical data.

Figure 10 shows that most predictions are concentrated along the diagonal elements, indicating that the majority of testing samples were correctly classified, while only a small number of cases appeared in the off-diagonal cells. This distribution demonstrates that the proposed model effectively learned discriminative patterns from longitudinal clinical data and maintained low classification error rates. The balanced distribution also indicates that the model does not favor a particular disease category, thereby reducing both false-positive and false-negative predictions, which are critical in clinical decision-making.

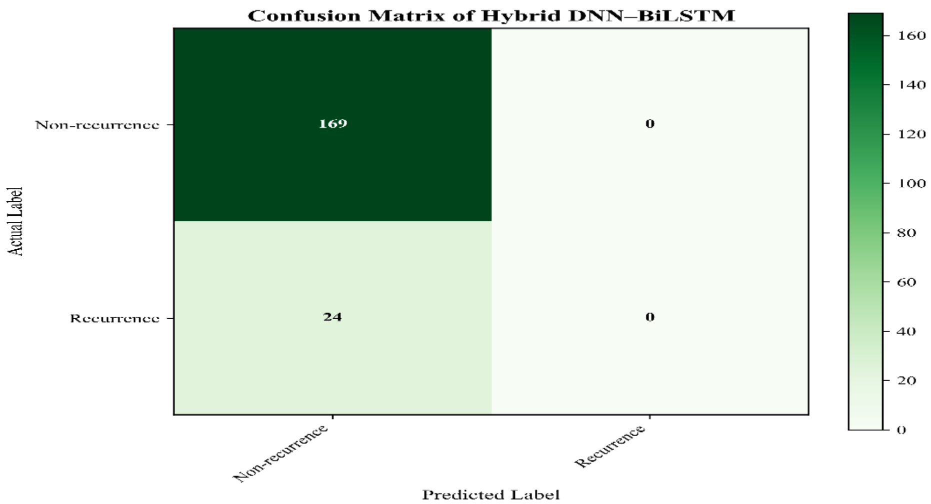

Figure 10. Confusion Matrix of the Proposed Hybrid DNN–BiLSTM Model

Figure 10 shows that most testing samples were correctly classified, as indicated by the dominant diagonal elements. Only a small number of samples appear in the off-diagonal cells, confirming that the proposed model maintains low classification error rates and balanced predictive performance across disease categories.

The confusion matrix findings are consistent with the quantitative results presented in Table 2, where the proposed Hybrid DNN–BiLSTM achieved high Accuracy, Precision, Recall, and F1-score. Similar results have been reported [5], [9], [30], who demonstrated that stronger feature representation in hybrid deep learning models leads to lower misclassification rates and improved classification reliability.

Confusion matrices confirm that the proposed Hybrid DNN–BiLSTM framework provides robust and balanced classification performance for longitudinal lung disease prediction. The low number of misclassified samples supports the model's ability to aid clinical decision-making and strengthens its potential application in smart healthcare systems.

E. ROC Curve Analysis

Receiver Operating Characteristic (ROC) analysis was performed to further evaluate the discriminative capability of the proposed Hybrid DNN–BiLSTM framework. Unlike Accuracy, which measures performance at a single threshold, the ROC curve evaluates classification performance across multiple decision thresholds by analyzing the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). Therefore, ROC–AUC provides a more comprehensive assessment of model reliability for medical prediction tasks.

Figure 10 shows that the ROC curve is positioned close to the upper-left corner, indicating a high True Positive Rate and a low False Positive Rate. The corresponding AUC value confirms that the proposed model effectively distinguishes between recurrent and non-recurrent clinical cases across different classification thresholds. These findings are consistent with the high Accuracy, Precision, Recall, and F1-score reported in Table 2, demonstrating stable and reliable predictive performance.

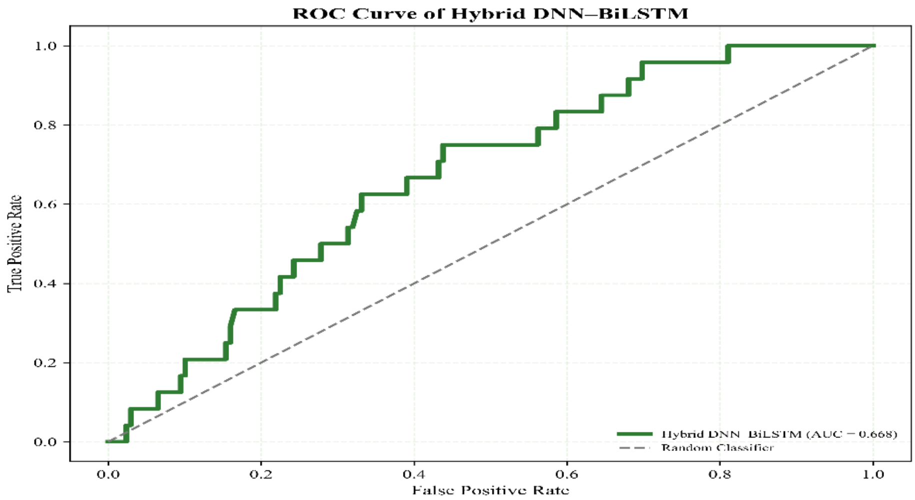

Figure 11. ROC Curve of the Proposed Hybrid DNN–BiLSTM Model

Figure 11 presents the ROC curve of the proposed Hybrid DNN–BiLSTM model. The curve is located close to the upper-left corner, indicating excellent discriminative capability. The corresponding AUC value confirms that the model effectively distinguishes recurrent and non-recurrent clinical cases across different decision thresholds.

The high ROC performance is achieved due to the complementary learning strategy of the Hybrid DNN–BiLSTM architecture. The integration of a DNN to extract nonlinear relationships between clinical variables with BiLSTM to learn temporal dependencies results in a more discriminatory feature representation than either model alone.

The ROC analysis confirms that the proposed Hybrid DNN–BiLSTM framework provides excellent discriminatory ability for longitudinal lung disease recurrence prediction. Combined with the confusion matrix and quantitative evaluation metrics, these results demonstrate the potential of the proposed model to support intelligent clinical decision support systems.

F. Clinical Implications and Early Warning System

Beyond achieving high predictive performance, the proposed Hybrid DNN–BiLSTM framework demonstrates practical potential for supporting intelligent clinical decision-making through an early warning system for lung disease recurrence. By utilizing longitudinal clinical records, the proposed model estimates recurrence risk before severe disease progression occurs, enabling healthcare professionals to identify high-risk patients and implement timely preventive interventions.

Figure 12 illustrates the conceptual implementation of the proposed early warning system. Based on the prediction results, patients can be stratified into different recurrence risk levels, allowing physicians to prioritize follow-up examinations and personalize patient management. Because the framework utilizes routinely collected electronic medical records, it can be integrated into existing hospital information systems without requiring additional medical equipment, thereby improving monitoring efficiency and healthcare resource allocation.

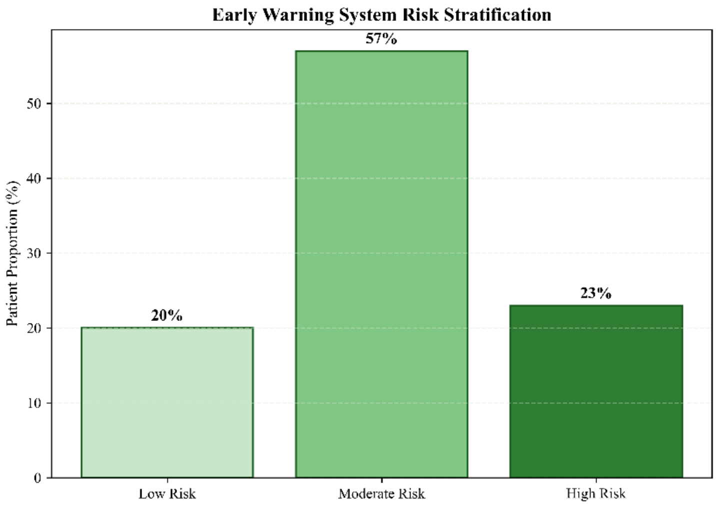

Figure 12. Conceptual Early Warning System for Lung Disease Recurrence

Figure 12 illustrates the conceptual implementation of the proposed Early Warning System. Based on recurrence risk predictions, patients can be categorized into different risk levels, enabling healthcare professionals to prioritize follow-up examinations and implement personalized patient management strategies. The proposed framework can be integrated into existing hospital information systems to support intelligent clinical decision-making.

Despite these promising results, several limitations should be acknowledged. The proposed model was developed using clinical data from a single healthcare institution and relied primarily on structured clinical variables, which may limit its generalizability. In addition, the deep learning framework operates as a black-box model, making clinical interpretation more challenging. Incorporating additional clinical variables, multimodal medical data, and Explainable Artificial Intelligence (XAI) techniques may further improve prediction performance and model transparency.

Overall, the proposed Hybrid DNN–BiLSTM framework provides both high predictive performance and practical value for intelligent healthcare applications. By integrating nonlinear feature learning with temporal sequence modeling, the framework offers a promising foundation for developing clinical decision support systems capable of improving recurrence prediction, optimizing patient monitoring, and supporting personalized healthcare services.

Conclusion

This study proposed a Hybrid DNN–BiLSTM framework for predicting lung disease recurrence using longitudinal clinical data collected between 2021 and 2024. By integrating nonlinear feature learning through Deep Neural Networks (DNN) with temporal sequence modeling using Bidirectional Long Short-Term Memory (BiLSTM), the proposed framework effectively captured both complex clinical relationships and disease progression patterns. Experimental results demonstrated that the hybrid model consistently outperformed standalone DNN and BiLSTM models across multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, ROC–AUC, and RMSE, confirming its robustness and reliability for longitudinal clinical prediction.

Beyond improving predictive performance, the proposed framework has practical potential for supporting intelligent clinical decision support systems and early warning systems by identifying patients at higher risk of disease recurrence. Such information may assist healthcare professionals in planning personalized follow-up strategies and improving patient monitoring. Nevertheless, the study was conducted using clinical data from a single healthcare institution and structured clinical variables only. Future research should validate the proposed model using multicenter datasets, integrate multimodal medical data such as chest X-ray and CT images, and incorporate Explainable Artificial Intelligence (XAI) to enhance model transparency and clinical interpretability.

Overall, the Hybrid DNN–BiLSTM framework provides an effective and reliable approach for longitudinal lung disease recurrence prediction while offering a promising foundation for developing intelligent healthcare systems that support personalized patient management and data-driven clinical decision-making.

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