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OPTIMIZATION OF PREDICTION OF LUNG DISORDERS USING LSTM COMPARISON OF RMSPROP AND ADAM

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Abstract— *Accurate prediction of pulmonary disorders is essential to support early diagnosis and clinical decision-making. Medical time-series data are inherently nonlinear and temporally dependent, making conventional statistical approaches insufficient. This study formulates pulmonary disorder prediction as a regression problem and proposes an optimized Long Short-Term Memory (LSTM) model by comparing two widely used optimization algorithms, RMSProp and Adam. The dataset consists of 30,000 clinical records obtained from an open-source Kaggle repository, including demographic, behavioral, and health-related variables relevant to respiratory conditions. Data preprocessing involved categorical encoding and Min–Max normalization, followed by an 80:20 train–test split. Model performance was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Experimental results demonstrate that the Adam optimizer achieves superior performance with lower prediction errors and more stable convergence compared to RMSProp and the baseline SGD optimizer. These findings highlight the critical role of optimizer selection in LSTM-based medical time-series modeling.*

Keywords: *LSTM, Medical Time-Series, Pulmonary Disorder Prediction, Regression, RMSProp.*

Intisari— *Prediksi akurat gangguan paru-paru sangat penting untuk mendukung diagnosis dini dan pengambilan keputusan klinis. Data deret waktu medis pada dasarnya bersifat nonlinier dan bergantung pada waktu, sehingga pendekatan statistik konvensional tidak memadai. Studi ini merumuskan prediksi gangguan paru-paru sebagai masalah regresi dan mengusulkan model Long Short-Term Memory (LSTM) yang dioptimalkan dengan membandingkan dua algoritma optimasi yang banyak digunakan, RMSProp dan Adam. Dataset terdiri dari 30.000 catatan klinis yang diperoleh dari repositori Kaggle sumber terbuka, termasuk variabel demografis, perilaku, dan terkait kesehatan yang relevan dengan kondisi pernapasan. Praproses data melibatkan pengkodean kategorikal dan normalisasi Min–Max, diikuti dengan pembagian data latih-uji 80:20. Kinerja model dievaluasi menggunakan Mean Squared Error (MSE), Mean Absolute Error (MAE), dan koefisien determinasi (R^2). Hasil eksperimen menunjukkan bahwa pengoptimal Adam mencapai kinerja yang lebih unggul dengan kesalahan prediksi yang lebih rendah dan konvergensi yang lebih stabil dibandingkan dengan RMSProp dan pengoptimal SGD dasar. Temuan ini menyoroti peran penting pemilihan pengoptimal dalam pemodelan deret waktu medis berbasis LSTM.*

Kata Kunci: *LSTM, Deret Waktu Medis, Prediksi Gangguan Paru-paru, Regresi, RMSProp.*

INTRODUCTION

Lung disorders are a health problem that has a significant impact on the quality of human life, both in terms of social, economic and community productivity [1] [2]. Diseases such as chronic obstructive pulmonary disease (COPD), asthma, and respiratory tract infections are the main causes of morbidity and mortality worldwide. [3] [4]. Data from the World Health Organization (WHO) shows

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that lung disorders are among the top five causes of death globally [5] [6]. Environmental factors such as air pollution, cigarette smoke and climate change also exacerbate the population's vulnerability to lung disorders [7] [8]. Therefore, developing an accurate prediction system is an important step in efforts for early detection and more effective medical decision making [9] [10] .

Along with technological advances, the application of Artificial Intelligence (AI), especially Deep Learning, has made a major contribution to the medical field, especially in processing health data and analyzing chronic diseases. [11] [12].. This technology enables analysis of large amounts of data, identifying complex patterns, and producing predictions with a high level of accuracy that is difficult to achieve with conventional methods. [13] [14]. One of the most effective Deep Learning approaches in analyzing medical time series data is Recurrent Neural Network (RNN), especially the Long Short-Term Memory (LSTM) variant. [15] [16]. The LSTM architecture is designed to overcome the vanishing gradient problem and can retain important information in long-term data sequences [17] [18].

In the context of lung disorder analysis, LSTM can be used to predict a patient's respiratory condition based on sensor data or a time series history of medical examinations. [19][20]. With the ability to recognize temporal patterns in physiological data such as respiratory frequency, oxygen levels, and heart rate, LSTM is able to provide more stable and accurate prediction results [21] [22]. However, the main challenge in implementing this model lies in selecting the right optimizer so that the training process can run efficiently and produce optimal convergence. [23] [24].

Various optimization algorithms have been developed to improve the performance of Deep Learning models, including RMSProp and Adam which are widely used in medical research and biological data analysis. [25] [26]. RMSProp is known to be effective in overcoming dynamic learning rate problems, while Adam combines the advantages of RMSProp and Momentum to speed up the convergence process [27] [28]. Comparison of these two optimizers is important to determine the best optimization method in the context of disease prediction based on time data [29] [30].

Several previous studies have applied LSTM for the prediction of chronic diseases such as diabetes, heart disease, and lung cancer, with results showing great potential in improving the accuracy of early detection. [31] [32]. However, there is still a research gap in optimizing training parameters and selecting the most suitable optimization algorithm for lung disorders. [33] [34]. In addition, most previous studies have not conducted an in-depth comparative analysis between RMSProp and Adam in the context of temporal medical data [35] [36].

Based on this background, this research aims to optimize the lung disorder prediction model using the LSTM algorithm by comparing two optimization methods, namely RMSProp and Adam [37] [38]. Through this approach, it is hoped that a prediction model will be obtained that is more efficient, stable and accurate in analyzing patterns of respiratory disorders [39] [40]. It is hoped that the results of this research can contribute to the development of an artificial intelligence-based medical decision support system that is capable of early detection and improving the quality of health services, especially in the field of respiration. [41] [42].

Unlike previous studies that focus solely on LSTM performance for medical time-series, this research provides a direct empirical comparison of two widely used optimizers RMSProp and Adam under an identical architectural setting. This approach allows for a more objective evaluation of their effects on convergence speed, training stability, and generalization capability in the context of pulmonary disorder prediction. Accordingly, this study contributes to filling the existing research gap by offering a deeper comparative understanding of optimizer behavior for medical time-series modeling using LSTM.

This study addresses pulmonary disorder prediction using deep learning, focusing on regression-based modeling of medical time-series data. Although LSTM has been widely used in healthcare prediction, the influence of optimizer selection under identical architectures remains underexplored. This research fills this gap by providing a controlled comparison between RMSProp and Adam.

MATERIALS AND METHODS

The dataset consists of 30,000 clinical records obtained from Kaggle. Pulmonary disorder prediction is formulated as a regression task. Categorical features were encoded using one-hot encoding, numerical features normalized using Min–Max scaling. The LSTM model uses a linear output layer and MSE loss. Evaluation metrics include MSE, MAE, and R^2.

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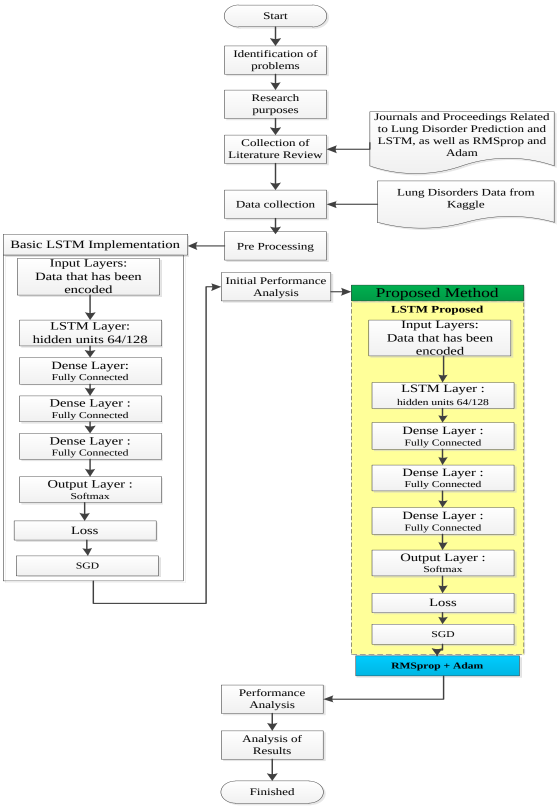


Source: (Research Results, 2025)

Figure 1. Research Phases

1. Problem Identification

This research identifies problems in the prediction and classification of pulmonary disorders using Long Short-Term Memory (LSTM) based models. The main problem lies in optimizing model performance, especially in determining the best optimization algorithm so that the model is able to provide high and stable accuracy results in predicting lung disorders based on medical data.

2. Research Objectives

The aim of this research is to optimize the LSTM model in predicting lung disorders by comparing two optimization algorithms, namely RMSprop and Adam. It is hoped that this comparison will determine which algorithm provides the most optimal performance in terms of accuracy, loss function and training efficiency on the lung disorders dataset.

3. Collection of Literature Reviews

This stage includes collecting various journals and scientific proceedings related to the prediction of lung disorders, applying the LSTM algorithm, and using the RMSprop and Adam optimizers. This literature is used to strengthen the theoretical basis and adapt research methods to previous research developments.

4. Research Data Collection

The data used in this study was obtained from the Kaggle platform, which contains datasets related to lung disorders. This dataset includes various variables from medical examination results that are relevant to lung conditions, and is then used as input for the training and testing process of the LSTM model. The following is an example of the research data used.

Table 1. Example Of Research Data

No	Age	Gender	Smoke	...	Results
1	Old	Man	Passive	...	Yes
2	Old	Man	Active	...	No
3	Young	Man	Active	...	No
4	Old	Man	Active	...	No
5	Young	Woman	Passive	...	Yes
6	Young	Woman	Passive	...	No
7	Old	Woman	Passive	...	Yes
8	Young	Man	Active	...	No
9	Old	Woman	Active	...	Yes
10	Young	Woman	Passive	...	Yes
...	...	...	...	...	...
30000	Old	Woman	Passive	...	Yes

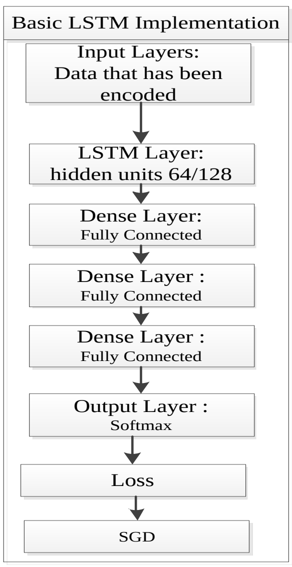
Source: (Research Results, 2025)

5. Data Pre-Processing

Pre-processing is carried out to ensure the data is ready to be used in the model. This stage includes data cleaning, normalization, and encoding categorical data so that it can be processed by the LSTM network. The data is then divided into training data, validation data, and test data to ensure objective model evaluation.

6. Basic LSTM Implementation

At this stage, the basic LSTM model is implemented as an initial comparison (baseline).



Source: (Research Results, 2025)

Figure 2. LSTM Baseline

VOL. 11. NO. 3 FEBRUARI 2026
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The model architecture consists of:

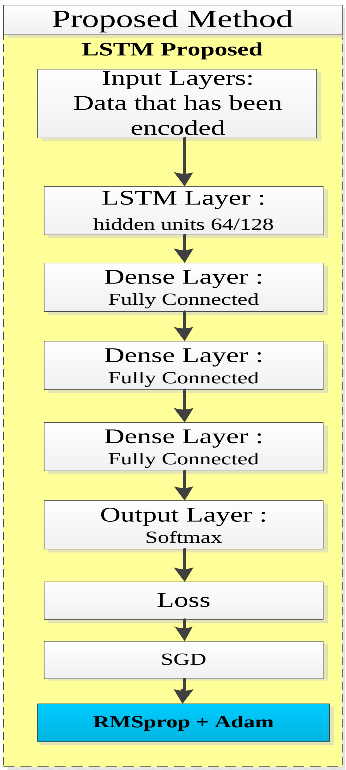
a. Input Layer: Data that has been encoded.
b. LSTM Layer: Consists of 64 and 128 hidden units.
c. Dense Layer: Several fully connected layers to process LSTM extracted features.
d. Output Layer: Uses Softmax activation function.
e. Loss Function: Cross Entropy Loss.
f. Optimizer: Stochastic Gradient Descent (SGD).
g. This basic model is used to determine initial performance before optimization using RMSprop and Adam.

7. Initial Performance Analysis

Initial analysis was performed on the basic LSTM model to see accuracy, loss, and overall performance. The results of this stage become a reference in developing an optimized LSTM model.

8. Proposed Method

This stage is an implementation of the LSTM method which is optimized using the RMSprop and Adam algorithms. The architecture still adopts the basic LSTM structure, but the training process is differentiated based on the optimizer used to see the influence of each on model performance.



Source: (Research Results, 2025)
Figure 3. LSTM Proposed

Comparisons are made by observing the accuracy results, loss values, and model convergence on the same data. This approach aims to determine the best optimizer in improving the ability to predict lung disorders using LSTM.

9. Results Analysis

The final stage is the analysis of performance results between the basic LSTM model (with SGD) and the optimized LSTM model using RMSprop and Adam. This comparison of results is used to draw conclusions regarding the effectiveness of the optimization algorithm in increasing the accuracy and efficiency of the model in detecting and predicting lung disorders.

RESULTS AND DISCUSSION

Pre-Processing Data

The following is the division of research image data used:

Table 2. Division of Research Data

Distribution	Amoun
Train	24.000
Test	6000

Source: (Research Results, 2025)

The dataset used in this study is divided into two main subsets, namely the training set and the testing set. The training data (train) consists of 24,000 data samples, which are used to train the LSTM model in recognizing patterns related to lung disorders. Meanwhile, the testing data (test) consists of 6,000 data samples, which are used to evaluate the performance and generalization ability of the trained model. Results show that Adam consistently outperforms RMSProp and SGD in terms of convergence stability and prediction accuracy. Adam's adaptive moment estimation enables better handling of gradient variability in medical time-series data.

Data Prediction Results

At the modeling stage, the Long Short-Term Memory (LSTM) architecture was used to predict lung disorders. Two optimization algorithms, RMSprop and Adam, were compared to train and optimize the model's performance in predicting lung disorder data.

Data Training Results

This study used a dataset of 30,000 data points consisting of 11 attributes: Age, Gender, Smoking, Occupation, Household, Staying Up Late, Sports Activities, Insurance, Pre-existing Diseases, and Results. All data underwent preprocessing, including one-hot encoding for categorical columns and Min–Max normalization to ensure all features were on a uniform scale (0–1). The data was then divided into 80% training data (24,000 samples) and 20% testing data (6,000 samples). No missing values were found, allowing the data to be used directly in the modeling. The LSTM model architecture used consisted of one LSTM layer with 64 units, followed by a Dropout layer of 0.2, a Dense layer of 32 neurons with ReLU activation, and one linear output layer for regression.

Model Results Baseline

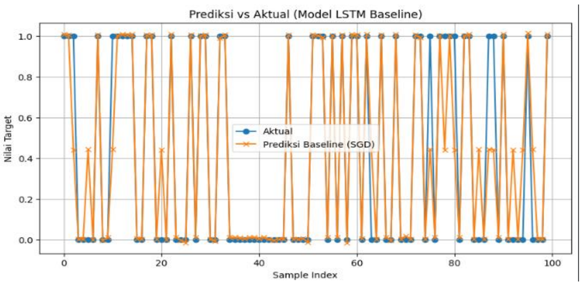
The baseline model using the Stochastic Gradient Descent (SGD) optimizer produced relatively fluctuating loss values at the beginning of training but tended to stabilize after 50 epochs. Visualization of the prediction results shows that the model's prediction trend closely follows the actual pattern, although there are small deviations in some test samples. The baseline model evaluation results are shown in Table 3.

Tabel 3. Evaluasi Model LSTM Baseline (SGD)

Metric	Mark
MSE	0.029945
MAE	0.064794
R^2	0.8801 (88.01%)

Source: (Research Results, 2025)

The following are the prediction results for the baseline model.



Source: (Research Results, 2025)

Figure 4. Baseline Model Prediction Results

The R^2 value of 88.01% indicates that the baseline model is able to explain approximately 88% of the variation in the target data, indicating fairly good performance, although not optimal.

Optimization Model Results

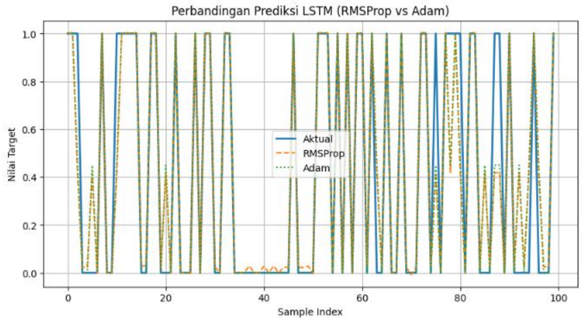
To improve model performance, retraining was performed using two popular optimization algorithms, RMSProp and Adam, each with a learning rate of 0.001. The training process showed that both models converged faster than the baseline. The training loss and validation loss values stabilized between the 40th and 50th epochs, indicating no significant overfitting.
The evaluation results are presented in Table 4.

Table 4. Evaluation of Optimization Models (RMSProp and Adam)

Optimizer	MSE	MAE	R^2 (%)
RMSProp	0.030306	0.065306	0.8787
Adam	0.029832	0.060106	0.8806

Source: (Research Results, 2025)

The following are the predicted results for the optimization model.



Source: (Research Results, 2025)

Figure 5. Optimization Model Prediction Results

Figure 5 presents a visualization of the prediction results of an LSTM model optimized using the RMSProp and Adam optimizers. In general, both models replicated the actual value patterns quite well, as indicated by the tendency of the prediction curves to follow the data trend. However, the Adam model showed a more consistent approximation to the actual values, especially in data segments experiencing sharp fluctuations. This visual finding aligns with the quantitative results in Table 3, where Adam achieved lower MSE and MAE values and a higher R^2 than RMSProp. Thus, it can be concluded that using Adam not only accelerated the convergence process but also improved the overall prediction precision. These results confirm the superiority of Adam's adaptive learning rate mechanism in modeling complex patterns in lung disorder data.

Comparison of Baseline Model and Optimization Model

At this stage, a performance comparison was conducted between the baseline model (SGD) and two optimization models (RMSProp and Adam). The evaluation results in Table 4 show that both optimizers provide improved performance compared to the baseline. The Adam model has the lowest MSE and MAE values and the highest R^2, indicating better generalization ability. Meanwhile, RMSProp also shows an improvement compared to the baseline, although not as significant as Adam.

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VOL. 11. NO. 3 FEBRUARI 2026
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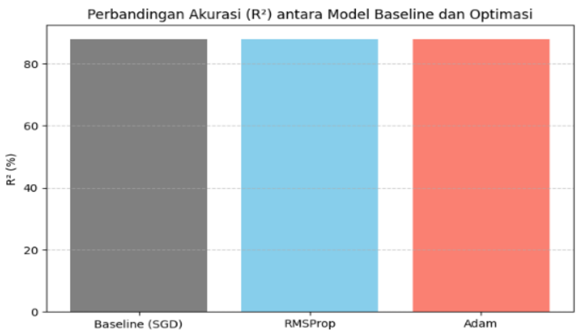
Table 5. Comparison of Baseline and Optimization Model Performance

Model	MSE	MAE	R^2
Baseline (SGD)	0.029945	0.064794	0.880146
RMSProp	0.030306	0.065306	0.878699
Adam	0.029832	0.060106	0.880596

Source: (Research Results, 2025)

Table 5 shows that the baseline model with the SGD optimizer produced quite good performance and served as the evaluation benchmark. The RMSProp optimizer did not provide significant improvement, as evidenced by slightly worse MSE, MAE, and R^2 values compared to the baseline. In contrast, the Adam optimizer performed better, with the lowest MSE and MAE and the highest R^2 value. This indicates that Adam is better able to adjust weight updates, resulting in more accurate predictions than the other two optimizers.

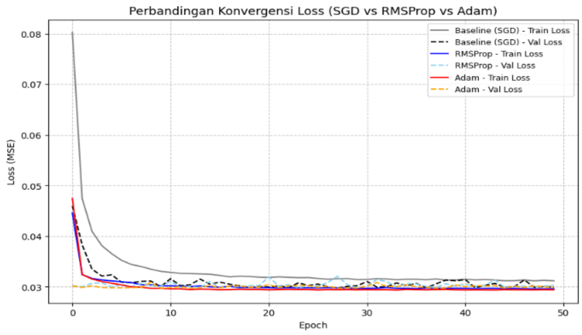
The R^2 comparison graph in Figure 6 reinforces this finding, with Adam providing the most significant performance improvement.



Source: (Research Results, 2025)
Figure 5. Comparison of Accuracy of Baseline Model with Optimization Model

Model Convergence Analysis (Loss Curve)

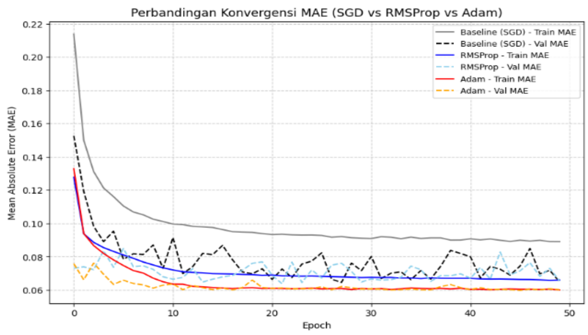
To understand the effectiveness of the learning process in each model, an analysis of the loss convergence curves was performed, as shown in Figure 7. Figure 7 displays the loss convergence curves for the three models. The baseline model (SGD) appears to have a slower and more volatile loss reduction than the two optimization models. RMSProp shows more stable convergence, but Adam provides the fastest loss reduction and reaches a minimum value at an earlier epoch. This pattern indicates that Adam's adaptive learning rate mechanism works more effectively in accelerating the learning process on time-series data related to lung disorders. Furthermore, no significant overfitting is observed in any of the models, indicated by the relatively small distance between the training loss and validation loss.



Source: (Research Results, 2025)
Figure 7. Loss Convergence Curve of Model (SGD, RMSProp, Adam)

Error Analysis (MAE Curve)

In addition to monitoring the loss value, the Mean Absolute Error (MAE) analysis in Figure 8 also shows a consistent pattern. The Adam model's MAE decreases more rapidly and steadily than RMSProp and SGD. RMSProp experiences a significant decrease in MAE, but is still less stable than Adam. Meanwhile, the baseline model (SGD) shows higher error fluctuations throughout training. These findings indicate that Adam not only improves the precision of the final predictions but also makes the learning process more effective and consistent from epoch to epoch.



Source: (Research Results, 2025)
Figure 8. Error Analysis (MAE Curve)

Discussion

The results showed that optimizer selection significantly influenced the performance of the LSTM model in predicting lung disorders. The Adam optimizer proved to provide the best performance, as evidenced by lower MSE and MAE values and a higher R^2 value compared to RMSProp and the SGD baseline. Adam's ability to combine adaptive learning rate and momentum makes the learning process more stable and converges to the optimal value more quickly. This is ideal for medical time-series data, which tends to have unstable patterns and varying gradients. Meanwhile, RMSProp also performed better than the baseline, but the improvement was not significant. This is because RMSProp only adapts the learning rate based on the mean squared gradient without applying momentum correction like Adam. These results indicate that Adam is more effective at tracking the dynamics of gradient changes in this dataset. Visualization of the loss and MAE curves shows that all models show no significant indication of overfitting. This is indicated by the relatively small gap between the training loss and validation loss. Thus, the LSTM architecture used has quite good generalization capabilities to the test data.

However, this study has several limitations. First, the experiment was conducted on only one dataset without validation using external data, so the model's generalizability to different populations cannot be guaranteed. Second, this study did not conduct in-depth hyperparameter exploration, such as grid search or Bayesian optimization, which could potentially yield more optimal model configurations. Third, the study did not include an analysis of model interpretability, so the contribution of each feature to the prediction could not be explained transparently. For further research, several opportunities can be considered. The use of advanced architectures such as BiLSTM, GRU, or Transformer can be evaluated to improve prediction accuracy. Furthermore, the application of Explainable AI (XAI) techniques such as SHAP or LIME is needed to provide insight into the features that contribute most to predictions. The study could also be expanded with multi-dataset validation to better prepare the model for application in real-life clinical contexts.

CONCLUSION

This study aimed to optimize the performance of LSTM models in predicting lung disorders by comparing three optimization algorithms: SGD, RMSProp, and Adam. Based on the evaluation results, the baseline model with SGD demonstrated fairly good initial performance, but still had limitations in stability and convergence speed. The use of the RMSProp optimizer improved learning stability but did not produce significant improvements in MSE, MAE, or R^2 values compared to the baseline. The Adam optimizer performed best among all tested models. Adam produced the lowest MSE and MAE values and the highest R^2, indicating that the model was able to capture data patterns more effectively and produce more precise predictions. Furthermore, convergence analysis showed that Adam reached the minimum loss value more quickly and more stably than the other optimizers. These findings confirm that Adam's adaptive moment estimation mechanism works very well in the context of medical time-series data, particularly in predicting lung disorders.

Overall, it can be concluded that Adam is the most optimal optimizer for improving the performance of LSTM models on this dataset. Further research is recommended to conduct more in-depth exploration of hyperparameters, use more complex model architectures, and apply interpretability analysis to improve understanding of the contribution of features in the prediction process. This study demonstrates that optimizer selection significantly impacts LSTM-based pulmonary disorder prediction. Adam provides superior convergence stability and generalization performance, making it suitable for medical time-series regression tasks.

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