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Comparative Analysis of LSTM Architectures for BPJS Drug Expenditure Forecasting Using Walk-Forward Validation

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ABSTRACT

Drug demand planning in health facilities collaborating with BPJS Kesehatan is an important aspect in maintaining drug availability and improving service efficiency. However, drug expenditure data generally forms complex time series patterns that are fluctuating, nonlinear, and influenced by trend and seasonal components, making them difficult to model using conventional forecasting methods. Therefore, this study aims to compare the performance of Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Stacked LSTM models in forecasting BPJS patient drug expenditure by medication type at Basuki Rahmat Pharmacy using Walk-Forward Validation. The dataset used consists of monthly drug expenditure transaction data from January 2023 to May 2025 covering 41 types of drugs. The data preprocessing stages include data cleaning, transformation into time series format, Min-Max normalization, and windowing for input-output sequence generation. Time series characteristic analysis was conducted using the Augmented Dickey-Fuller (ADF) test, trend analysis, and seasonality analysis. The results showed that most drug data were stationary with p-values below 0.05, although several drugs still exhibited non-stationary patterns requiring additional transformation. Trend analysis indicated both increasing and decreasing consumption patterns, while seasonality analysis showed that all drug data exhibited seasonal patterns. The forecasting models were evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental results using Walk-Forward Validation showed that the Bidirectional LSTM model achieved the best forecasting performance with MAE of 51.99, RMSE of 72.06, and MAPE of 402.90, outperforming Single LSTM and Stacked LSTM models. These findings indicate that Bidirectional LSTM is more effective in capturing complex temporal dependencies in BPJS drug expenditure data and has potential to support decision-making in drug inventory management within healthcare facilities.

I. INTRODUCTION

Health is a fundamental aspect in human life that requires special attention, especially in ensuring the availability of adequate medicines for the community. In the health service system in Indonesia, the Social Security Agency (BPJS) has a vital role as a provider of medical service guarantees for all levels of society [1]. One of the main challenges in the health service system is to ensure the availability of drugs in pharmacies and hospitals so that the service process is not interrupted. The phenomenon of stock shortage and drug overstock still often occurs and has a direct impact on the quality of health services. This condition not only causes financial loss, but also has the potential to hinder the continuity of the BPJS patient treatment process[2]. Therefore, the problem of drug inventory imbalance needs to be further studied through a systematic scientific approach to produce predictive solutions that are able to support drug

stock management more accurately and sustainably. Pharmacies that cooperate with BPJS Kesehatan, including Basuki Rahmat Pharmacy, face the dynamic demand for drugs that tend to fluctuate in every service period. Inaccuracy in estimating the amount of drug expenditure can cause an imbalance in inventory, either in the form of a shortage of drugs needed by patients or excess stock that increases the risk of waste and expiration [3]. This condition shows that the pharmaceutical management system that is still manual and reactive has not been able to accommodate the complexity of the dynamic and sustainable drug usage pattern[4]. The problem of drug stock management not only has an impact on the financial aspect, but also has the potential to hinder the continuity of health services to BPJS patients. Therefore, a prediction approach is needed that is able to anticipate drug needs more accurately and adaptively[5]. Various conventional forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA) with a sMAPE value of 31-41%, have been widely used in the management of TB drug inventory. However, the method has limitations in capturing nonlinear patterns, seasonal fluctuations, and long-term dependence on drug time series data[6]. A number of previous studies have shown that Long Short-Term Memory (LSTM) is an effective method in forecasting complex and fluctuating time series data. The application of LSTM on patient transaction data and drug sales shows the model's ability to capture temporal patterns that cannot be optimally modeled by conventional statistical approaches[7], [8]. The LSTM model is also proven to be able to process large amounts of historical data more adaptively, thus producing predictions that are close to actual values in various case studies in the pharmaceutical and health sectors, the application of LSTM in the health and pharmaceutical sectors is also widely used in previous research. The LSTM Multivariate Model is used to predict the need and use of drugs in hospitals, with results showing MAE = 10.239, MAPE = 1.979%, high prediction accuracy and potential for hospital drug inventory planning. increased accuracy compared to conventional methods, as well as contributing to supporting drug inventory management efficiency [9]. In addition, the use of LSTM in drug sales prediction in the pharmacy network produces MAPE < 10% and lower prediction error in most drug items, so it is considered effective for stock planning and drug distribution [10]. Research related to the expenditure and drug consumption of health insurance patients also indicates the great potential for the implementation of LSTM. The LSTM model is able to accurately capture long-term health spending patterns based on patient historical data, thus providing competitive performance compared to classical statistical and regression models[11]. In general, the deep learning approach, especially LSTM, is seen as a promising solution in large-scale health data analysis that has a high level of complexity, and has the potential to support the improvement of the efficiency of the health service system in Indonesia [12].

Various further studies show that the application of LSTM in forecasting drug needs not only increases prediction accuracy, but also is able to reduce the risk of stock imbalances such as stockout and overstock. This is due to LSTM's ability to model seasonal patterns, trends, and complex demand fluctuations in time series data[13]. Emphasizing that the integration of a prediction model based on historical data of BPJS patients can provide a more realistic picture of drug needs compared to conventional approaches, thus supporting the efficiency of pharmaceutical logistics management.

In addition, the development of hybrid and deep learning methods also strengthens the role of LSTM in the health sector. It shows that the LSTM-based model has an advantage in capturing nonlinear relationships and long-term dependencies compared to models such as ARIMA [14]. This is important because BPJS patient drug expenditure data is generally dynamic and influenced by various factors, such as disease patterns, health service policies, and changes in the number of patient visits. Thus, the use of LSTM is considered more adaptive in dealing with the complexity of the data [15].

Forecasting research based on time series data currently widely utilizes deep learning methods such as Long Short-Term Memory (LSTM) because they are capable of effectively capturing temporal data patterns. In addition, the implementation of specialized time series validation methods such as Time Series Cross Validation (TSCV) or walk-forward validation is considered more appropriate than conventional data splitting because it preserves the chronological order of historical data during the training and testing processes. Research conducted by Dian Nuswantoro University showed that optimizing the LSTM model using the TSCV approach improved forecasting performance on Indonesian banking stock data, resulting in more stable and accurate predictions. The experimental results demonstrated that the model was capable of capturing long-term dependencies in financial time series data, with BBCA and BMRI achieving high accuracy levels ($R^2 > 0.95$), while BBCA recorded the lowest MAPE value of 2.34%. Furthermore, the model maintained consistent reliability across all testing folds despite market fluctuations[16].

Based on these findings, this study focuses on the application of the Long Short-Term Memory (LSTM) model to predict BPJS patient drug expenditure at Basuki Rahmat Pharmacy. The study location was selected because the dataset represents the drug consumption patterns of health insurance patients and reflects fluctuating drug expenditure behavior over time, making it suitable for time series forecasting using deep learning approaches. The results of this study are expected to improve forecasting accuracy and support strategic decision-making related to drug supply planning, inventory control, and pharmaceutical management in healthcare facilities. In addition, the implementation of forecasting models is expected to reduce the risk of stock shortages and overstock conditions that may affect healthcare service quality. Academically, this research contributes to the

implementation and evaluation of deep learning methods, particularly LSTM architectures, in pharmaceutical management and healthcare decision support systems. Furthermore, this study provides a comparative evaluation of several LSTM architectures, including Single LSTM, Stacked LSTM, and Bidirectional LSTM, to identify the most effective architecture for forecasting BPJS drug expenditure patterns using multivariate time series data in healthcare inventory management[17].

II. METHODOLOGY

In the process, this research method begins with data collection, data pre-processing, model design, model evaluation, and model implementation as described in the flowchat.

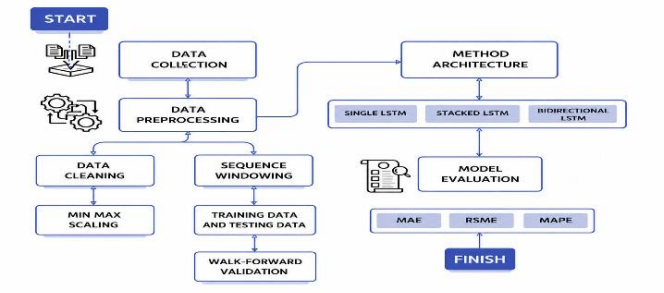

Figure 1. Proposed Methodology

A. Data colection

This research used secondary data collected manually from Basuki Rahmat Pharmacy, sourced from the pharmacy's internal record regarding drug expenditure for BPJS patients during the period of January 2023 to May 2025. The dataset consisted of monthly drug usage records, including drug names and the amount of drug expenditure for each month. A total of 29 months of time series data were utilized in this study to identify periodic patterns and trends in drug demand.

The unit of analysis in this research was defined as each type of drug within one monthly observation period, enabling systematic monitoring and evaluation of drug consumption patterns over time. Since the data were structured as time series data, the chronological order of observations was maintained throughout the analysis process to avoid data leakage and preserve temporal dependencies.

Prior to modeling, the dataset underwent a preprocessing stage that included data cleaning, consistency checking, and handling of missing values and abnormal records to improve data quality and model stability. In addition, the data were normalized before being used in the Long Short-Term Memory (LSTM) model to facilitate the learning process and improve forecasting performance. The data collection and preparation processes were conducted systematically to ensure the completeness, consistency, and reliability of the dataset. Therefore, the resulting data were considered suitable for time series forecasting and the development of drug expenditure prediction models using the Long Short-Term Memory (LSTM) approach.

B. Data Preprocessing

The data preparation stage was carried out to prepare the raw data before modeling. This process began with data cleaning by removing duplicate, empty, and invalid data to maintain data consistency. Before applying normalization, an initial analysis of the time series data was conducted to identify trends, fluctuations, and stationarity characteristics. The analysis indicated that BPJS drug expenditure data showed dynamic and fluctuating consumption patterns over time. Therefore, preprocessing and normalization were necessary to improve data stability before training the LSTM model. The dataset was then normalized using the Min-Max Scaling method to homogenize the value range and support a more stable training process. After normalization, the data was transformed into sequential data using the windowing technique to generate input-output pairs suitable for the LSTM network structure. Finally, the dataset was divided into training and testing data according to the predetermined proportion for model evaluation.

C. Method Architecture

The Single LSTM architecture consists of an input layer, a single LSTM layer, and a Dense output layer. The input layer receives multivariate time series data representing BPJS drug expenditure patterns. The LSTM layer processes sequential information using the forget gate, input gate, and output gate mechanisms to learn temporal dependencies from historical data. Finally, the Dense layer generates the forecasting output for the next prediction period. This architecture has a relatively simple structure and lower computational complexity, making it suitable for limited time series datasets while reducing the risk of overfitting.

The Stacked LSTM architecture is composed of multiple LSTM layers arranged sequentially between the input layer and the Dense output layer. The first LSTM layer captures basic temporal patterns from the BPJS drug expenditure data, while the subsequent LSTM layers learn deeper and more complex nonlinear relationships from the sequential information. The final Dense layer is used to generate forecasting outputs. This architecture provides higher representation capability compared to Single LSTM, although it also increases computational complexity and the potential risk of overfitting.

The Bidirectional LSTM architecture consists of an input layer, forward and backward LSTM layers, a merging process, and a Dense output layer. The forward LSTM processes sequential data from past to future, while the backward LSTM processes the sequence in the opposite direction. The outputs from both directions are combined to produce richer temporal representations before being passed to the Dense layer for forecasting. This architecture enables the model to utilize temporal information more

comprehensively, although it requires higher computational resources and more complex training processes.

D. Model Evalution

Model evaluation was carried out after the entire LSTM architecture produced prediction outputs based on the testing data. This process aimed to measure the accuracy level of each model in predicting BPJS patient drug expenditure. In this study, three evaluation metrics were employed, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were compared across all models to identify the architecture with the lowest forecasting error. The combination of these evaluation metrics provides a comprehensive assessment of the model's capability in handling fluctuations in time-series data.

In addition to the temporal train-test split approach, this study also implemented walk-forward validation to evaluate the robustness and generalization capability of the LSTM models on sequential time-series data. In this approach, the model was iteratively trained using historical observations and tested on subsequent future observations while preserving chronological order. This validation method is considered more appropriate for time-series forecasting because it simulates real-world forecasting scenarios and minimizes the risk of data leakage.

$$\text{MAPE} : \frac{1}{n}\sum_{i=1}^{n} \left| \frac{\text{Ai}-\text{F}i}{\text{A}i} \right| \times 100\% \quad (1)$$

- Ai = ith actual value
- Fi = the value of the ith forecast result
- n = amount of test data

$$\text{MAE} : \frac{1}{n}\sum_{i=1}^{n} \left| Ai - Pi \right| \quad (2)$$

- Ai = actual valuepolicy
- Fi = forecast value
- $Ai - Fi$ = absolute difference between actual and forecast values
- n = amount of data

$$\text{RSME} : \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Ai - Fi)2} \quad (3)$$

- Ai = actual value
- Fi = forecast value
- $(Ai - Fi)2$ = the power difference between the actual and forecast values
- n = amount of data

E. Model implementation

The model with the lowest error value based on MAE, RMSE, and MAPE evaluation metrics was selected as the best forecasting model and used in the implementation stage. To ensure robustness and avoid data leakage in time series forecasting, the model evaluation applied a walk-forward validation approach while maintaining the temporal order of the data. The selected model was then used to predict future BPJS patient drug expenditure using the most recent historical data, and the prediction results were visualized through a comparison graph between actual and predicted values to evaluate the model's ability to capture trend patterns and data fluctuations. This implementation is expected to support more accurate and efficient drug inventory planning at Basuki Rahmat Pharmacy by reducing the risk of stock shortages and overstock conditions.

III. RESULT AND DISCUSSION

A. Data Capture

The dataset obtained from Basuki Rahmat Pharmacy consisted of monthly drug expenditure records for BPJS patients from January 2023 to May 2025. During the data cleaning stage, invalid records, duplicate entries, and data that did not represent monthly transactions were removed to improve data consistency and reliability.

TABEL I
BPJS DRUG DATASET

Drug name	Sum	Price	Total
Acarbose 50mg (Diabetes Mellitus)	1170	13037	897.420
Adalat oros 30mg (Hypertension)	90	15208	456.240
Allopurinol 100mg (Uric Acid)	60	244	7.320
Amlodipine 10mg (Hypertension)	1170	5135	154.050
Amlodipine 5mg (Hypertension)	420	1316	41.250
Berotec (Asthma Disorders)	1	104.819	104.819
Bisoprolol 5mg (Heart)	60	646	19.380
Candesartan 16mg (Heart)	330	13277	398.310
- - - - - - - - - -	- - -	- - -	- - - - -
Vit B1 (Supportive Therapy)	750	116	87.000

The dataset was then checked for missing values, where empty entries were replaced with zero values to indicate the absence of drug expenditure during a particular period. In addition, abnormal or inconsistent transaction records were identified and adjusted to reduce potential noise in the forecasting process. After the cleaning process, the data were systematically organized into a chronological time series structure, making the dataset suitable for historical pattern analysis and the development of Long Short-Term Memory (LSTM)-based forecasting models.

B. Data Cleaning

The dataset taken from Basuki Rahmat Pharmacy includes records of drug expenditure for BPJS patients for the period of January 2023 to May 2025. At the data cleaning stage, invalid records and entries that do not represent monthly transactions are deleted. The entire month column is then checked to identify the missing data, and the blank value is replaced with a zero that represents the absence of drug spending in that period. This process produces neatly arranged data in the form of a time series. With this structure, the dataset is ready to be used for the analysis of historical drug use patterns and the development of LSTM-based prediction models.

TABEL 2
PREPROCESSING DATA

Drug Name	January 2023	February 2023	-	January 2024	February 2024	-	May 2025
Acarbose 50 mg (Diabetes Mellitus)	1170	840	-	840	870	-	1050
Adalat oros 30 mg (Hypertension)	90	30	-	120	90	-	180
Allopurinol 100mg (Uric Acid)	60	Zero	-	150	150	-	120
Amlodipine 10mg (Hypertension)	1170	1050	-	1080	870	-	870
Amlodipine 5mg (Hypertension)	420	330	-	360	300	-	270
……..	-	-	-	-	-	-	-
Vit B1 (Supportive Therapy)	Zero	30	-	30	90	-	150

TABEL 3
PREPROCESSING RESULT DATA

Drug Name	January 2023	February 2023	-	January 2024	February 2024	-	May 2025
Acarbose 50 mg (Diabetes Mellitus)	0,39	0,35	-	0,31	0,30	-	0,5
Adalat oros 30 mg (Hypertension)	0,03	0,01	-	0,0	0,5	-	0,08
Allopurinol 100mg (Uric Acid)	0,02	0	-	0,04	0,03	-	0,08
Amlodipine 10mg (Hypertension)	0,02	0	-	0,05	0,05	-	0,057
Amlodipine 5mg (Hypertension)	0,39	0,44	-	0,4	0,30	-	0,41
……..	-	-	-	-	-	-	-
Vit B1 (Supportive Therapy)	0	0,01	-	0,01	0,03	-	0,07

C. Min-max Scaling

Data normalization in this study was carried out using the Min-Max Scaling method to transform the data values into a range between 0 and 1. This process was intended to improve data consistency and optimize the learning performance of the LSTM model during training, the Min-Max Scaling formula is presented as follows;

$$X_{norm} = \frac{\mathrm{X}-\mathrm{X}_{min}}{\mathrm{X}_{max}-\mathrm{X}_{min}} \quad (4)$$

- X_{norm} = normalization result value
- $\mathrm{X}_{max}-\mathrm{X}_{min}$ = value of a filter

TABEL 4
MIN MAX SCALING RESULT DATA

Drug Name	January 2023	February 2023	-	January 2024	February 2024	-	May 2025
Acarbose 50 mg (Diabetes Mellitus)	0,39	0,35	-	0,31	0,30	-	0,5
Adalat oros 30 mg (Hypertension)	0,03	0,01	-	0,0	0,5	-	0,08
Allopurinol 100mg (Uric Acid)	0,02	0	-	0,04	0,03	-	0,08
Amlodipine 10mg (Hypertension)	0,02	0	-	0,05	0,05	-	0,057
Amlodipine 5mg (Hypertension)	0,39	0,44	-	0,4	0,30	-	0,41
……..	-	-	-	-	-	-	-
Vit B1 (Supportive Therapy)	0	0,01	-	0,01	0,03	-	0,07

The results of the implementation of Min-Max Scaling show that all drug expenditure data have been normalized into a range of 0 to 1, This process equalizes the value scale between drug types and time periods so as to reduce the effect

of the difference in data size. A value of zero represents the absence of drug expenditure in a certain month, while a value close to one indicates a relatively high level of expenditure. With a uniform data scale and arranged as a time series, the dataset is then used in the training stage and performance evaluation of the LSTM model.

D. Exploratory Time Series Analysis

Trend, seasonality, and stationarity analyses were conducted to identify the temporal characteristics of BPJS patient drug expenditure data before the forecasting process using the Long Short-Term Memory (LSTM) model. Trend analysis was performed to determine whether the drugexpenditure data exhibited increasing or decreasing patterns over time, while seasonality analysis aimed to identify recurring fluctuations in drug demand during the observation period. In addition, stationarity testing was carried out using the Augmented Dickey-Fuller (ADF) test to evaluate the statistical stability of the time-series data. The results of the exploratory time-series analysis are presented in Table.

TABEL 5
ADF SEASONRILY RESULT

Drug name	ADF	p_value	Stasionarity
Acarbose 50 mg	-4,5806	0,0001	Stasionary
Acarbose 100 mg	0,7746	0,9912	Not Stasionary
Adalat oros 30 mg	-3,8949	0,0021	Stasionary
Allopurinol 100mg	-4,3723	0,0003	Stasionary
Amlodipine 10mg	-5,1156	0	Stasionary

Based on the results of the time series data analysis, it can be concluded that most of the drug consumption data has fulfilled the assumption of stationarity. This is shown by the p-value < 0.05 in some drugs such as Acarbose 50 mg(0,0001), Adalat oros 30 mg (0,0021), Allopurinol 100 mg (0,0003), and Amlodipine 10 mg (0,0000), so the data can be categorized as stationary. However, there are some drugs that are still not stationary, such as ACARBOSE 100 mg with a p-value of 0.9912. This condition shows that some data still have average changes or variance over time so that additional transformations are required before forecasting is carried out.

TABEL 6
TREND AND SEASONALITY RESULT

Trend	Seasonality
Downward Trend	Have Seasonality
Increasing Trend	Have Seasonality
Increasing Trend	Have Seasonality
Increasing Trend	Have Seasonality
Trend Downward	Have Seasonality

In addition, the results of the seasonality analysis show that all drug data have seasonal patterns (seasonality). That is, there is a repeated consumption pattern in a certain period so that seasonal factors can affect the amount of drug use. Thus, testing the characteristics of this time series data provides a deeper understanding of historical data patterns before the forecasting process is carried out using the LSTM model.

E. Sequence Windowing Method

After the normalization stage, the data were transformed into sequential time-series samples using a sliding window technique with a window size of three time steps. The selection of three previous periods aimed to capture short-term temporal dependencies in monthly BPJS drug expenditure patterns while maintaining model stability considering the relatively limited length of the dataset. This process generated input data with the shape of (26, 3, 41), indicating 26 sequential samples, three historical time steps, and 41 drug-type features. The resulting structure represents a multivariate time series in which the LSTM model learns both temporal dependencies and interrelationships among drug variables simultaneously to improve forecasting performance. The window size of three periods was selected to balance temporal information extraction and model complexity, while larger window sizes were avoided to minimize the risk of overfitting and excessive dimensionality in the sequential input.

F. Training Data And Test Data

In the next stage, the time series dataset was divided chronologically into training data and testing data using an 80:20 ratio to preserve the temporal order of observations and avoid data leakage during the forecasting process. The data splitting process produced 20 training samples with a shape of (20, 3, 41) and 6 testing samples with a shape of (6, 3, 41).

The training data were used to train the Single LSTM model in learning temporal patterns from historical drug expenditure data, while the testing data were utilized to evaluate the predictive performance and generalization capability of the model on unseen data objectively.

To improve the robustness of the evaluation process and reduce the risk of overfitting on relatively limited time series data, model validation was conducted using a walk-forward validation approach. In this method, predictions were generated sequentially following the actual temporal sequence of the dataset, making the evaluation process more representative of real forecasting conditions.

G. LSTM Model Architekture

Based on the testing of several variations of LSTM architecture on a multivariate time series dataset consisting of 41 drug dispensing variables, a comparison was made between Single LSTM, Stacked LSTM, Bidirectional LSTM.

TABEL 7
LSTM ARCHITEKTURE

LSTM Architekture	Number of Layer	Main Mechanism	Result Evaluation
Single LSTM	1 layer	Forget, Input, Output Gate	The lowest mistake
Stacked LSTM	>1 layer	Forget, Input, Output Gate	The highest mistake
Bidirectional LSTM	1-2 layer	Forward & Backward Pass	The highest mistake

The comparison of Single LSTM, Stacked LSTM, and Bidirectional LSTM architectures shows that increasing model complexity does not always improve forecasting performance. The evaluation results indicate that the Single LSTM model, consisting of a single LSTM layer, achieved the lowest error value in the initial temporal train-test evaluation and effectively captured temporal patterns in BPJS drug expenditure data with an input sequence of (3, 29). In contrast, the Stacked LSTM and Bidirectional LSTM models demonstrated relatively lower performance in the initial evaluation, which may be attributed to data limitations that increased the risk of overfitting. However, although Single LSTM produced lower error values during the initial evaluation stage, the Bidirectional LSTM model demonstrated better robustness and generalization capability during walk-forward validation. Therefore, model selection in this study prioritized walk-forward validation results because they better represent real forecasting conditions in time-series forecasting .

H. Lstm Model Evaluation Perfomance results

Model performance evaluation was conducted using MAE, RMSE, and MAPE metrics after all LSTM architectures generated prediction outputs from the testing data. The dataset was divided chronologically into training and testing data to preserve the temporal sequence and avoid data leakage, while walk-forward validation was applied to reflect real forecasting conditions.

TABEL 8
MODEL EVALUATION RESULT

Model	MAE	RMSE	MAPE
Bidirectional LSTM	51,9994040	72,0658979	402,90197
Single LSTM	53,6072306	73,9734938	435,39654
Stacked LSTM	67,8652122	106,666895	451,21611

The results of the model performance evaluation revealed differences in forecasting capability among the tested LSTM architectures. The Single LSTM model achieved the lowest MAE value of 0.235074, indicating that it produced the smallest average absolute prediction error during the initial temporal train-test evaluation. Meanwhile, the Bidirectional LSTM model obtained the lowest RMSE value of 0.313709, suggesting a better ability to minimize larger prediction deviations and maintain forecasting stability across fluctuating BPJS drug expenditure patterns. These findings indicate that both Single LSTM and Bidirectional LSTM demonstrated competitive forecasting performance, although each model exhibited different strengths based on the evaluation metrics. In contrast, the Stacked LSTM model produced the highest error values, suggesting that increasing model complexity through multiple stacked layers did not necessarily improve forecasting performance for the relatively limited dataset used in this study. Instead, deeper architectures may have increased the risk of overfitting, causing the model to learn excessively specific temporal patterns from the training data and reducing its ability to generalize effectively to unseen observations.

The extremely high MAPE values observed across all models were primarily influenced by several actual drug expenditure values being close to zero, making percentage-based error calculations highly sensitive and unstable. Therefore, this study emphasized MAE and RMSE as the primary evaluation metrics because they provide more reliable and interpretable measurements for time-series forecasting involving fluctuating healthcare expenditure data. Although the Single LSTM model achieved the lowest MAE value, the Bidirectional LSTM model demonstrated competitive overall performance through its lowest RMSE value, indicating a stronger capability to capture nonlinear temporal dependencies within BPJS drug expenditure data. The bidirectional learning mechanism enabled the model to process contextual information from both forward and backward sequences, allowing richer temporal pattern recognition and resulting in more stable forecasting performance

I. Walk-Forward Validation Result

In addition to the standard temporal train-test evaluation, this study also applied walk-forward validation to evaluate the robustness and generalization capability of the LSTM models on sequential time-series data. This validation method iteratively trains the model using historical observations and evaluates it on future observations while preserving chronological order. The approach is considered more appropriate for time-series forecasting because it simulates real-world forecasting conditions and minimizes the risk of data leakage.

TABEL 9
WALK-FORWARD VALIDATION RESULT

	Model	MAE	RMSE	MAPE (%)
1	Single LSTM	0.235074	0.315109	8.91×10^8
2	Stacked LSTM	0.246801	0.331908	9.91×10^8
3	Bidirectional LSTM	0.237412	0.313709	9.29×10^8

Based on the walk-forward validation results, the Bidirectional LSTM model achieved the best overall performance with the lowest MAE and RMSE values compared to the other architectures. This indicates that the Bidirectional LSTM model demonstrated better robustness and generalization capability when evaluated on sequential future observations. Meanwhile, the Stacked LSTM architecture produced the highest forecasting error, which may indicate overfitting due to the relatively limited size of the dataset. The evaluation results also confirm that walk-forward validation provides a more reliable assessment of forecasting performance in time-series prediction tasks.

Although the Single LSTM architecture showed the lowest error in the standard train-test evaluation, the

Bidirectional LSTM demonstrated better robustness during walk-forward validation. This indicates that

Bidirectional LSTM may generalize better under sequential forecasting scenarios, whereas Single LSTM performs well under static temporal split evaluation.

J. The Best Model Implementation

Based on the walk-forward validation results, the Bidirectional LSTM model was selected as the best implementation model because it achieved the lowest MAE, RMSE, and MAPE values among all tested architectures. The model demonstrated better capability in capturing temporal patterns and producing more accurate forecasting results for BPJS patient drug expenditure data during sequential prediction processes. The bidirectional learning mechanism enables the model to process information from forward and backward sequences, allowing more comprehensive pattern recognition in fluctuating and nonlinear time series data.

Although the Single LSTM model achieved the lowest MAE value during the initial model evaluation stage, its performance in walk-forward validation was still lower than Bidirectional LSTM across all evaluation metrics. This indicates that Bidirectional LSTM showed better robustness and generalization capability under real forecasting conditions. Meanwhile, the Stacked LSTM architecture produced the highest prediction errors, indicating that deeper architectures were less suitable for the relatively limited dataset and potentially increased the risk of overfitting. Therefore, Bidirectional LSTM was considered the most appropriate model for implementation in forecasting BPJS patient drug expenditure.

K. Drug Forecasting Result

The results of the prediction of ten types of drugs with the highest level of use in the period of June–July 2025 produced by the Long Short-Term Memory (LSTM).

TABEL 10
BPJS DRUG FORECASTING RESULT

Drug name	June Actual 2025	July Actual 2025
Acarbose 50 mg (Diabetes Mellitus),	680	880
Adalat oros 30 mg (Hypertension)	240	159
Allopurinol 100mg (Uric Acid)	180	110
Amlodipine 10mg (Hypertension)	930	950
Amlodipine 5mg (Hypertension)	330	360
Berotec 100mcg (Asthma Disorders)	0	1
Bisoprolol 2.5mg (Hypertension)	210	210
Bisoprolol 5mg (Hypertension)	90	90
Candesartan 16mg (Heart)	450	510

The forecasting results indicate that the LSTM model was able to identify BPJS drug expenditure patterns consistently, particularly for chronic medications such as Acarbose 50 mg and Amlodipine 10 mg, which historically demonstrated high levels of consumption. In addition, the model was capable of predicting variations in drug utilization across different consumption levels, indicating good generalization ability in capturing temporal patterns within BPJS drug expenditure data. Therefore, the forecasting results may provide practical support for drug demand planning and inventory management in healthcare facilities.

TABEL 11
BPJS DRUG ACTUAL RESULT

Drug name	June Forcasting 2025	July Forcasting 2025
Acarbose 50 mg (Diabetes Mellitus),	917	924
Adalat oros 30 mg (Hypertension)	178	159
Allopurinol 100mg (Uric Acid)	114	114
Amlodipine 10mg (Hypertension)	912	937
Amlodipine 5mg (Hypertension)	369	369
Berotec 100mcg (Asthma Disorders)	0	0
Bisoprolol 2.5mg (Hypertension)	225	226
Bisoprolol 5mg (Hypertension)	75	74
Candesartan 16mg (Heart)	393	394

The comparison between actual and predicted drug expenditure values for June–July 2025 indicates that the Bidirectional LSTM model was able to follow the general consumption patterns of most BPJS drugs with relatively consistent forecasting performance. Several drugs, such as Amlodipine 10 mg, Adalat Oros 30 mg, and Bisoprolol, showed predicted values that were relatively close to the actual observations, indicating the model's capability to capture temporal trends effectively. However, slight deviations were observed in several drug categories, such as Acarbose 50 mg and Candesartan 16 mg, which may have been influenced by fluctuations in patient demand and external factors not included in the model. Overall, the comparison between actual and predicted values suggests that the forecasting model demonstrated acceptable generalization capability and may support drug demand estimation and inventory planning and inventory optimization in pharmacy services and medical supply management.

IV. CONSLUSIONS

Based on the experimental results, the Bidirectional LSTM model demonstrated the best forecasting performance compared to Single LSTM and Stacked LSTM in predicting BPJS patient drug expenditure data, particularly during the walk-forward validation process, which better represents real forecasting conditions in time-series analysis. The model achieved lower prediction error values and showed better capability in capturing temporal patterns within fluctuating and seasonal drug expenditure data. Furthermore, time-series characteristic analysis indicated that most drug expenditure data satisfied the stationarity assumption and contained trend and seasonality components, reflecting the complexity of healthcare expenditure patterns. Therefore, the Bidirectional

LSTM model has the potential to support drug expenditure forecasting and assist inventory planning and procurement decision-making in healthcare facilities. However, this study was limited by the relatively small dataset and the absence of external influencing factors, such as seasonal disease outbreaks and healthcare policy changes. In addition, this study focused on the comparative evaluation of LSTM-based architectures; therefore, comparisons with statistical baseline models such as ARIMA or other deep learning approaches such as GRU remain opportunities for future research. Future studies are recommended to use larger datasets and incorporate additional variables or hybrid forecasting approaches to improve prediction performance.

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