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Forcasting Analysis of Drug Use in Hospitals Based on Multivariate Long Short-Term Memory Networks

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ABSTRACT

Effective drug inventory management is crucial for maintaining service quality and cost efficiency in hospitals. Inaccurate procurement planning can cause stockouts or overstock conditions, disrupting healthcare operations. This study presents a predictive model for outpatient drug consumption using a Multivariate Long Short-Term Memory (LSTM) network. The dataset comprises historical records from the general, pediatric, and maternity polyclinics at RSIA Fatimah Hospital, Probolinggo Regency, East Java, Indonesia, collected in January 2023. The variables include timestamp, polyclinic name, drug name, and quantity used. Data preprocessing involved cleaning, one-hot encoding for categorical features, min-max normalization, and time-based train-test splitting to avoid data leakage. The multivariate LSTM model was trained for 500 epochs under various configurations, evaluated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Three model groups (A, B, C) with distinct neuron counts and batch sizes were tested to assess performance variations. Model B1 achieved the best results, with the lowest MAE (10.239), MAPE (1.979%), and highest R^2 (0.199). Although the R^2 value indicates limited variance explanation, Nonetheless, the model remains useful for operational forecasting, the model effectively captures temporal patterns in drug consumption, demonstrating its potential as a decision-support tool for optimizing hospital pharmaceutical inventory management.

INTRODUCTION

Drug management represents one of the most critical components of hospital operations, where pharmaceutical procurement contributes to approximately 40–50% of total operational expenses (Nathaniel, 2023). Inefficient drug forecasting and procurement planning can cause either stockouts or overstock conditions, both of which disrupt service quality and financial efficiency. RSIA Fatimah, a maternal and child hospital in Probolinggo Regency, East Java, still performs drug need planning manually based on historical transaction summaries. This manual process often results in mismatches between drug supply and outpatient demand, leading to inventory surpluses of up to 20% in certain months and shortages for high-demand medications. Therefore, a more accurate forecasting model is needed to optimize procurement and minimize losses. Various forecasting methods have been used in healthcare logistics, such as linear regression (Wahyudi et al., 2024). exponential smoothing (Anshory et al., 2020) and ARIMA(Bayangkari Karno, 2020). However, these traditional statistical models often fail to capture nonlinear and dynamic temporal patterns commonly found in hospital drug demand (Mbonyinshuti et al., 2024). Recent advances in deep learning have shown promising results in time-series forecasting, where Long Short-Term Memory (LSTM) models outperform conventional methods in capturing long-term dependencies (Devaraj et al., 2021; Husaini et al., 2025). Furthermore, studies such as (Ma et al., 2022), and (Tang et al., 2024) emphasize the role of explainable deep learning models for improving interpretability and predictive stability. Despite these developments, their application in hospital pharmacy management remains limited. This study proposes a Multivariate LSTM model that integrates multiple operational variables, including time, polyclinic name, drug name, and usage quantity. These variables were selected because they represent essential temporal and contextual dimensions influencing hospital drug demand. The main contributions of this study are as follows:

1. To provide a predictive model that supports pharmacists and hospital management in planning drug needs more accurately.
2. To adapt the LSTM method into a multivariate framework by incorporating temporal, polyclinic, drug name, and quantity variables.
3. To encourage the development of deep learning methods for operational-level drug need forecasting at RSIA Fatimah.

This research strengthens previous findings emphasizing the importance of machine learning algorithms in pharmacy management. (Anshory et al., 2020) showed that LSTM yields lower error values than conventional statistical methods in pharmaceutical sales forecasting. (Yanti et al., 2024) demonstrated the effectiveness of LSTM in predicting drug stock needs in primary healthcare facilities with low prediction error. (Ashari & Sadikin, 2020) also affirmed the advantage of LSTM in capturing complex temporal patterns in sales data. By referencing these prior studies, this research establishes its novelty through the implementation of a Multivariate LSTM model that integrates contextual hospital data variables, enabling a more practical and operationally relevant prediction approach for hospital pharmacy management.

RESEARCH METHODS

This study adopts a quantitative experimental design to develop a Multivariate Long Short-Term Memory (LSTM) model for forecasting outpatient drug consumption at RSIA Fatimah Hospital, Probolinggo, East Java. The research framework consists of several main stages: data collection, data preprocessing, model development, model evaluation, and performance comparison.

Material

The research data was obtained from the Hospital Management Information System (SIMRS) of RSIA Fatimah. The dataset consists of 1,500 records of outpatient drug usage from the general, pediatric, and maternity polyclinics for January 2023. The variables used include timestamp, polyclinic name, drug name, quantity used, and stock information. This data was selected as it represents real-world hospital drug management conditions relevant for predictive model development.

Table 2. Parameters for drug stock prediction

No.	Variable Name	Description
1	*tanggal* (date)	Date of drug usage
2	*jam* (hour)	Hour of drug administration
3	*menit* (Minute)	Minute of drug administration
4	*detik* (second)	Second of drug administration
5	*nama_poli*	Polyclinic name
6	*jumlah_obat*	Quantity of drug Used per Patient
7	*nama_obat*	Drug Name

Method

The method describes the workflow of the multivariate LSTM prediction technique. Figure 1 illustrates the steps involved.

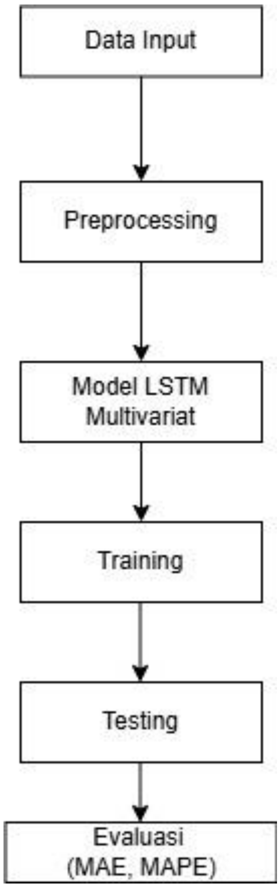


Figure 1 System Design

The research involves several key steps:

1. Data Preparation

Data was exported from the SIMRS application of RSIA Fatimah and compiled into a spreadsheet format (Excel/CSV). The dataset contains records of outpatient drug usage from the general, pediatric, and maternity polyclinics for January 2023, serving as the basis for the prediction model.

Tabel 3. Sample patient drug data

tanggal	***jam***	***menit***	***detik***	***nama_poliklinik***	***jumlah_obat***	***nama_obat***
2023/01/01	12	7	26	*poli_umum*	12	acetyl sistein tab
2023/01/01	9	23	32	*poli_umum*	0	abate
...	...	...	...	...	...	...
2023/01/30	10	12	35	*poli_anak*	0	imboost syr 60 ml
2023/01/30	12	35	47	*poli_anak*	0	imboost tab
2023/01/31	16	35	32	*poli_kandungan*	0	bisolvon solution
2023/01/31	17	52	31	*poli_kandungan*	0	bisolvon syr flu

2. Data Preprocessing

Data preprocessing was conducted to ensure the dataset's quality and compatibility with the LSTM model. The steps involved data cleaning (removing missing and duplicate entries, and replacing missing numeric values using median imputation), categorical encoding using one-hot encoding for drug name and polyclinic variables, normalization through the Min–Max scaling technique for numerical features, and temporal splitting into training and testing subsets. To prevent temporal data leakage, the split was performed chronologically, with 80% of the data used for training and 20% for testing.

3. Model LSTM Multivariate

The LSTM model was built to predict drug requirements considering multiple variables (multivariate). The model structure generally consists(Mohsen et al., 2021):

3.1. Data Input

Data exported from SIMRS (pharmacy dashboard), patient visit reports, and internal hospital data in Excel or CSV format.

3.2. Data Preprocessing

Selecting relevant data (data selection), then cleaning it from incomplete or unnecessary attributes (data cleaning) (Yusiana et al., 2022)

3.3. Multivariate LSTM Model

Building the predictive model using the LSTM algorithm implemented in Python on Google Colab with the TensorFlow/Keras deep learning framework(Eka P, 2021).

3.4. Training and Testing

The dataset was divided into training and testing subsets using a chronological split to maintain the temporal order of observations and prevent data leakage. Eighty percent (80%) of the earliest sequential records were used to train the LSTM model, while the remaining 20% were reserved for testing. During training, the model learned temporal dependencies by updating weights iteratively through the backpropagation algorithm over 500 epochs. The Adam optimizer and Mean Squared Error (MSE) loss function were applied to minimize prediction errors during this stage.

In the testing phase, the trained model was evaluated using unseen test data to measure its generalization ability. The testing process involved predicting drug consumption values for the test period and comparing them to the actual recorded quantities. The performance of the model was quantified using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2) as evaluation metrics.

3.5. Evaluation

Model evaluation was performed after training completion to validate the predictive accuracy and robustness of the developed LSTM model. MAE and MAPE were used to assess average prediction deviations and percentage-based accuracy, while R^2 measured the model's ability to explain data variance. The evaluation results were compared across different LSTM architectures (Model A, B, and C) to determine the most optimal configuration in terms of predictive precision and stability. The evaluation strictly followed the temporal testing protocol to avoid any form of data leakage or biased validation.

4. Model Training and Testing

The training process involved testing several parameter configurations, including the number of hidden neurons, epochs, and batch size, to obtain the best-performing model (Alhanaf et al., 2024). The training data was used to train the network, while the test data was used for validation.

5. Evaluation Metrics

Model evaluation was conducted using two primary metrics:

- Mean Absolute Error (MAE) : is used to evaluate the average absolute discrepancy between real and forecasted values.
- Mean Absolute Percentage Error (MAPE) : Measures the prediction error rate in percentage terms.

This stage ensures the developed model can not only learn historical patterns but also reliably predict future drug usage.

RESULTS AND DISCUSSION

The results and discussion explain the modeling using the Multivariate Long Short-Term Memory (LSTM) method to predict outpatient drug usage at RSIA Fatimah and test the predictions using internal validation data (min-max) and observational data to demonstrate the method's accuracy.

Data Preparation

Data was obtained from the SIMRS of RSIA Fatimah and compiled into a spreadsheet (Excel/CSV). The dataset contains records of drug usage from the general, pediatric, and maternity outpatient clinics in January 2023, utilizing 1,500 data rows for predictive modeling.

Data Standarization

Normalization was applied to all variables to standardize the data scale, ensuring each variable contributes equally to the model training process. Original values were transformed to a range between 0 and 1 using Min-Max Scaling. The standardized data was then reshaped into a supervised learning format, representing the relationship between variable values at a previous time (t-1) and the current time (t). This facilitates the multivariate LSTM model in more effectively recognizing temporal patterns and inter-variable relationships.

Tabel 4. Normalized supervised learning data sample.

date	var1(t-1)	0.000000	0.000667	...	0.998666	0.999333
hour	var2(t-1)	0.461538	0.500000	...	0.653846	0.538462
minute	var3(t-1)	0.400000	0.711111	...	0.422222	0.511111
second	var4(t-1)	0.574074	0.962963	...	0.537037	0.537037
polyclinics name	var1(t)	0.000667	0.001334	...	0.999333	1.000.000
drugs Quantity	var2(t)	0.500000	0.384615	...	0.538462	0.576923
drug name	var3(t)	0.711111	0.444444	...	0.511111	0.888889

Normalization helps accelerate training by reducing inter-attribute value variability and maintains stability during model weight updates. Structuring data in a supervised learning format clarifies the learning direction, enabling the model to leverage historical patterns for more accurate drug usage predictions.

Model Training

To examine the effect of data volume on model performance, the training process was designed using three incremental subsets of the dataset, denoted as Groups A, B, and C. Each group represented a different portion of sequential data extracted from the same time-series records of outpatient drug usage. Specifically, Group A utilized 1,050 records, Group B used 1,200 records, and Group C used 1,350 records. These subsets were arranged chronologically to preserve temporal dependencies and avoid data leakage. The purpose of this setup was to simulate how variations in data richness influence the predictive accuracy and generalization capability of the Multivariate LSTM model.

Within each group, three model configurations (e.g., A1–A3, B1–B3, C1–C3) were trained by varying the number of hidden neurons, dense layer size, epochs, and batch size while keeping other hyperparameters constant. This experimental design enables a comparative analysis between model capacity and dataset scale, aiming to identify the optimal balance between training data size and model complexity.

Tabel 5. Model Groups

Model Group	Model Variants		
A	A1	A2	A3
B	B1	B2	B3
C	C1	C2	C3

Table 5. categorizes the Multivariate LSTM models used in the study into three main scenarios: A, B, and C. Each scenario contains three model variants tested to find the optimal configuratio.

1. **Model A**

Tabel 6. Tuning Model Parameters for Group A

Model	Training Data	Hidden Neurons	Dense	Epoch	Batch Size
A1	1050	12	25	500	200
A2	1050	24	25	500	100
A3	1050	24	25	500	200

Table 6. shows the configuration for Group A LSTM models with 1050 training data rows. Model variations (A1-A3) differ in the number of hidden layer neurons, uniform dense layer neurons, batch size, and other fixed parameters like the number of epochs (500). These configuration differences aim to find the model with the highest accuracy and lowest error.

2. **Model B**

Tabel 7. Tuning Model Parameters for Group B

Model	Training Data	Hidden Neurons	Dense	Epoch	Batch Size
B1	1200	12	15	500	200
B2	1200	24	20	500	200
B3	1200	36	25	500	200

Table 7. shows the configuration for Group A LSTM models with 1050 training data rows. Model variations (A1-A3) differ in the number of hidden layer neurons, uniform dense layer neurons, batch size, and other fixed parameters like the number of epochs (500). These configuration differences aim to find the model with the highest accuracy and lowest error.

3. **Model C**

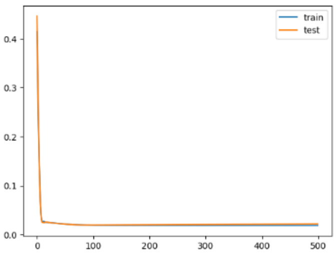
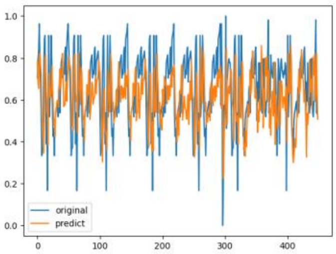
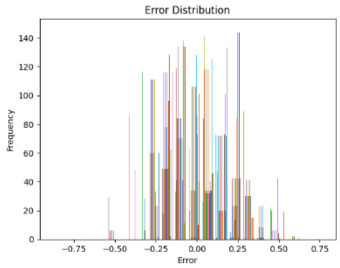
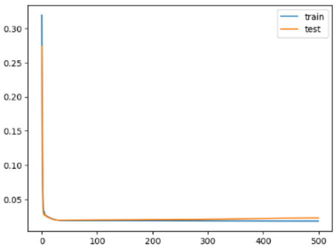
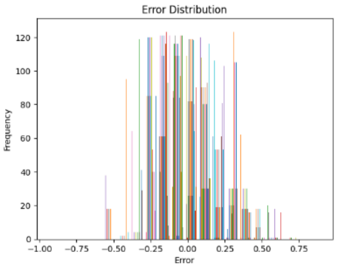
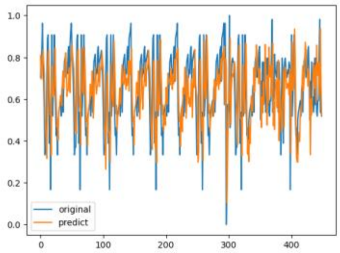
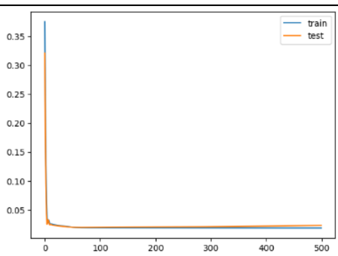
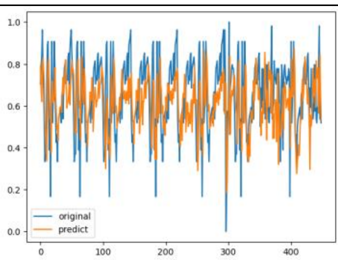
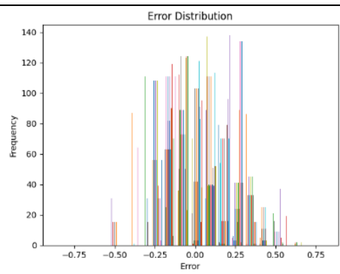
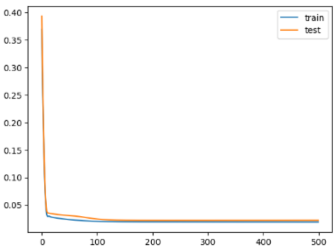
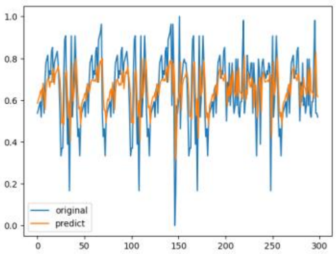
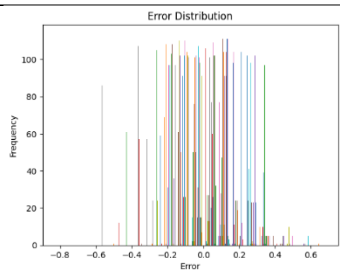
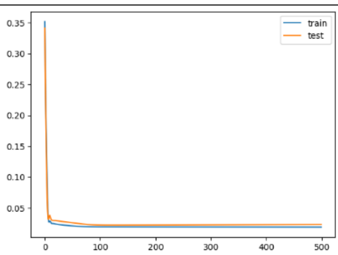
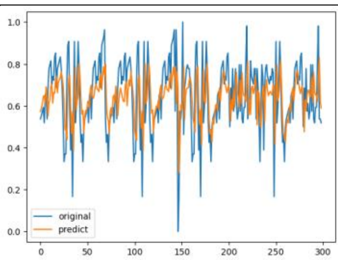
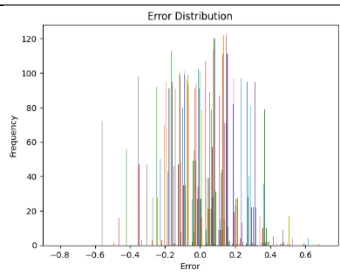
Tabel 8. Tuning Models Parameters for Group C

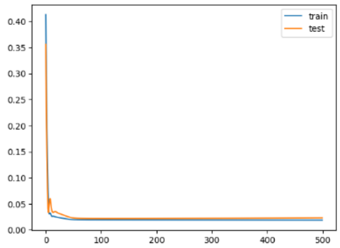
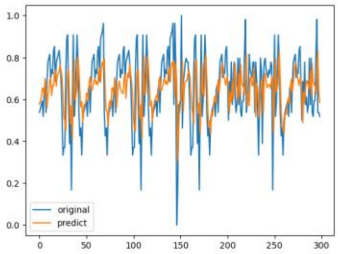
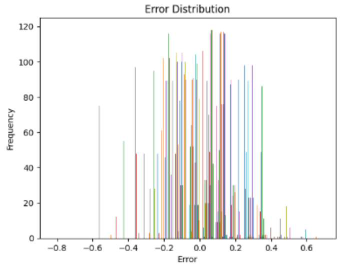
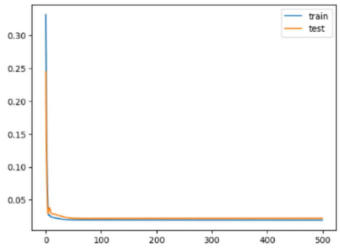
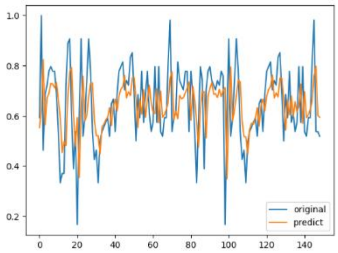
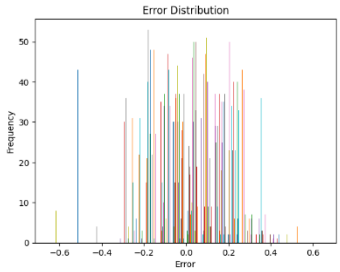
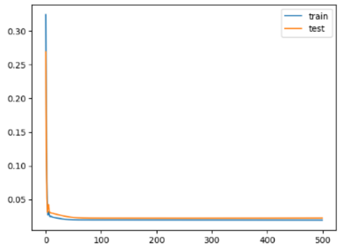
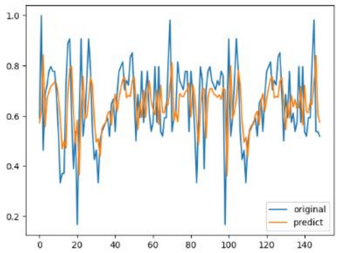
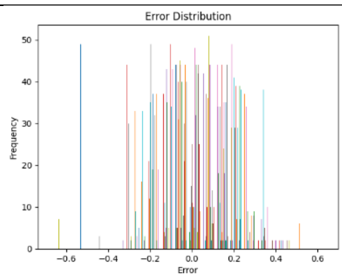
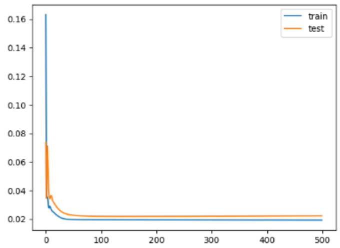
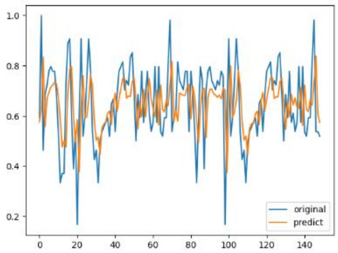
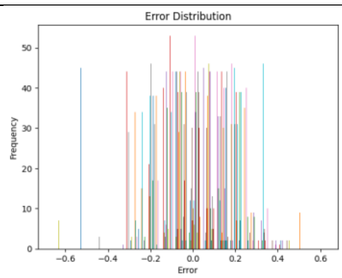
Model	Training Data	Hidden Neurons	Dense	Epoch	Batch Size
C1	1350	12	25	500	200
C2	1350	36	25	500	200
C3	1350	24	25	500	200

Table 8. presents the configuration for Group C LSTM models trained with 1350 data records. Model variations (C1–C3) differ in the number of hidden neurons and batch size, while the epoch parameter was fixed at 500. Each model employed the ReLU activation function in the hidden layers and a linear activation function in the output

layer to ensure numerical continuity for regression output. The Adam optimizer was applied with a learning rate of 0.001, and the loss function was defined as Mean Squared Error (MSE), which is suitable for continuous prediction tasks. These hyperparameter choices were derived from established literature on LSTM time-series forecasting (Devaraj et al., 2021; Nketiah et al., 2023) and further adjusted empirically through preliminary experiments to achieve stable convergence. This configuration aimed to balance computational efficiency and predictive accuracy while maintaining model generalizability.

Tabel 9. Graphic Model

Model	Accuracy	Error	Distribution
A1			
A2			
A3			
B1			
B2			

Model	Accuracy	Error	Distribution
B3			
C1			
C2			
C3			

Tabel 10. Result for Models A, B and C

Model	Train RMSE	Test RMSE	MAE	MAPE	R^2
A1	0.137	0.172	12.238	1.249	0.014
A2	0.135	0.173	12.084	1.445	0.001
A3	0.136	0.180	12.859	1.348	-0.074
B1	0.137	0.150	10.239	1.976	0.199
B2	0.136	0.155	10.778	1.979	0.141
B3	0.136	0.155	10.730	1.985	0.145
C1	0.138	0.149	10.338	22.378	0.046
C2	0.138	0.152	10.465	22.552	0.0168
C3	0.138	0.152	10.505	22.657	0.015

Table 10. presents the evaluation results of all LSTM models in Groups A, B, and C based on Train RMSE, Test RMSE, MAE, MAPE, and R^2 metrics. These indicators jointly provide a comprehensive perspective of model accuracy and generalization capability. Among all tested configurations, Group B exhibited the most stable and balanced performance across metrics. Model B1, in particular, achieved the lowest MAE (10.239) and the lowest MAPE (1.979%), indicating smaller average prediction deviations from actual values. The R^2 value of 0.199 reflects that, although the model explains a limited proportion of the data variance, it performs relatively

better than the other tested models under identical experimental conditions. Therefore, Model B1 can be considered the most optimal configuration in terms of relative predictive accuracy and consistency, while acknowledging that the overall explanatory power remains moderate due to the inherent variability of outpatient drug usage data.

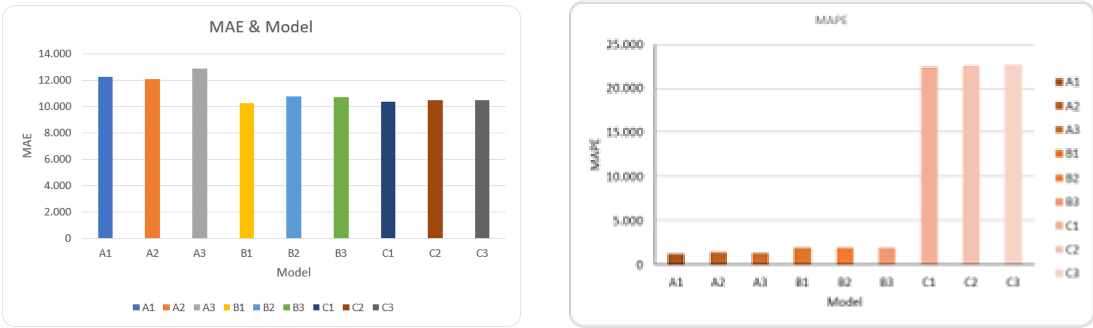


Figure 2 . Graph of model A, B, C Results for MAE and MAPE

DISCUSION

Utilizing predictive techniques for determining drug procurement quantities in hospital pharmacy management is an emerging field. This study, by applying Multivariate LSTM, offers a novel and optimal approach. Effective drug management is fundamental to ensuring the continuity of healthcare services. Inaccurate procurement planning often leads to stockout or overstock risks, impacting service quality and cost efficiency (Yanti et al., 2024). This study demonstrates that a multivariate LSTM model can provide drug usage predictions with a relatively low error rate, albeit with performance variations across configuration.

Compared with the study of Qianli (Ma et al., 2022), which developed the Difference-Guided Representation Learning Network (DGRL-Net) to capture dynamic temporal evolution in multivariate time series classification, this study focuses on forecasting drug consumption in outpatient pharmacy management. While Ma's approach integrates difference-guided LSTM and multiscale CNN to enhance feature representation, the current research employs a standard multivariate LSTM architecture to optimize prediction accuracy.

The test results show that model B1 achieved the best performance with an R^2 of 0.199 and MAE of 10.239. This indicates the model can explain some data variance and reduces prediction error compared to other configurations. Compared to Group A models, which showed low MAPE but R^2 values close to zero, Group B models are more stable and consistent. Meanwhile, Group C models, despite recording low Test RMSE, exhibited very high MAPE values (22.378–22.657), making them less representative for predicting outpatient drug usage in a hospital polyclinic context. These findings support previous research affirming the superiority of LSTM over traditional methods. Anshory et al. proved that LSTM yields lower MAPE than Least Square, Exponential Smoothing, and ARIMA(Mbonyinshuti et al., 2024) methods in pharmaceutical sales forecasting(Anshory et al., 2020). Yanti et al (Yanti et al., 2024) also showed that the LSTM algorithm minimizes prediction error for drug stock in puskesmas, helping prevent both shortages and surpluses. Furthermore, Ashari & Sadikin reinforced that LSTM outperforms traditional regression methods in capturing non-linear temporal patterns in sales data(Ashari & Sadikin, 2020). The practical implication of these results is the potential need to integrate LSTM-based prediction models into hospital management information systems. This would allow pharmacy management to plan drug procurement more accurately, reduce budget waste risk, and improve drug availability according to patient needs. This research also opens opportunities for further development by adding external variables, expanding the historical data period, and exploring advanced deep learning architectures like BiLSTM or GRU to further optimize prediction performance.

CONCLUSION

This study developed a multivariate LSTM model to predict outpatient drug usage at RSIA Fatimah Probolinggo. The testing process showed that model B1 delivered the best performance with the highest R^2 (0.199) and lowest MAE (10.239), indicating superior predictive capability compared to other configurations. These results confirm that selecting parameter configurations, particularly the number of neurons and batch size, plays a crucial role in enhancing prediction quality. This finding aligns with previous studies demonstrating the advantage of LSTM in handling time series data compared to traditional statistical methods. (Anshory et al., 2020)proved that LSTM produces the lowest MAPE compared to Least Square, Exponential Smoothing, and ARIMA for pharmaceutical sales forecasting. Yanti et al (Yanti et al., 2024)also showed the effectiveness of LSTM in predicting drug stock needs in community health centers with low relative error, while Ashari & Sadikin. (Ashari & Sadikin, 2020) affirmed LSTM's superiority in recognizing complex temporal patterns in sales data. Based on these results, this study confirms that implementing multivariate LSTM can be an effective solution to support decision-making in hospital pharmaceutical drug management. Integrating the prediction model into the hospital management information system has the potential to improve drug procurement efficiency, reduce stockout and overstock risks, and support sustainable healthcare services. Future research could focus on adding external variables, expanding the historical data range, and exploring advanced deep learning architectures to obtain more optimal prediction results.

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