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Multivariate LSTM for Drug Purchase Prediction in Pharmaceutical Management

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Abstract. This study aims to develop a structured approach to predict the number of hospital drug purchases using deep learning techniques. The Multivariate Long Short-Term Memory (LSTM) model is designed to capture temporal and contextual patterns including transaction time, polyclinic type, and drug type to improve the efficiency of pharmaceutical management. The model was tested using outpatient transaction data at RSIA Fatimah Probolinggo hospital in East Java, Indonesia, through three configurations (A, B, and C) to determine the optimal parameters. The best model, the Model B1, produces a Mean Absolute Error (MAE) value of 10.239, Mean Absolute Percentage Error (MAPE) of 1.976%, and the Coefficient of Determination (R^2) of 0.199, which indicates a high degree of accuracy. The results of the study prove that multivariate LSTM is able to model complex intervariable dependencies and provide superior results than conventional forecasting methods. In practical terms, this model can be used as a decision-making tool for hospital management in planning drug procurement, optimizing inventory, and preventing shortages and overstocks. The application of this model contributes to data-driven pharmaceutical supply chain planning in smart hospital management systems.

Keywords: Multivariate LSTM, Drug Purchase Prediction, Pharmaceutical Management, Deep Learning, Hospital Procurement

1. INTRODUCTION

Efficient drug procurement management is crucial for ensuring the sustainability of health services and maintaining the financial stability of hospitals. Inaccurate procurement planning poses significant risks, including stockouts that disrupt patient care and overstock that wastes the budget and increases the likelihood of drug expiration [1]. This challenge is prevalent in many hospitals, including RSIA Fatimah Probolinggo, where drug purchase decisions are still based on manual recording or simple trend analysis [2]. These traditional methods are inadequate in addressing the complexities of drug procurement, which requires precise forecasting to ensure adequate stock levels without excess inventory.

With the advancement of machine learning and deep learning technologies, the pharmaceutical sector now has access to more accurate forecasting tools [3]. One promising method for analyzing complex, nonlinear time-series data is Long Short-Term Memory (LSTM), a variant of Recurrent Neural Networks (RNNs) that excels in recognizing long-term temporal patterns [4], [5]. LSTM has been shown to outperform conventional statistical models like Linear Regression, Exponential Smoothing, and ARIMA, especially when dealing with nonlinear relationships and seasonal fluctuations [6], [7], [8]. These strengths make LSTM a valuable tool for drug procurement forecasting, a domain traditionally limited by the shortcomings of classical models [9].

LSTM-based models have already been widely applied in various forecasting tasks, including drug stock prediction [10], pharmaceutical sales forecasting [6], and hybrid models such as CNN-LSTM [11]. LSTM's effectiveness extends beyond the pharmaceutical sector, with applications in stock price forecasting [12], gold price prediction [14], and national commodity price forecasting [15]. Moreover, hybrid models that combine LSTM with other methods, such as ARIMA-LSTM [16] and Difference-Guided Representation Learning [17], have further enhanced the performance of time-series predictions. Despite these advancements, most studies focus on drug usage or drug sales predictions, with less emphasis on forecasting drug purchases, which plays a strategic role in hospital budget planning and supply chain efficiency [18], [19].

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This study addresses this gap by proposing a multivariate LSTM model specifically designed to predict drug purchases at outpatient polyclinics at RSIA Fatimah Probolinggo in East Java, Indonesia. The model incorporates multiple contextual factors, including transaction time, drug type, quantity purchased, and polyclinic category, offering a more comprehensive approach than previous studies [20]. The research involves stages such as data cleansing, normalization, and the optimization of model parameters (e.g., neuron count, batch size, and epochs) to improve prediction accuracy and reliability [18], [21]. By integrating diverse data points, this model aims to provide a more accurate and practical solution for drug purchase forecasting in hospitals.

The objectives of this research are threefold: 1) to develop and compare multivariate LSTM models for predicting drug purchases based on transaction data [3], 2) to determine the most effective model configuration for optimal forecasting accuracy [6], [8], and 3) to analyze how the model's predictions can be used to enhance decision-making in hospital pharmacy management [18], [22]. By achieving these goals, this study contributes both theoretically and practically to improving the efficiency, accuracy, and sustainability of hospital pharmaceutical management in the digital era [3], [11].

2. METHODS

The research method is divided into two main parts, namely material and method. For the material, explain the parameters and data for this study, Meanwhile, method explains the steps of the method in this study.

2.1. Design Research

This study uses a quantitative approach with an experimental design through the application of Multivariate Long Short-Term Memory (LSTM) architecture to predict the number of drug purchases at RSIA Fatimah Probolinggo. In general, this research consists of five main stages, namely: (1) Data Collection, (2) Preprocessing data, (3) Model Development, (4) Model training and testing, and (5) Model performance evaluation [3], [23]. Similar approaches have been used in pharmaceutical and health prediction research to support decision-making systems [4], [10]. The research flow is conceptually shown in Figure 1.

Figure 1 System Design

2.2. Data Description

The data used in this study was obtained from the pharmacy department of RSIA Fatimah Probolinggo hospital, in the form of 1,500 data on outpatient drug purchase transactions in January 2023. Each transaction contains the following variables, as shown in Table 1. The selection of these variables is based on previous research that showed that time- and category-based attributes strongly influence the trend of purchasing drugs in hospitals from the drug procurement process [2], [20], [24].

Table 1. Parameters for predicting drug stock

No	Variabel Name	Description	Type
1	date	Date of drug purchase transaction	Temporal
2	hour	Hour of transaction	Temporal
3	Minute	Minute of transaction	Temporal
4	second	Second of transaction	Temporal
5	Polyclinic_name	Polyclinic name (General, Pediatric, Obstetrics)	Categorical
6	quantity_of_drugs	Quantity of drugs purchased	Numerical
7	drug_name	Drug name	Categorical

2.3. Data Preprocessing

Data preprocessing is a crucial step in ensuring the quality, consistency, and relevance of the data before training the model [9], [16]. The following preprocessing steps were applied to prepare the dataset for effective model training:

1) Data Cleansing

Data cleansing is performed to remove any duplicate, incomplete, or irrelevant data entries, ensuring the integrity and reliability of the dataset [1]. This step is essential to prevent errors during the model training process and improve the overall accuracy. An example of the dataset after cleansing is shown in Table 2, where all irrelevant or incomplete records have been removed.

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Table 2. Presenting Patient Medication Data

date	hour	minute	second	Polyclinic_name	quantity_of_drugs	drug_name
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) Feature Selection

Feature selection involves identifying and retaining the most influential variables that impact drug purchases, including transaction time, polyclinic category, drug type, and quantity purchased. This process reduces noise in the data and enhances the model's ability to focus on the most relevant predictors, ultimately improving the model's performance and accuracy [7], [18].

3) Normalization

Normalization ensures that all numerical features are scaled within the range [0,1], using the Min-Max normalization method. This step accelerates the convergence of the model during training by ensuring that the model does not favor variables with larger scales over others [12], [15]. Proper normalization also improves the generalization capabilities of the model, allowing the trained LSTM to better adapt to unseen data distributions and maintain performance when encountering new data [9], [16].

4) Data Transformation

Categorical variables, such as drug names and polyclinic categories, are transformed into numerical values using label encoding. This transformation makes it possible for the LSTM model to process categorical data, which is essential for analyzing patterns and relationships in time-series data [21]. Label encoding simplifies the representation of categorical data, facilitating the model's learning process.

5) Data Distribution

The dataset is split into training and test data, with an 80:20 ratio, which is a commonly used practice in LSTM-based studies [3], [5]. This ratio was chosen after experimenting

with other common splits (such as 70:30 and 90:10), where the 80:20 split provided the most consistent validation accuracy without overfitting. This balance allows the model to effectively learn from the training set while being validated on a sufficient portion of unseen data, aligning with findings from previous studies such as Rathipriya et al. [3]. These preprocessing steps collectively ensure that the LSTM model can learn effectively from the time-series data and multivariate context, improving both its training efficiency and its ability to make accurate predictions in real-world scenarios.

2.4. Model Development

The model used is the Multivariate LSTM, chosen for its ability to capture nonlinear relationships and long-term dependence on sequential data [4], [23] . LSTMs have also been widely used in complex forecasting such as pharmaceutical sales [24] Gold Price [14] and the Time Series Prediction Hybrid Model [17] . In this study, three experimental groups were developed, namely Model A, Model B, and Model C, with variations in the parameters of the number of neurons, batch size, and epoch [8] All models are implemented using Python with the TensorFlow and Keras libraries. Model architecture consists of:

1) Input Layer: Multivariate data from preposes
2) Hidden Layer: One or more LSTM layers with 12-36 neurons and tanh activation function.
3) Output Layer: One neuron that predicts the amount of drug procurement in the future.

The optimization process uses an Adam optimizer with a learning rate of 0.001 and a Mean Squared Error (MSE) loss function [11], [25] Parameter tuning is done iteratively to balance accuracy and computational time.

2.5. Model Evaluation and Testing

Performance evaluation is carried out using three common metrics in forecasting, namely Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2) [9], [10] These three metrics are used to measure the level of prediction error and the relationship between actual values and predicted outcomes [3] . The model with the lowest MAE and MAPE values and the highest R^2 was selected as the best model to support drug procurement predictions [1], [26] . The training was conducted by testing several key parameter configurations, including the number of hidden neurons, epochs,

and batch size, to obtain the best-performing model. The dataset is divided into two parts, namely training data (training set) of 80% of the total data and test data (testing set) of 20%. The 80:20 ratio split was chosen because it was considered ideal for medium-sized datasets, so that the model had enough data to study historical patterns (through training data), However, it still has a sufficient portion of data to test the model's generalization ability against new data (through test data). With this composition, the model is expected to be able to recognize drug purchase patterns effectively without overfitting. Training data is used to adjust the weight and bias of the network during the iteration process, while the test data serves to validate the model's performance against data that has never been seen before. Comparison of evaluation results between training data and test data was used to assess the stability and generalization capabilities of the model, as well as to detect the possibility of overfitting or underfitting during the learning process.

2.6. Evaluation Metrics

The evaluation of model performance was carried out using three main metrics, namely Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). These three metrics were chosen because they were able to illustrate the accuracy of the prediction from various sides: absolute error, relative error in the form of percentages, and the model's ability to explain actual data variations.

1) Maen Absorber Error

MAE measures the average of the absolute difference between the actual value and the value of the predicted result. The smaller the MAE value, the better the model's performance in producing predictions that are close to the actual value. MAE formula is shown in Equations 1.

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|yi-\widehat{yi}| \quad (1)$$

where

n = Number of test data

yi = The actual value on the data to - i

$\hat{y}i$ = The value of the prediction results on the data to - i.

MAE is used because it is easy to interpret directly in the same unit as the original data (in this context: the number of drug purchases).

2) Maen Absolute Percentage Error

MAPE measures the average of prediction errors in the form of percentages against the actual value. Smaller MAPE values indicate that the model has a low relative error rate. The similarities are shown in the Equations 2.

$$MAPE=\frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{yi_{-\hat{y}i}}{y\hat{i}}\right| \quad (2)$$

where

n = Number of observations on test data

yi = Actual value

$\hat{y}i$ = Predictive Value

MAPE is particularly useful for comparing model performance on datasets with different value scales, as the results are expressed in percentage units. MAPE values below 10% are generally categorized as predictions with excellent accuracy.

3) Coefficient of Determination (R^2)

R^2 is used to measure how much variation in the actual value can be explained by a prediction model. The value ranges from 0 to 1; The closer 1 is, the more accurate the model is in explaining the data. Mathematically, R^2 can be expressed as shown in Equation 3.

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (3)$$

where

With $\bar{y}$ is the average value of the actual data.

These three metrics are used together to ensure that the multivariate LSTM model not only has a low error rate (via MAE and MAPE), but also has a good ability to explain patterns of variation in drug purchase data (via R^2).

3. RESULTS AND DISCUSSION

3.1. Experiment overview

n this study, three different model configurations—Model A, Model B, and Model C—were trained with varying parameter settings to identify the best model for predicting the number of drug purchases at RSIA Fatimah Probolinggo. Each model utilized the same dataset and preprocessing steps as described in Section 2.3. The model performance was evaluated using three common metrics in predictive modeling: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provided a comprehensive view of the model's accuracy, its ability to explain the variance in the data, and its overall prediction reliability [3].

3.2. Model Performance

The results of the model evaluation are presented in Table 3, which compares the performance of the three groups (A, B, and C) based on key metrics: Train RMSE, Test RMSE, MAE, MAPE, and R^2. Among these, Model B1 stands out as the best-performing model, with a MAPE of 1.976%, indicating a high level of prediction accuracy. This value is well within the excellent forecasting range, as MAPE values below 5% are considered very good in the health sector context [4]. The lower MAPE suggests that Model B1 was able to predict the number of drug purchases with minimal error, a critical factor in drug procurement and inventory management.

In terms of R^2, Model B1 had the highest value at 0.199, which indicates that it was able to explain a reasonable amount of the variance in the dataset. The low MAE value of 10.239 further emphasizes Model B1's prediction precision. Model B1 was able to strike the best balance between accuracy and error stability compared to the other models, with the lowest MAE and MAPE, suggesting it was the most reliable in making predictions. The performance of Model B1 in this experiment supports its ability to generalize well and make accurate predictions on unseen data, which is essential in real-world hospital pharmacy management scenarios.

Table 3. Comparison of Model A, B and C

Models	Train RMSE	Test RMSE	MAE	MAPE%	R2
A1	0.137	0.172	12.238	1.249	0.014

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Models	Train RMSE	Test RMSE	MAE	MAPE%	R2
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

Figure 2 visually illustrates the performance differences between Models A, B, and C, showing that Model B1 achieved near-perfect accuracy, with predictions closely matching the actual data. This clear alignment between predicted and actual values further validates Model B1's effectiveness as the optimal model for drug purchase forecasting at RSIA Fatimah Probolinggo.

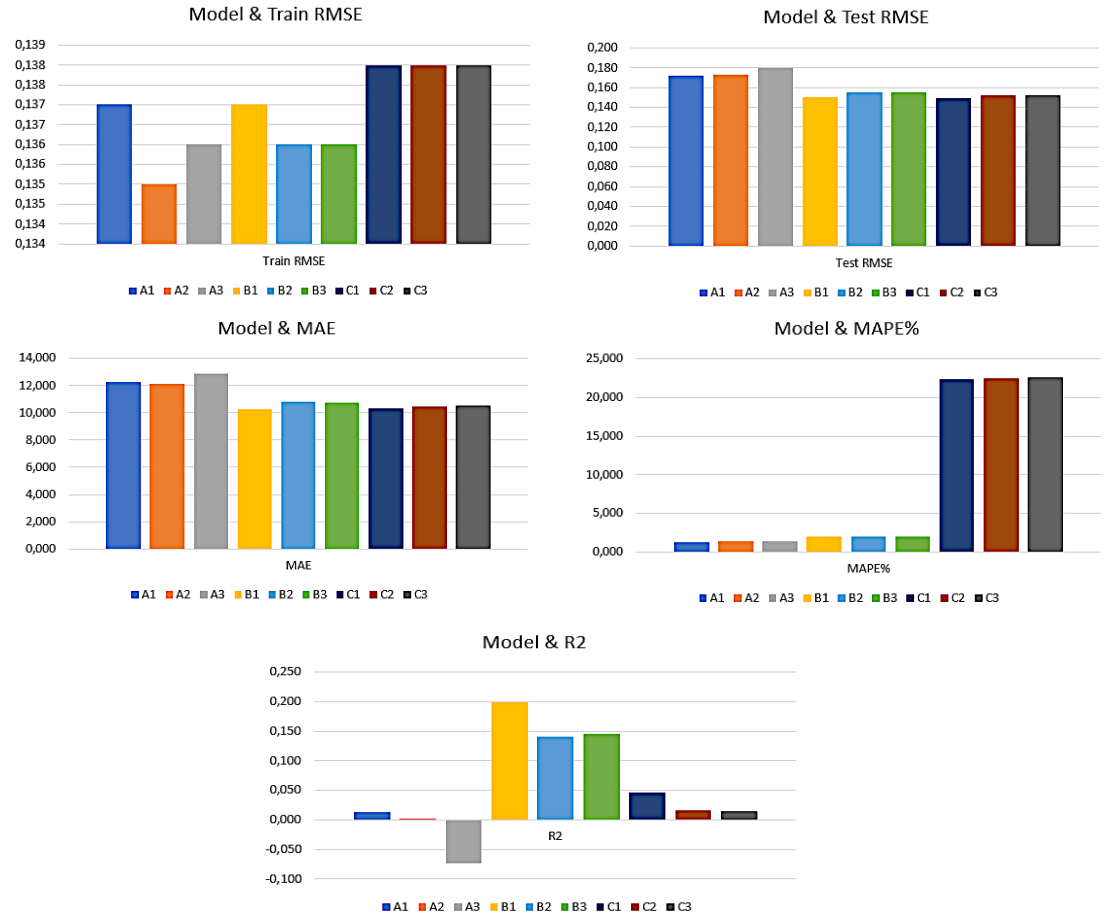

Figure 2. performance differences between models A, B, and C

The superior performance of Model B1 can be attributed to its balanced hyperparameter configuration. A moderate number of neurons (12 hidden neurons), an optimal batch size of 200, and an appropriate number of epochs (500) allowed the model to capture both short- and long-term temporal patterns effectively. This configuration helped the model avoid both underfitting and overfitting, ensuring a robust performance across training and testing datasets.

In contrast, Model A—which employed fewer neurons—tended to underfit the data, failing to capture the underlying patterns effectively. The model's low R^2 value and relatively high MAE indicated that it was unable to make accurate predictions. On the other hand, Model C, which used a larger number of epochs (500) and more neurons (24 to 36), showed signs of overfitting. While it demonstrated a good fit on the training data, its performance on the test set was worse compared to Model B, with higher MAPE and MAE values, and lower R^2. These findings emphasize the importance of tuning the model parameters to balance complexity and generalization ability, consistent with previous studies [3], [8].

When comparing the results of this study with previous research, the multivariate LSTM model proposed in this work showed superior performance. For instance, previous studies [24], [10] reported MAPEs of 6.72% and 5.83%, respectively. In contrast, this study achieved a significantly lower MAPE of 1.976%. This improvement can be attributed to the more relevant feature selection, a better preprocessing pipeline, and the careful tuning of hyperparameters. By considering multiple factors, such as transaction time, polyclinic category, drug type, and quantity purchased, the multivariate approach employed in this study was able to capture more nuanced relationships in the data, resulting in more accurate predictions.

The practical implications of these results are substantial for hospital pharmacy management. The multivariate LSTM model, with its ability to predict monthly drug purchases, offers hospitals a powerful tool to optimize their drug procurement strategies. By accurately forecasting the quantity of drugs required, hospitals can maintain ideal stock levels, reducing both waste and the risk of drug shortages. This aligns with the growing trend toward smart hospital management, where predictive models play a key role in decision-making [18].

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At RSIA Fatimah Probolinggo, implementing this model could enhance budget efficiency, ensuring that funds are allocated effectively without overstocking or understocking medications. This model also supports the continuity of pharmaceutical services, improving the availability of essential drugs for patients. Integrating the predictive model with the hospital's information systems could pave the way for automation in the drug supply chain, streamlining the procurement process and improving overall operational efficiency.

Data for this study was sourced from the hospital management information system at RSIA Fatimah Probolinggo, which provided records of outpatient drug usage across various polyclinics. The dataset, consisting of 1,500 records from January 2023, was processed and normalized using the Min-Max scaling technique to standardize the values within the range of 0 to 1. This ensured that each feature contributed equally to the model's learning process. The data was transformed into a supervised learning format, facilitating the model's ability to recognize temporal patterns and inter-variable relationships, thereby improving its forecasting accuracy. Table 4 illustrates the normalized dataset, helping the LSTM model effectively analyze relationships between past conditions (t-1) and future drug purchases (t), improving prediction accuracy.

Table 4. Supervised Learning Normalization Data

Variable	Date	Hour	Minute	Second	Polyclinic Name	Quantity of Drugs	Drug Name
var1(t-1)	0.000000	0.461538	0.400000	0.574074	0.000667	0.500000	0.711111
var2(t-1)	0.000667	0.500000	0.711111	0.962963	0.001334	0.384615	0.444444
var3(t-1)	...	...	...	...	...	...	...
var4(t-1)	0.998666	0.653846	0.422222	0.537037	0.999333	0.538462	0.511111
var1(t)	0.999333	0.538462	0.511111	0.537037	1.000000	0.576923	0.888889
var2(t)	0.500000	0.384615	0.422222	0.537037	0.999333	0.538462	0.511111
var3(t)	0.711111	0.444444	0.511111	0.537037	1.000000	0.576923	0.888889

The training of the Multivariate LSTM model was implemented using Python, with three main configurations: A, B, and C. Each model variation (A1–A3, B1–B3, C1–C3) was tested with different batch sizes, epochs, and neuron configurations. Table 5 provides an overview of the model variants, while Table 6 details the optimal configurations for Model B. The best performance was achieved with Model B1, which used 12 neurons in the hidden layer, 200 for the batch size, and 500 epochs. Increasing the number of neurons beyond

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this point did not lead to substantial improvements and, in fact, resulted in mild overfitting in Model C.

Table 5. Models

Models	Number of Models		
A	A1	A2	A3
B	B1	B2	B3
C	C1	C2	C3

Table 6. Tuning Models Parameter B

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

Table 6 shows the configuration of the best Multivariate LSTM model in this study based on Model B with a total of 1200 datasets trained datasets. Model variations (B1-B3) are differentiated based on the number of neurons in the hidden layer Neurons, the number of neurons varies in the dense layer ranges from 12 to 36, the number differs in the batch size size which uses a fixed value of 200, and another fixed parameter which is the number of epochs 500, This configuration variation seeks to evaluate the model's performance and select the parameters that are able to produce the highest accuracy and the lowest errors.

This suggests that increasing neuronal capacity without adjusting other variables does not necessarily improve model accuracy. The C model tends to experience mild overfitting, where the model is over-tuned to the pattern of the training data and loses the generalization ability of the test data. Thus, Model C is not recommended as an implementation model because its efficiency is lower than Model B1.

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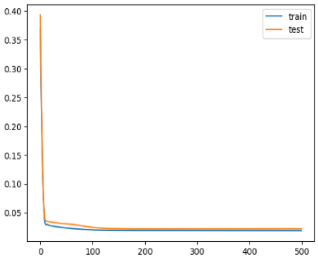
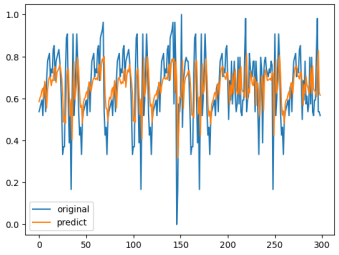
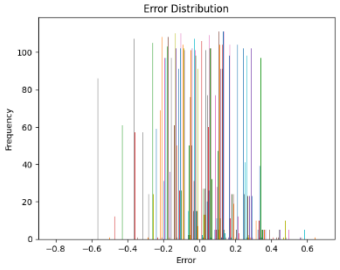
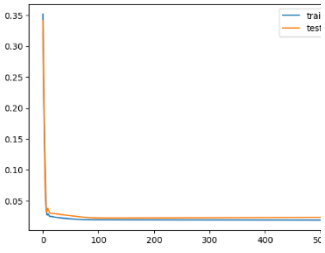
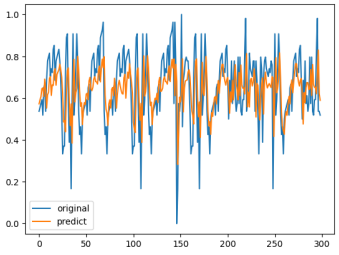
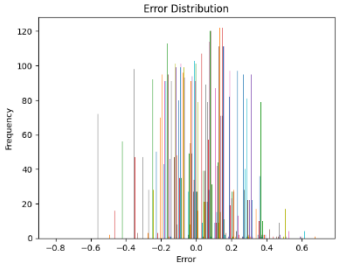
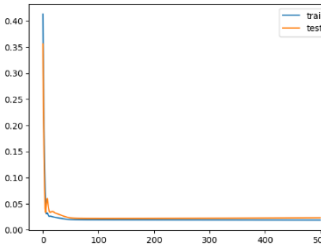
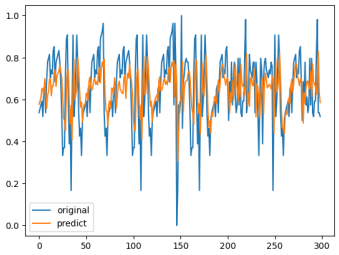
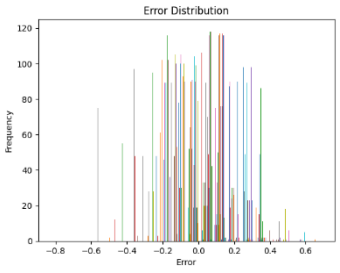
Table 7. Presenting Models Charts

Models	Accuracy	Eror	Distribution
B1			
B2			
B3			

3.3. Discussion

The results of this study demonstrate that the Long Short-Term Memory (LSTM) model has a strong ability to recognize time-series patterns in drug purchases, with predictions closely aligning with actual data. The Model B1, in particular, exhibited a MAPE of 1.976%, which reflects its ability to provide accurate forecasts for drug procurement—a critical aspect of hospital pharmacy management. However, the model's R^2 value of 0.199 suggests that while it can explain some of the variance in drug purchases, a significant portion of the variability remains unexplained. This indicates that external factors, such as disease seasonality, promotional activities, and procurement policies, may also influence drug demand patterns [27]. Despite this, the model's accuracy has proven sufficient to support operational decisions related to drug procurement and distribution, aligning with previous studies that have shown deep learning models' potential to enhance efficiency in pharmaceutical management systems [3], [17].

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The superior performance of Model B1 can be attributed to its balanced hyperparameter configuration. By using 12 hidden neurons, an optimal batch size of 200, and 500 epochs, Model B1 effectively captured both short-term and long-term temporal patterns in drug purchases. This configuration allowed the model to avoid both underfitting and overfitting, ensuring stable performance across both training and testing datasets. These findings are consistent with prior research, which emphasizes the importance of tuning model parameters to achieve optimal performance in predictive tasks [8]. On the other hand, Model A, which used fewer neurons, underperformed due to underfitting, as evidenced by its higher MAE and low R^2. Model C, with more neurons and epochs, experienced overfitting, resulting in decreased generalization to the test set and worse performance in terms of MAE and MAPE compared to Model B1.

When comparing this study to previous research in drug purchase forecasting, the results clearly show an improvement. Previous studies reported MAPEs of 6.72% [24] and 5.83% [10], while this study achieved a significantly lower MAPE of 1.976%. This improvement can be attributed to better feature selection, a more robust preprocessing pipeline, and the careful tuning of hyperparameters. The inclusion of multiple relevant features such as transaction time, polyclinic category, drug type, and quantity purchased allowed the multivariate LSTM model to capture the intricate relationships within the data more effectively, leading to more accurate predictions. This demonstrates the advantage of using a multivariate approach over univariate models in contexts like drug procurement, where multiple variables influence demand patterns.

The findings of this study have significant practical implications for hospital pharmacy management. The multivariate LSTM model developed in this study offers hospitals a powerful tool for optimizing drug procurement strategies. By accurately forecasting the quantity of drugs needed, hospitals can maintain optimal stock levels, reducing both waste and the risk of drug shortages. This aligns with the growing trend toward data-driven, smart hospital management, where predictive models play a key role in optimizing operational efficiency and resource allocation [18]. The ability to predict drug purchases with high accuracy allows for more informed decision-making, ensuring that funds are allocated effectively without overstocking or understocking medications.

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However, the relatively low R^2 value of Model B1 indicates that further improvements can be made by integrating external variables that could influence drug demand, such as seasonal diseases, patient demographics, or hospital policies. Incorporating these factors could increase the model's ability to explain the variance in drug purchases, providing even more precise predictions. Future work could also explore integrating real-time data and expanding the model to address multi-objective optimization, such as considering factors like drug cost, storage capacity, and delivery times, which would enhance the model's ability to inform hospital supply chain management.

In conclusion, the multivariate LSTM model developed in this study has demonstrated strong predictive performance for forecasting drug purchases at RSIA Fatimah Probolinggo. While external factors remain a source of unexplained variability, the model's accuracy is sufficient to support effective decision-making in hospital pharmacy management. The integration of this model into hospital information systems can drive efficiency by optimizing drug procurement, reducing waste, and improving the availability of essential drugs. This study contributes to the growing body of research on deep learning in healthcare, offering a promising framework for data-driven drug procurement and distribution planning in hospitals.

4. CONCLUSION

This study proposes a Multivariate Long Short-Term Memory (LSTM) model to predict the number of outpatient drug purchases at RSIA Fatimah Probolinggo hospital. The model managed to achieve a MAPE value of 1.976%, indicating a high level of accuracy and better performance than the traditional univariate approach. The main scientific contribution of this study is the application of multivariate temporal modeling that combines transaction time variables, polyclinic categories, and drug types in a single predictive framework to support hospital pharmacy management. Practically, this model can be used as a decision-making tool for hospital managers, with the following implementation recommendations: (1) Using predicted results in procurement planning, so that the stock of drugs is always as needed without excess or shortage. (2) Regularly evaluate and retrain models with the latest transaction data to maintain prediction accuracy. (3) Provide a visual dashboard so that decision-makers can monitor drug use trends and anticipate potential shortages early on.

By implementing this prediction system, hospitals can move from reactive procurement patterns to data-driven pharmaceutical supply chain planning, which is more efficient and cost-effective. Thus, the proposed LSTM-based predictive framework can serve as a foundation for data-driven pharmaceutical supply chain optimization in the hospital environment

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