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Optimizing Currency Circulation Forecasts in Indonesia: A Hybrid Prophet- Long Short Term Memory Model with Hyperparameter Tuning

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ABSTRACT

The core problem for decision-makers lies in selecting an effective forecasting method, particularly when faced with the challenges of nonlinearity and nonstationarity in time series data. To address this, hybrid models are increasingly employed to enhance forecasting accuracy. In Indonesia and other Muslim countries, monthly economic and business time series data often include trends, seasonality, and calendar variations. This study compares the performance of the hybrid Prophet-Long Short-Term Memory (LSTM) model with their individual counterparts to forecast such patterned time series. The aim is to identify the best model through a hybrid approach for forecasting time series data exhibiting trend, seasonality, and calendar variations, using the real-life case of currency circulation in South Sulawesi. The goodness of the models is evaluated using the smallest Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values. The results indicate that the hybrid Prophet-LSTM model demonstrates superior accuracy, especially for predicting currency outflow, with lower MAPE and RMSE values than standalone models. The LSTM model shows excellent performance for currency inflow, while the Prophet model lags in inflow and outflow accuracy. This insight is valuable for Bank Indonesia's strategic planning, aiding in better cash flow prediction and currency stock management.

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1. INTRODUCTION

Forecasting real-world systems is a critical need in various scientific fields. Still, decision-makers often struggle to find the most effective forecasting method, especially when dealing with complex time series data that exhibit nonlinearity and nonstationarity [1]. Traditional forecasting models frequently fall short in handling these complexities, highlighting the necessity for more advanced approaches that can accurately capture the underlying patterns in the data [2].

Most monthly time series data in economics and business in Indonesia and other Muslim countries include trend and seasonal patterns and are influenced by calendar variations. A trend is a long-term upward or downward tendency in time series data, while seasonality refers to regular fluctuations that occur at specific intervals. Calendar variation, on the other hand, refers to fluctuations or changes in time series data related to calendar effects or specific time periods. An example of data with trend, seasonal, and calendar variation patterns, used as a case study in this research, is the circulation of currency in the form of cash inflows and outflows at Bank Indonesia [3]. In this research, data on the inflow and outflow of funds in South Sulawesi Province were specifically chosen due to its predominantly Muslim population. As such, the circulation behaviors of currency in this region are heavily influenced by religious holidays, serving as a significant component of calendar variation in the time series data.

Currency is a vital form of cash payment essential for facilitating economic transactions. The management and flow of currency within banks and the general populace are governed by Bank Indonesia's Regulation No. 14/7/PBI dated June 27, 2012 [4]. Bank Indonesia (BI), as an autonomous state entity and the central bank of the Republic of Indonesia, has a singular goal of maintaining the stability of the Rupiah currency. As the central bank, BI formulates a plan to meet the country's currency needs, which involves forecasting the currency circulation, including inflow and outflow. Inflow refers to money entering BI through deposit activities, while outflow represents money leaving BI through withdrawal activities [3].

Currency forecasting and other financial areas are generally performed either by employing traditional or artificial intelligence-based models. Various traditional models, such AutoRegressive Integrated Moving Average (ARIMA) model [5], AutoRegressive Integrated Moving Average Exogenous (ARIMAX) model [6, 2] , Seasonal AutoRegressive Integrated Moving Average (SARIMA) [7], Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) [8], and Holt-Winters Exponential Smoothing [9] have been employed for forecasting in financial areas. These traditional methods are easy to use and have high computational speed. However, their accuracy is often limited due to financial data's non-linear and heteroscedastic nature. Consequently, recent research has increasingly focused on AI methods to achieve more accurate currency forecasts by addressing these issues. AI methods like Neural Network [10], Multi-Layer Perceptron (MLP) [11], Convolutional Neural Network (CNN) [12], Long Short Term Memory (LSTM) [13], and Prophet [14] have been utilized by numerous researchers for currency forecasting. While these AI models offer higher accuracy, they also present challenges such as convergence issues, high complexity, and difficulties in modeling linear components. In summary, traditional methods are less complex but AI methods provide greater accuracy.

Machine learning and deep learning, branches of Artificial Intelligence (AI), equip computers to learn from data. This is achieved by identifying patterns and connections within the data, allowing the computer to forecast future events and values. Unlike traditional methods that rely on predefined rules, machine learning thrives on any amount of data, constantly improving its predictions. This makes it a powerful tool not just for financial forecasting but for any situation involving historical data (time series) and the need to predict future outcome [15].

Generally, machine learning models are generally comprised of two parameters: model parameters and hyperparameters. The model learns model parameters during training, while hyperparameters need to be set before training and may change during training or remain constant. In this study, once set, hyperparameters remained constant throughout training. Therefore, finding the optimal hyperparameter configuration is crucial for developing a robust machine-learning model. Default hyperparameter settings do not always ensure the best performance, as the optimal values can vary depending on the dataset and problem domain. Hence, a range of hyperparameter values is explored to create an optimal machine learning model, a process known as hyperparameter tuning. While manual hyperparameter tuning is common, it requires a deep understanding of the model's hyperparameter settings. Manual tuning can be challenging due to the large number of hyperparameters, time-consuming model evaluations, and the complexity of specific problem domains. Consequently, researchers have introduced various hyperparameter optimization techniques to automate or semi-automate the hyperparameter tuning process [16].

In an effort to improve the accuracy of forecasting complex time series and combine the strengths of available forecasting models, hybrid models have become a promising research focus. The studies by [17] and [18] concluded that when multiple models are combined in a hybrid manner, they tend to provide better accuracy than individual models. This work proposes a hybrid model combining Prophet and Long Short-Term Memory (LSTM) for nonstationary data prediction. The Prophet model is a powerful forecasting tool designed to capture emerging patterns in time series data while also accounting for the effects of external factors such as holidays or specific seasons [19]. The LSTM model can predict more than one step into the future and is a highly powerful time series model capable of making long-term predictions [20].

There are research gaps from previous studies, namely the limited exploration of combining two machine learning models in a hybrid approach specifically for time series forecasting. While many studies have focused on traditional methods or AI models individually, the integration of two robust machine learning models, Prophet and LSTM, in a hybrid framework remains underexplored, particularly for complex, nonstationary data such as currency circulation in Indonesia. The difference between this research and previous studies lies in the application of a hybrid method combining the machine learning technique, Prophet, with the deep learning approach, LSTM. Moreover, the effectiveness of hyperparameter tuning in optimizing hybrid models has not been thoroughly investigated. Most existing studies either rely on default settings or manual tuning, which may not fully capture the potential of these models in delivering precise forecasts. This study addresses these gaps by proposing a hybrid Prophet-LSTM model and incorporating systematic hyperparameter tuning to achieve the best performance. By doing so, this research aims to demonstrate the superiority of hybrid models with optimized configurations in handling the intricate patterns of real-world nonstationary time series data. The model's goodness will be measured using the smallest Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values. It is expected that the results of this research can be used to forecast seasonal time series data with calendar variations more accurately, particularly for currency circulation in Indonesia. Furthermore, this research will benefit Bank Indonesia in optimizing currency circulation, improving cash flow predictions, and enhancing overall financial stability.

2. RESEARCH METHOD

2.1. Data Source

The data used in this study consists of 132 monthly observations of currency inflow and outflow in South Sulawesi Province, obtained from Bank Indonesia (www.bi.go.id) [21]. The first 120 data points, from January 2013 to December 2022, are used as training data, while the last 12 data points, covering January to December 2023, are used as testing data.

2.2. Facebook Prophet

Facebook has introduced a new time series forecasting algorithm called the Prophet algorithm. This algorithm is designed to handle complex time series data, accommodating different units of measurement while ensuring accurate forecasts without compromising computational speed. It is widely utilized in business and scientific research due to its notable advantages in time series data analysis and forecasting. The Prophet algorithm utilizes an additive model that captures nonlinear trends, periodicity, and holiday effects, resulting in precise forecasts with intuitive parameters. It employs a decomposable model consisting of trend, seasonal, and holiday components. What distinguishes Prophet from other traditional time series forecasting models is its approach of decomposing the series before making forecasts. This methodology effectively identifies holiday effects and trends in the data, making it highly resilient to missing data, sudden trend shifts, and outliers [22]. The Prophet algorithm comprises three primary components: trend, seasonality, and holidays. The trend component characterizes the overall trend observed in the time series data. The seasonality component captures recurring patterns or cycles in the data. The holidays component accounts for any specific events or holidays that may have an impact on the time series. These three components are represented mathematically by the equation 2 [23].

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

Where $g(t)$ is the trend component to model non-periodic changes in the time series value, $s(t)$ is the seasonality component, and $h(t)$ is the component for holidays that occur on a possibly irregular schedule over one or more periods. As for ϵ_t in the Prophet model, it captures unpredictable or unexplained changes that the model does not accommodate [24]. The process for Prophet modeling involves the following steps: a). Transforming the time series index into date format. b). Identifying calendar variations as Special Events. c). Conducting hyperparameter optimization for the Prophet model, considering a specified range of values (See in Table 1). d) Reconstruct the model using the training data, incorporating the optimal parameters determined from the tuning process. e). Utilize the Prophet model to generate forecasts for the test data.

Table 1. Prophet Hyperparameters

Parameter	Values
Holidays	calendar variations, None
Changepoint prior scale	0.001, 0.05, 0.08, 0.1, 0.5
Fourier order	1, 3, 7, 10
Seasonality prior scale	1, 3, 7, 10
Seasonality mode	Additive, multiplicative

The Holidays parameter incorporates holiday data into the forecasting analysis, emphasizing calendar variations such as Ramadan and December for outflow data and Eid al-Fitr and January for inflow data. Changepoint prior scale manages the model's adaptability in detecting shifts in trends, while Fourier order dictates the model's capacity to capture seasonal trends. Seasonality prior scale impacts the seasonal influences within the model, and seasonality mode determines the seasonal model type used, be it additive or multiplicative, affecting the fluctuation of seasonal components over time [25].

2.3. LSTM

LSTM, which stands for Long Short-Term Memory, is a type of Recurrent Neural Network (RNN) that capable of learning long-term relationships and dependencies, mitigating the issue of vanishing gradients by incorporating cell modes with constant errors. Unlike traditional RNNs, LSTM is structured with four interconnected neuron layers instead of just one layer. This architecture increases the model's parameters and computational cost by four times compared to a regular RNN [26]. Figure 1 illustrates the typical architecture of an LSTM framework.

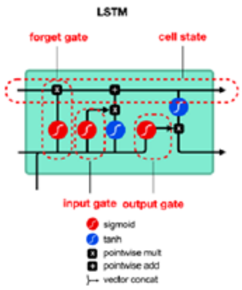


Figure 1. LSTM architecture

Figure 1 depicts the process of memory cell operations within individual LSTM neurons. This setup has three key gates: the input gate, the forget gate, and the output gate. Each gate is associated with specific activation functions, including three sigmoid activation functions and two tanh activation functions for each input to the neuron. The input gate assesses whether incoming data should be incorporated into the current cell state memory. The forget gate plays a role in deciding whether past memory should be retained or discarded. Meanwhile, the output gate determines the extent to which the cell state memory influences the final prediction outcomes [27].

The steps involved in LSTM modeling are as follows: a). Normalize the data using MinMaxScaler within the range of (0, 1). b). Convert the data into a supervised learning format, where the data at time step t-1 serves as the predictor variable. In contrast, the data at time step t serves as the target variable. c). Transform the data into a 3-dimensional matrix format with dimensions [samples, time steps, features]. d). Conduct hyperparameter tuning on the LSTM model using RandomSearchCV, which involves random search with k-fold cross-validation, where k=5. The smallest validation loss determines the optimal hyperparameter combination. Here are the various combinations of hyperparameter values (See Table 2). e). Reconstruct the model using the training data and the best hyperparameters obtained from tuning. f). Generate predictions on the training and testing data, then denormalize the prediction results.

Table 2. LSTM hyperparameters

Hyperparameter	Values
Number of layers	1
Dropout	0.20
Number of neurons	[20, 40, 60, 80, 100, 120, 150, 200]
Learning rate	[0.001, 0.0001, 0.00001]
Epochs	[20, 50, 100, 150, 200]

The hyperparameters used for LSTM modeling are the number of layers, dropout, number of neurons, learning rate, and epochs. Dropout is a technique used to combat overfitting by randomly deactivating neurons during training, thereby reducing the network's reliance on specific neuron weights. A dropout rate of 20% is commonly chosen as it strikes a balance between preserving model accuracy and mitigating overfitting. The number of neurons is crucial to the network's learning capacity. Typically, a higher number of neurons can grasp more complex structures from the data, albeit requiring more time for training. However, this increased learning capacity can lead to potential overfitting issues with the training data. The learning rate dictates the speed at which the network adjusts its parameters. The epoch number determines the total number of times the entire dataset is processed during training [28–30].

2.4. Hybrid Model

This research combines the Prophet method with LSTM sequentially to improve the prediction accuracy of the Prophet model. The main idea of this hybrid model is shown in algorithm 1 [31]. Firstly, the training data is modeled using the Prophet method. The input values of the Prophet model are ds (formatted date) and y (time series variable), and it makes predictions for the next 12 months. After obtaining the fitting and prediction results, the residual between the Prophet fitting values and the actual values is calculated, which is the result of subtracting the fitting values from the actual values, and the fitting error sequence of the Prophet model is obtained. Then, this sequence is used as the training dataset for the LSTM method, and the predicted values generated by the LSTM method are combined with the predicted values of the Prophet model, resulting in the prediction results of the hybrid model.

Algorithm 1 The Proposed Prediction Algorithm

Input: Time series data of inflow and outflow in South Sulawesi from January, 2013 to December, 2022, labeled as $\mathbf{y}_{train}$;
Output: Predicted values from the hybrid model, labeled as $\mathbf{y}_{prediction}$;
1: Utilize $\mathbf{y}_{train}$ as the training dataset for the Prophet model. Obtain fitting values $\mathbf{y}_{fit}$ and prediction values $\mathbf{y}_{prediction\_Prophet}$ from the Prophet model;
2: Compute the residual error sequence $\mathbf{y}_{residual}$ by subtracting the fitting value $\mathbf{y}_{fit}$ from the actual value $\mathbf{y}_{train}$;
3: Use $\mathbf{y}_{residual}$ as the training dataset for the LSTM model. Obtain predicted residual error values $\mathbf{y}_{prediction\_residual}$;
4: Calculate the hybrid model predictions $\mathbf{y}_{prediction}$ by adding the predicted error value $\mathbf{y}_{prediction\_residual}$ to the Prophet's predicted value $\mathbf{y}_{prediction\_Prophet}$;
5: Return the final predicted values $\mathbf{y}_{prediction}$.

2.5. Selection of The Best Model

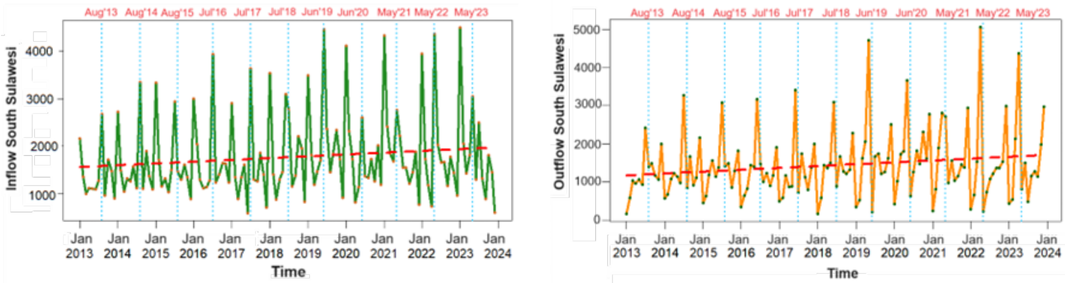
The selection of the best model from Prophet, LSTM, and Hybrid Prophet-LSTM is made by identifying the models with the smallest Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values. The MAPE and RMSE are calculated using the following formula [32]. where y_t is actual value, y_t is the forecast value, and n is the number of data points. MAPE measures the accuracy of the forecast by expressing the prediction error as a percentage of the actual values. RMSE measures the average magnitude of the forecast errors, focusing on larger errors due to its quadratic nature. Lower MAPE and RMSE indicates a more accurate model. A model is considered excellent if it has a MAPE value less than 10%, falls into the good category if it ranges from 10 to 20%, and meets the criteria for fair if it ranges from 20 to 50% [33].

$$\text{MAPE} = \frac{\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|}{n} \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{3}$$

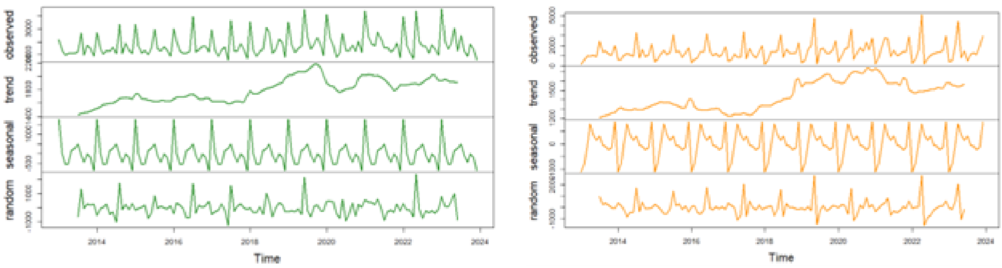
3. RESULT AND ANALYSIS

Two sets of data represent inflow and outflow in South Sulawesi Province, spanning monthly records from January 2013 to December 2023. The data for the last 12 months of 2023 are reserved for testing purposes. Figure 2 illustrates the complete dataset using a time series visualization. Figure 2 illustrates the annual pattern of the highest cash inflow in January and the highest cash outflow in December. The peak in January's cash inflow is linked to the preceding high cash outflow in December, which is related to Christmas and New Year's activities. Additionally, Figure 3, displaying the time series decomposition, highlights the presence of seasonal patterns in the data, evident from the residual pattern hovering around zero.



(a) and Outflow (b) in South Sulawesi Province

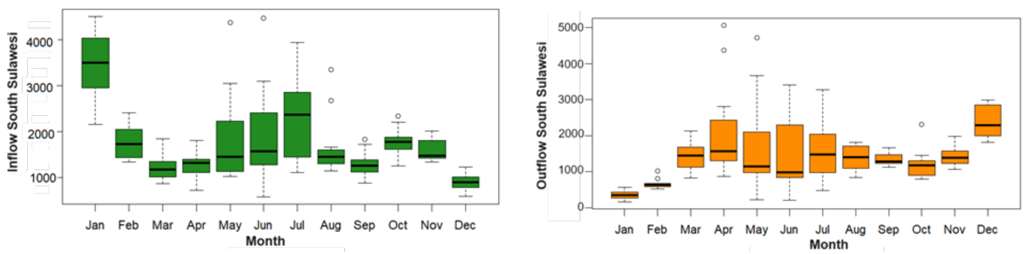
Figure 2. Time Series Plot of Currency Inflow



(a) and Outflow (b) in South Sulawesi

Figure 3. Time Series Decomposition of Currency Inflow

The annual rise in inflow and outflow doesn't align precisely with the same month each year; instead, there's a noticeable shift by one period earlier. This suggests the presence of a calendar variation effect influencing cash flow amounts. Figure 4's boxplot further supports this notion, depicting the monthly fluctuations in inflow and outflow alongside the calendar variation effect attributed to Eid al-Fitr celebrations.



(a) and Outflow (b) in South Sulawesi

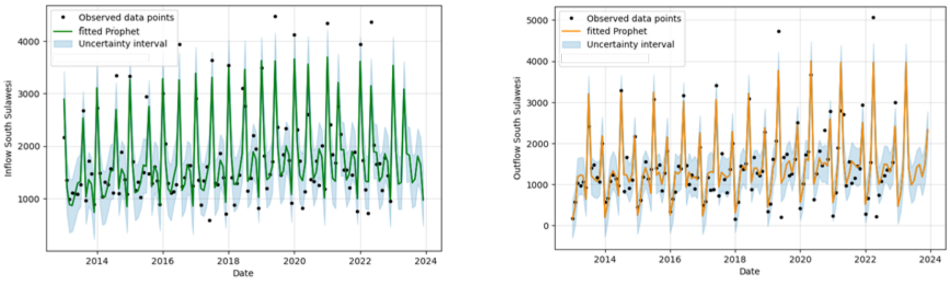
Figure 4. Boxplot of Currency Inflow

3.1. Prophet model prediction results

After applying hyperparameter tuning, the best parameters for the model were obtained, as presented in Table 3. The fitting and prediction results of the Prophet model are shown in Figure 5, where the black points represent the actual values, the green curve for inflow data, and the orange curve for outflow data in the middle of the figure represents the fitting and prediction values of the Prophet model, and the light blue area represents the 95% confidence interval of the Prophet model. Figure 5 shows that the Prophet model used for time series modeling seems to adequately follow the trend and variations of the actual data (black dots). The green and orange lines, which represent the fitted results from the Prophet model, tend to capture the peaks and troughs of the actual data with relatively high accuracy, although there are some periods where the model does not fully capture the movements of the actual data, especially at some extreme points where calendar variations occur. Overall, the fitting results indicate that the model is effective in depicting the general trend and seasonal variations in the data, but there may still be room for improvement, particularly in capturing unexpected peaks and troughs or sharp fluctuations in calendar variations.

Table 3. The best parameter combination for the Prophet model

Parameter	Values	
	Inflow	**Outflow**
Holidays	calendar variations	calendar variations
Changepoint prior scale	0.5	0.5
Fourier order	7	7
Seasonality prior scale	1	10
Seasonality mode	Multiplicative	additive



(a) and Outflow

(b) currency in South Sulawesi predicted by Prophet model

Figure 5. Inflow

As previously explained, due to the interpretability of the Prophet model, it can generate a decomposition diagram that separates the components of trend, holiday, and yearly components, as presented in Figure 6. This allows us to understand better how each component contributes to the pattern of changes in the dataset. Based on Figure 6, it is evident that the graphs for the trend components of inflow (a) and outflow (b) show a long-term trend that gradually increases year by year, indicating consistent growth. There is a slight decline in the trend around early 2020, which is suspected to be due to the COVID-19 pandemic, but overall, it does not affect the growth charts of inflow and outflow in South Sulawesi. The holiday component graph for inflow data (c) illustrates a very clear and regular calendar variation pattern with peaks consistently occurring every January and Eid al-Fitr each year, indicating significant annual fluctuations in inflow data. Similarly, the holiday component for outflow data (d) shows very clear fluctuations in December and Ramadhan. The yearly component graphs for inflow data (e) and outflow data (f) show monthly fluctuations throughout the year with more pronounced variations during certain periods, especially around the time of Eid al-Fitr and towards the end of the year.

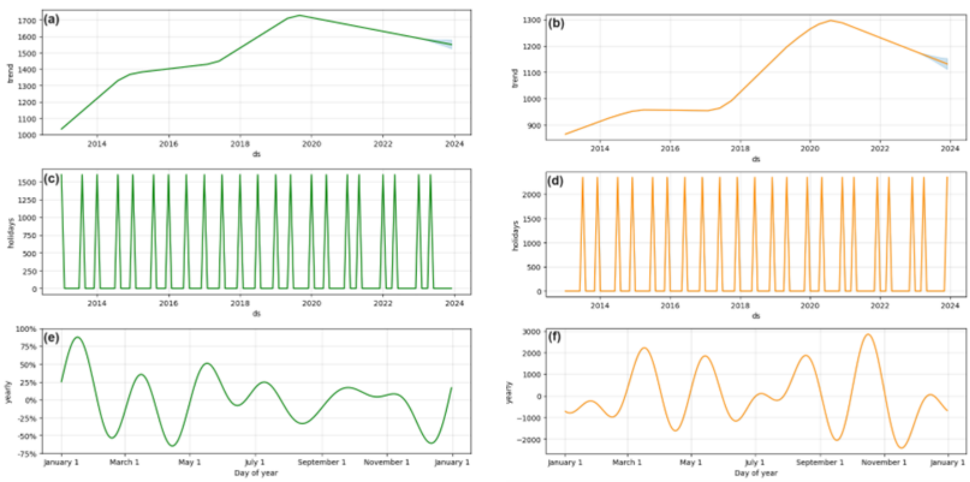


Figure 6. The components of the Prophet model for inflow (a,c,e) and outflow (b,d,f) in South Sulawesi

3.2. LSTM model prediction results

Before initiating LSTM modeling, it's crucial first to normalize the data using the MinMax Scaler, which adjusts the range of data to (0,1). This normalization step is fundamental for LSTM modeling as it enhances training speed, mitigates issues related to gradients, boosts overall model performance, and aligns with the requirements of the tanh activation function utilized in LSTM layers [30]. Following normalization, the data is reformatted into a supervised learning structure where current time data $(Y = X_t)$ is treated as the target output, and data from the previous time step $(Xt - 1)$ serves as the input. This format is essential for helping the model discern patterns and understand the relationships between inputs and outputs, thereby enabling more accurate future predictions. The data is subsequently converted into a 3-dimensional array to suit the needs of LSTM and general deep-learning model structures. This conversion is typically done using the numpy.reshape() function, forming arrays with dimensions (120,1,1) for training data and (12,1,1) for testing data. The subsequent phase involves establishing the LSTM model by defining its architecture and conducting hyperparameter tuning through RandomSearchCV with a 5-fold cross-validation. This process tests various parameter settings to identify the LSTM configuration that minimizes the Mean Squared Error (MSE), with the findings presented in Table 4.

Table 4. The best parameter combination for the LSTM model

Hyperparameter	**Value**	
	Inflow	**Outflow**
Neurons	60	200
Dropout	0.20	0.20
Learning rate	0.001	0.001
Epochs	80	20

3.3. Hybrid model prediction results

As outlined in section 2.4, the LSTM model is developed using the residuals from the Prophet model to produce residual predictions from the training dataset. The LSTM model is developed, and hyperparameter tuning is performed based on the architecture detailed in Table 2, targeting the residuals data from the Prophet model. The optimal hyperparameter settings for using LSTM to model the Prophet residuals for both inflow and outflow data are summarized in Table 5. These predictions are then combined with the forecast data from the Prophet model to produce the outcomes of the hybrid Prophet-LSTM model.

Table 5. The best parameter combination for the Hybrid Prophet-LSTM model

Hyperparameter	**Value**	
	Inflow	**Outflow**
Neurons	60	200
Dropout	0.20	0.20
Learning rate	0.001	0.001
Epochs	80	20

3.4. Best Model

The findings of this research are that the predictions of the LSTM and hybrid Prophet-LSTM models are very close and overlap with the actual data, as shown in Figure 7, indicating that these models are highly accurate in their forecasts. Conversely, the Prophet model does not follow the fluctuations of the actual data values and tends to differ significantly, leading to the conclusion that the Prophet model has poor predictive accuracy. The MAPE and RMSE scores for both inflow and outflow data are displayed in Figure 8. The model with the lowest values is considered the best performing. Figure 8 reveals that the hybrid Prophet-LSTM model exhibits superior accuracy over the standalone Prophet and LSTM models, particularly in outflow data, where both MAPE and RMSE values decrease markedly. This indicates that combining Prophet and LSTM leads to more precise forecasts than using each model independently. This indicates that combining Prophet and LSTM leads to more precise forecasts than using each model independently. Specifically, for the outflow data, the lower MAPE and RMSE values of the hybrid model, as shown in Figure 8, demonstrate that it has the lowest error rate, indicating the highest predictive accuracy among the models. This suggests that the hybrid approach successfully leverages the strengths of both models, leading to improved forecasting performance.

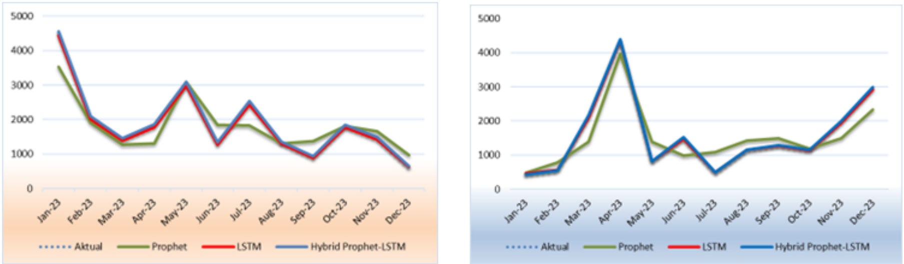
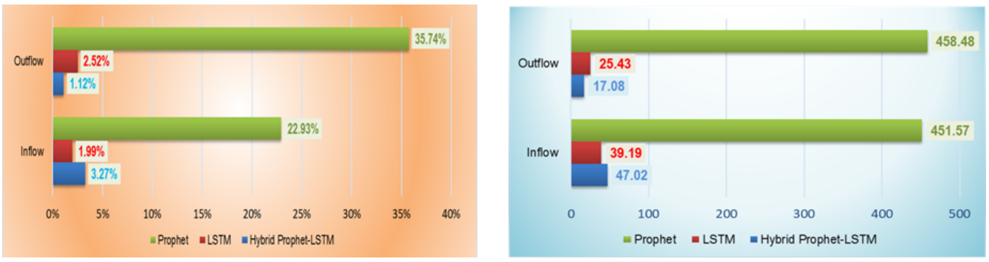


Figure 7. Plot of model predictions with actual data for inflow and outflow



(a) and RMSE

(b) values

Figure 8. Comparison of forecasting performance based on MAPE

The results of this research are supported by previous studies, specifically the third outcome of the M4 competition [17] and research by [2], which indicates that, on average, hybrid models tend to produce more accurate forecasts than individual models. These findings align with the conclusion that combining the Prophet and LSTM models leads to more precise forecasts than using each model independently. However, for inflow data, the LSTM model alone outperforms the others, which is corroborated by the initial outcomes of the M4 competition [17] and [34], indicating that hybrid models do not always outperform simpler models. On the other hand, the standalone Prophet model shows less accuracy, with higher MAPE and RMSE values for both inflow and outflow data, suggesting it may not be optimal for handling such data.

A comparison of the results of this research with those of previous studies can be summarized as follows. This research evaluated Prophet, LSTM, and Hybrid Prophet-LSTM models, finding that the Hybrid Prophet-LSTM model demonstrated superior accuracy, particularly for outflow currency data in South Sulawesi, with lower MAPE and RMSE values. However, for inflow currency data, the LSTM model alone outperformed the others. In the study by [2], ARIMAX, RBFN, and Hybrid ARIMAX-RBFN models were compared, and the hybrid model generally outperformed individual linear and non-linear models in forecasting the inflow and outflow of cash in Central Java. Similarly, [35] found that the Hybrid ARIMAX-DNN model improved forecast accuracy and outperformed individual models for currency inflow and outflow in East Java. [36] compared SARIMA, FFNN, and Hybrid SARIMA-FFNN models, concluding that the hybrid model improved forecast accuracy and outperformed individual models for currency inflow and outflow in Kediri, East Java Province. [33] used a time decomposition method, Extreme Learning Model (ELM), and Hybrid decomposition method-ELM, and found that the hybrid model produced the smallest error values in forecasting inflow and outflow in Indonesia. The M4 Competition [17] compared various statistical and AI models, highlighting that hybrid models produced more accurate forecasts on average. These findings collectively suggest that hybrid models, which combine individual methods' strengths, offer enhanced forecasting accuracy across various contexts and data sets.

4. CONCLUSION

This research evaluated the performance of Prophet, LSTM, and Hybrid Prophet-LSTM models in forecasting currency inflow and outflow in South Sulawesi. The findings reveal that the Hybrid Prophet-LSTM model demonstrated superior accuracy, particularly for outflow currency data, with lower MAPE and RMSE values compared to standalone models. For inflow data, the LSTM model alone outperformed the others. These results align with previous studies, such as the M3 competition and research by other scholars, which indicate that hybrid models generally produce more accurate forecasts than individual models. However, it was also observed that hybrid models do not always outperform simpler models, as evidenced by the LSTM model's superior performance for inflow data. The novelty of this research lies in the application of a hybrid Prophet-LSTM model to forecast currency circulation in Indonesia, specifically in South Sulawesi, which is characterized by seasonal and calendar variations. This approach combines the strengths of the Prophet model, which effectively captures seasonal and calendar effects, and the LSTM model, which handles non-linearity and heteroscedasticity. The use of hyperparameter tuning further enhances the predictive performance of the hybrid model, marking a significant improvement over previous methodologies. The results of this research support the notion that hybrid models can enhance forecasting accuracy by leveraging the strengths of individual models [17]. This study contributes to the existing body of knowledge by demonstrating the effectiveness of hybrid Prophet-LSTM models in capturing the complexities of currency inflow and outflow patterns, providing a more reliable forecasting tool for financial management. Despite the promising results, the study highlights that hybrid models do not always outperform simpler models in all contexts [34]. This finding suggests that the choice of forecasting models should be context-specific, considering the unique characteristics of the data being analyzed. This research is limited to a hybrid model combining machine learning and deep learning in a series structure applied to univariate data. Future research should explore the application of advanced hybrid models, such as Prophet and LSTM with machine learning techniques like XGBoost or Neural Prophet , to improve forecasting accuracy. Additionally, expanding the analysis to include other regions or sectors can provide a more comprehensive understanding of the model's applicability. Further studies could also investigate the impact of different hyperparameter tuning strategies and the inclusion of additional external factors that may influence currency circulation patterns.

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6. DECLARATIONS

AUTHOR CONTIBUTION

All authors contributed significantly to this research. The first author was primarily responsible for conceptualizing the study, performing the analysis, and drafting the manuscript. The second and third authors contributed to the methodology design and assisted in the data preparation and model implementation. All authors participated in critically revising the manuscript for important intellectual content and approved the final version to be published.

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COMPETING INTEREST

The authors declare that they have no competing interests. All conclusions and opinions expressed in this paper are those of the authors and do not necessarily reflect the policies or positions of any organizations they are affiliated with.

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