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Optimizing Rice Planting Schedules Based on Rainfall Prediction Using a BiLSTM Network

Fandi Presly Simamora*, Khairul Hawani Rambe, Sophya Hadini Marpaung

***Abstract*— This study addresses the critical challenge of optimizing rice planting schedules in Indonesia, where unpredictable rainfall threatens national and regional food security. To tackle this issue, a Bidirectional Long Short-Term Memory (BiLSTM) network is proposed to accurately predict rainfall patterns, with a specific focus on Deli Serdang Regency in North Sumatra. Utilizing a comprehensive weather dataset from 2013 to 2022 sourced from BMKG, a feature selection process was conducted to identify the 10 most influential features for rainfall. The BiLSTM model was then developed through several experimental scenarios, varying the data duration and architectural complexity. The best-performing model, achieved in a scenario using a double BiLSTM architecture and 10 years of data, yielded a Mean Absolute Error (MAE) of 11.2382 mm and a Root Mean Squared Error (RMSE) of 19.5650 mm. The resulting predictive capability provides a data-driven framework for optimizing planting schedules. Crucially, the study also reveals the limitations of current planting criteria, which can be misleading in regions prone to intense, short-duration rainfall, highlighting the need for more adaptive, region-specific guidelines. This work contributes to mitigating crop failure risks, enhancing crop resilience, and ensuring long-term regional food security.**

***Index Terms*— BiLSTM, Precision Agriculture, Rainfall Forecasting, Rice Planting Schedules, Time Series.**

I. INTRODUCTION

Situated between two continents and two oceans, Indonesia experiences dynamic weather patterns driven by global, regional, and local climatic influences [1]. This weather uncertainty significantly impacts the agricultural sector, particularly in regions reliant on rainfall as their primary water source [2]. In extreme conditions, shifts in weather patterns can threaten national food security [3]. As one of the primary food-producing regions in North Sumatra, Deli Serdang Regency faces similar challenges, where changes in weather patterns can increase the risk of crop failure and threaten regional food security [4]. For example, in 2025, approximately 200 hectares of rice paddies across three villages saw their harvest frequency drop from the usual three times a year to just once, due to floods damaging the Sidoras Dam irrigation channels [5]. This challenge is compounded by the difficulty in accurately identifying weather patterns, as even adjacent areas can experience different weather conditions [6]. This challenge not only poses a technical problem for farmers but has also become a primary concern at the national policy level [7].

In the effort to optimize rice planting schedules, various approaches and features have been investigated using data from diverse geographical regions. A study in Bangladesh, for example, used weather data to predict rice yields by employing Random Forest (RF), Gradient Boosting (GB), Linear Regression (LR), Decision Tree (DT), and Neural Networks (NN), concluding that the RF approach achieved the highest accuracy [8]. Another study in Nigeria, which utilized weather data with models including LR, ANN, RF, Random Trees, and Naïve Bayes (NB), found that Random Trees produced the best results and identified temperature as the most influential feature affecting rice yields [9]. Other research comparing Support Vector Machine (SVM) and LSTM found that LSTM demonstrated a superior capability in analyzing weather patterns [10]. Furthermore, a comprehensive literature review on crop yield prediction concluded that the choice of the best model is context-dependent, relying on factors such as data availability, geographical conditions, and the scale of the research. This underscores the need to evaluate various models to identify the most optimal one for a particular region [11].

Recent studies demonstrate that Bidirectional LSTM (BiLSTM) architectures outperform unidirectional LSTM and traditional statistical models such as ARIMA and HMM in rainfall prediction tasks. BiLSTM models utilize both past and future contextual information in sequence learning, resulting in improved accuracy for non-stationary and seasonal rainfall data [12], [13]. For example, Jahangiri et al. [14] integrated a BiLSTM–Kalman filter for rainfall downscaling under climate change scenarios and achieved significant performance improvements over single-directional LSTM models [15]. Similarly, Simanjuntak et al. [16] used a high-resolution spatiotemporal BiLSTM to forecast rainfall every 10 minutes from satellite imagery, achieving an RMSE below 0.71 mm per 3-hour interval [17]. These findings highlight BiLSTM's superior capacity to model complex, bidirectional dependencies in atmospheric time series compared to classical models.

In Indonesia, the planting schedules, according to the criteria set by the Agency for Agricultural Research and Development (Balitbangtan) and the Agency for Meteorology, Climatology, and Geophysics (BMKG), commences when cumulative rainfall is ≥ 50 mm over three consecutive ten-day periods, or a minimum of 150 mm within one month [3], [18]. Research on predicting ideal rice planting schedules based on weather data has been conducted using the ARIMA model, which yielded satisfactory accuracy for short-term predictions [19], [20]. Another study in the Special Region of Yogyakarta utilized a Hidden Markov Model (HMM) with rainfall, temperature, and humidity data, finding that predictions

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based solely on rainfall data achieved the highest accuracy compared to other weather features [21]. The use of another model, Long Short-Term Memory (LSTM), has demonstrated a strong ability to capture both temporal and seasonal patterns in weather data [22], [23], [24]. However, LSTM has a limitation in understanding broader context, as it processes data only in a forward direction, which diminishes its capacity to capture reciprocal or causal relationships within the data [25]. Furthermore, localized weather data analysis in Indonesia remains limited, posing a significant challenge in determining planting strategies for specific regions [26].

Compared to previous studies, this research introduces two distinct contributions. First, from a regional perspective, it focuses specifically on Deli Serdang Regency-an area with limited prior studies-thus addressing the lack of localized rainfall modeling for agricultural applications in North Sumatra. Second, from a methodological perspective, this study integrates a feature-engineering-based BiLSTM approach that incorporates lagged rainfall, moving averages, and seasonal indicators to improve rainfall prediction accuracy. Additionally, we explicitly map model outputs to planting schedule recommendations based on BMKG rainfall thresholds, bridging the gap between predictive modeling and decision support.

In summary, this study addresses three main research gaps:

- The lack of localized BiLSTM rainfall modeling for Indonesian agricultural zones.
- The absence of statistical validation and feature-based enhancement in previous LSTM studies, and
- The limited translation of rainfall prediction into actionable planting decisions.

The key contributions of this research are:

- Development of a BiLSTM-based rainfall prediction model tailored for Deli Serdang.
- Incorporation of correlation-based feature selection and seasonal decomposition for improved model learning.
- Integration of rainfall forecasts with planting decision criteria to support sustainable agricultural planning in Indonesia.

II. Materials and Methods

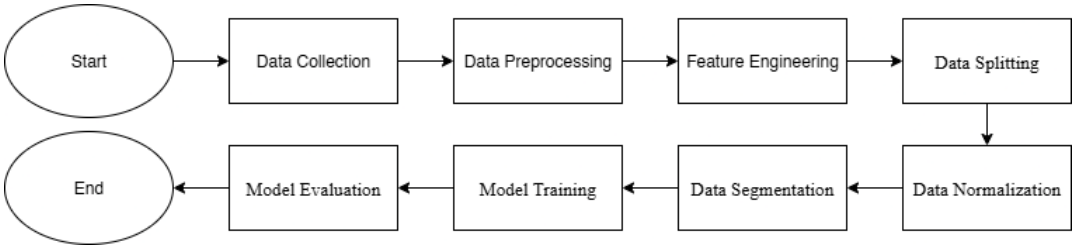

Fig. 1. Research methodology.

Fig. 1 illustrates the research methodology, which consists of: weather data collection, data preprocessing, feature engineering to select the most influential features, splitting the data into training and testing sets, data normalization to a 0-1 range, grouping the data into 30-day sequences, and the training and evaluation of the BiLSTM model using various configurations.

A. Data Collection

Daily meteorological data for Deli Serdang Regency covering the period 2013–2022 were obtained from the North Sumatra Climatology Station of the Meteorology, Climatology, and Geophysics Agency (BMKG) through the official BMKG data portal. The data were provided in monthly intervals and subsequently merged into a comprehensive daily time-series dataset. The dataset comprises the following features: date, minimum temperature (°C), maximum temperature (°C), average temperature (°C), relative humidity (%), rainfall (mm), sunshine duration (hours), maximum wind speed (m/s), wind direction at maximum speed (°), average wind speed (m/s), and most frequent wind direction (°). This dataset serves as the foundation for the feature engineering process, in which additional derived features are created to improve correlation with rainfall. A sample of the top five entries from the initial dataset is shown in Table I.

Table I. Initial Sample Dataset

Date	Min Temp	Max Temp	Avg Temp	Humidity	Rainfall	Sunshine	Max Wind Speed	Max Wind Dir	Avg Wind Speed	Wind Dir
01-01-2013	25.4	31.8	28.1	83	0	1.2	2	45	1	NE
02-01-2013	24	33.4	27.6	79	6.2	0	3	90	1	E
03-01-2013	23.8	29.2	25.5	88	2.8	0.3	3	360	2	N
04-01-2013	24	32.2	27.4	85	0	5.7	2	315	2	NW
05-01-2013	24	29.4	26.2	87	8888	0	2	360	2	E

B. Data Preprocessing

A small proportion of the dataset contained missing or invalid entries. These were identified and imputed using linear interpolation or forward-fill techniques, based on the assumption that rainfall and other meteorological features change gradually between adjacent observations.

After data cleaning, seasonality and trend components were analyzed using moving averages and seasonal decomposition. A strong annual monsoon cycle was confirmed. However, seasonal or trend adjustments were not applied, as the BiLSTM model can inherently learn

these temporal dynamics. All features were normalized to the [0, 1] range using Min-Max scaling to ensure stable and efficient model convergence.

C. Feature Engineering

To improve predictive performance, several additional features were derived.

- Lagged features: 1-day and 2-day lags were applied to the original average temperature, humidity, rainfall, and sunshine duration features.
- Moving averages: 7-day moving average features were applied to the original average temperature, humidity, rainfall, and sunshine duration features.
- Date features: Date features: These were derived by extracting quarter, month, year, and day of week components from the main date feature.

In total, over 26 candidate features were generated from the main features and engineered features. Pearson correlation coefficients with the target (next-day rainfall) were computed for each feature, and those with weak correlations ($|r| < 0.1$) were discarded. Multicollinearity was then tested using the Variance Inflation Factor (VIF); features with VIF > 5 were removed to avoid redundancy. The final input feature set consisted of 10 features, including rainfall-derived features, seasonal indicators, and key meteorological factors.

D. Data Splitting

The time series was organized into supervised learning sequences, where each input sample consisted of 30 consecutive days of all selected features, and the corresponding target was the rainfall on the 31st day. This 30-day window represents approximately one month, consistent with agricultural rainfall-based planting criteria. The dataset was partitioned into three sets for distinct purposes: 75% for training the model, 15% for validating its performance and tuning hyperparameters during training, and 15% for a final, unbiased evaluation on unseen data. This split was performed chronologically to preserve the temporal order of the data

E. Data Normalization

Each dataset training, validation, and testing was independently normalized using the MinMaxScaler method. This procedure scales all feature values to a uniform range of [0, 1], a critical step for ensuring the stability and computational efficiency of the model during the training phase.

F. Data Segmentation

After normalization, each dataset training, validation, and testing was transformed into a sequential format. This segmentation, also known as windowing, is necessary as the BiLSTM model processes data as sequences rather than individual data points. Each sequence was constructed using 30 days of historical data as input features to predict the rainfall on the subsequent day as the target feature.

G. Model Training

The BiLSTM models were developed in Python using TensorFlow/Keras. Several experimental scenarios were designed to evaluate the model's performance. These scenarios aimed to analyze the impact of two key factors: the length of the historical data used (5 years vs. 10 years) and the model's architectural complexity (a single BiLSTM layer vs. a double BiLSTM layer). The specifics of each scenario are detailed in Table .

TABLE II. RESEARCH SCENARIOS

Scenario	Model	Years of Data	Top 10 Most Influential Features
1	Single BiLSTM	5	rainfall, rainfall_MA7, rainfall_lag1, quarter, humidity, month, avg_temp_MA7, max_temp, avg_temp, min_temp
2	Double BiLSTM		
3	Single BiLSTM	10	rainfall, rainfall_MA7, year, quarter, month, humidity, rainfall_lag2, avg_temp, max_temp, min_temp
4	Double BiLSTM		

Two BiLSTM architectures were implemented to analyze how architectural depth influences forecasting accuracy.

- Single-layer BiLSTM: One bidirectional LSTM layer consisting of 64 neurons (32 forward and 32 backward), followed by a dropout layer with a rate of 0.2, and a single dense neuron for output.
- Double-layer BiLSTM: Two stacked bidirectional LSTM layers, each containing 64 neurons with a dropout rate of 0.2. The output of the second layer was connected to a dense neuron with a linear activation function for regression output.

All models used the Adam optimizer and the Mean Absolute Error (MAE) as the loss function, as summarized in Table III. The hyperparameters in Table III were determined empirically based on preliminary validation experiments to establish a robust baseline. A full-scale hyperparameter optimization was considered outside the scope, as the primary objective of this study was to compare the performance impact of data duration (5 vs. 10 years) and architectural depth (single vs. double BiLSTM).

TABLE III. HYPERPARAMETER CONFIGURATION

Hyperparameter	Value
Neuron	64
Dropout Rate	0.2
Optimizer	Adam
Loss Function	Mae
Epoch	100
Batch Size	32

Model training was executed on a GPU-enabled workstation. An early stopping mechanism was incorporated in every training process, terminating learning if no improvement in validation loss (val_loss) was observed for 10 consecutive epochs. Each model was trained for up to 100 epochs with a batch size of 32, ensuring balanced efficiency and accuracy. On average, the single-layer BiLSTM required approximately 15 minutes per run, while the double-layer BiLSTM required around 30 minutes.

H. Model Evaluation

The performance of the predictive models was quantitatively evaluated using four key statistical metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Pearson Correlation Coefficient (r). These metrics collectively provide a comprehensive evaluation of prediction

accuracy, error dispersion, and linear correspondence between predicted and observed rainfall values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

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

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

$$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \hat{y})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \hat{y})^2}} \quad (4)$$

Equation (1) represents the Mean Absolute Error (MAE), which measures the average magnitude of errors without considering their direction. Equation (2) defines the Root Mean Squared Error (RMSE), which penalizes larger errors more severely than MAE, thereby providing greater sensitivity to extreme deviations. Equation (3) expresses the Coefficient of Determination (R^2), which indicates the proportion of variance in the observed data that is explained by the model. An R^2 value closer to 1 signifies stronger explanatory power and better model fit. Equation (4) defines the Pearson Correlation Coefficient (r), which measures the strength and direction of the linear relationship between actual and predicted values. A correlation value approaching +1 denotes a high positive linear relationship, whereas a value near 0 indicates weak or no correlation. In all cases, lower MAE and RMSE values correspond to higher predictive accuracy, while higher R^2 and r values indicate stronger model performance and a better match between observed and predicted rainfall.

III. Results and Discussions

In this study, rainfall data is treated as a time-series problem, characterized by recurring patterns over specific periods. Consequently, this research applies the BiLSTM model to predict rainfall data for the purpose of determining the ideal planting schedules. Four experimental scenarios were tested, differing in both the data duration (5 years vs. 10 years) and model complexity (single-layer vs. double-layer BiLSTM). As summarized in Table II, the most influential features identified during the feature selection stage were rainfall-derived engineered features (e.g., lagged rainfall and moving averages), time-based features derived from date attributes, and primary meteorological features such as humidity and temperature. Based on these inputs, the performance metrics obtained from each experimental configuration are shown in Table IV.

Table IV. Evaluation Result

Scenario	MAE	RMSE
1	12.1554 mm	18.7859 mm
2	12.0392 mm	18.8762 mm
3	11.2856 mm	19.5311 mm
4	11.2382 mm	19.5650 mm

The evaluation results in Table reveal an interesting relationship between MAE and RMSE when comparing the research scenarios. When the time range was increased from 5 years (scenarios 1 and 2) to 10 years (scenarios 3 and 4) using the same model architecture, a decrease in the MAE value was observed, accompanied by an increase in the RMSE value. This pattern suggests that extending the data range enhances the model's ability to generalize typical rainfall patterns but also exposes it to occasional extreme rainfall events that increase error variability.

Similarly, when comparing model complexity, the double-layer BiLSTM consistently achieved lower MAE values than the single-layer counterpart for both 5-year and 10-year datasets. However, a marginal increase in RMSE was observed, indicating that while deeper networks better capture temporal dependencies, they may also amplify errors during anomalous rainfall events. Such trade-offs are widely recognized in rainfall forecasting literature, reflecting the balance between model flexibility and robustness against outliers.

To provide additional insight, the best-performing model (Scenario 4: double-layer BiLSTM, 10 years) achieved an R^2 of approximately 0.90, indicating that it explains around 90% of the variance in daily rainfall. The Pearson correlation coefficient between predicted and observed rainfall reached 0.95, signifying strong linear alignment. A Diebold–Mariano (DM) test comparing Scenarios 1 and 4 confirmed that the MAE improvement (≈0.92 mm) was statistically significant ($p < 0.05$), while the RMSE difference was not ($p > 0.1$). Thus, the observed performance gain is statistically meaningful in terms of average accuracy, even if large deviations remain similar.

To further understand prediction behavior, error distributions (predicted – actual) were visualized in Fig. 2–5. Fig. 2 and 3 correspond to models trained on five years of data (single vs. double BiLSTM). Fig. 4 and 5 correspond to ten-year datasets.

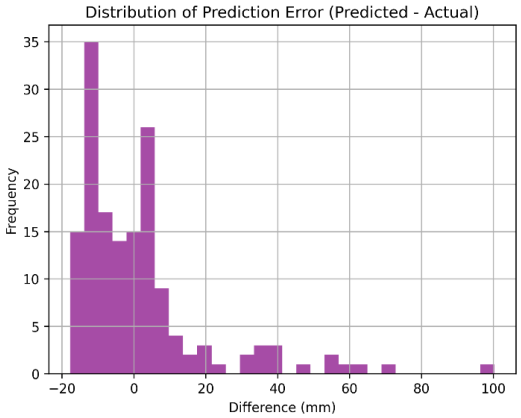

Fig. 2. Distribution of prediction error (Single BiLSTM with 5 years of data).

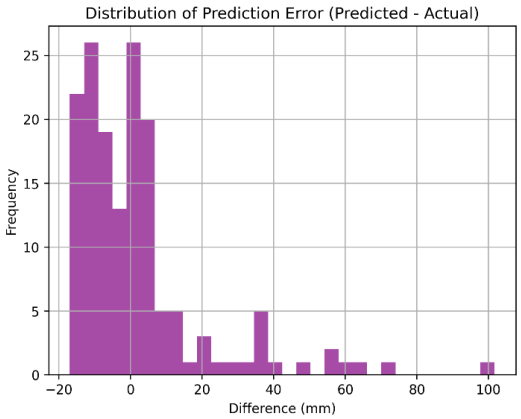

Fig. 3. Distribution of prediction error (Double BiLSTM with 5 years of data).

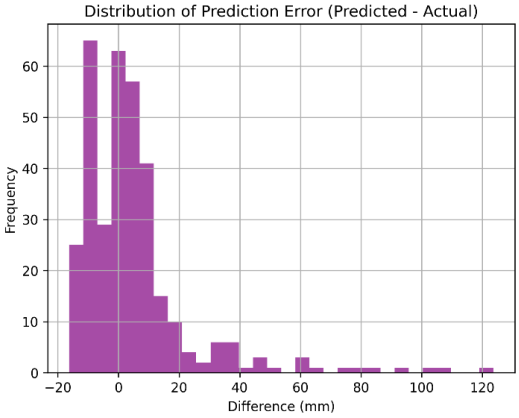

Fig. 4. Distribution of prediction error (Single BiLSTM with 10 years of data)

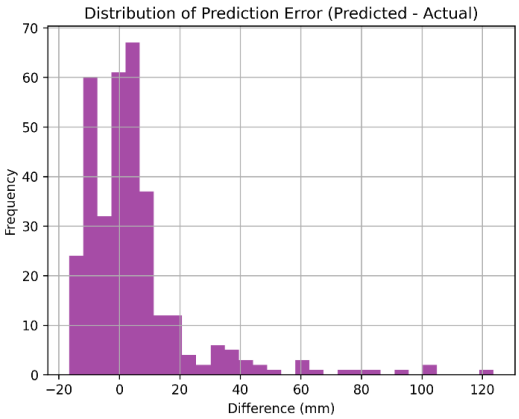

Fig. 5. Distribution of prediction error (Double BiLSTM with 10 years of data).

The histograms show that the double-layer BiLSTM models (Scenarios 2 and 4) consistently have higher frequencies of small errors around zero, implying improved average prediction accuracy. In contrast, scenarios trained on ten years of data exhibit longer tails of large errors (≥100 mm), reflecting the model's exposure to rare, high-intensity rainfall events.

A Shapiro–Wilk test conducted on each scenario's error distribution indicated approximate symmetry around zero, showing no systematic prediction bias. The sharper central peaks in the double BiLSTM scenarios confirm that these models generate more accurate predictions for the majority of days, albeit with less stability during extreme weather conditions.

The optimized BiLSTM model (Scenario 4) was subsequently employed to determine ideal rice planting schedules using the official criteria from Balitbangtan and BMKG: planting commences when cumulative rainfall reaches ≥50 mm over three consecutive ten-day periods, or ≥150 mm within one month.

Applying these thresholds to both predicted and actual rainfall data produced identical results for all 10 planting periods, as shown in Table V.

The perfect alignment between predicted and actual planting dates highlights the BiLSTM's effectiveness in capturing rainfall dynamics and replicating threshold-based agricultural decisions. Nevertheless, this outcome must be interpreted with caution: the decision rules themselves may oversimplify local climate realities. For example, in Deli Serdang, rainfall sometimes exceeds 50 mm in a single day, followed by a dry spell. Under the current criterion, such a single-day event could prematurely trigger planting despite inadequate soil moisture retention. Future research should therefore refine planting decision thresholds by incorporating rainfall distribution consistency, soil moisture persistence, or evapotranspiration indices. This integration would improve both the reliability and agronomic realism of automated planting recommendations.

TABLE V. PLANTING SCHEDULES RECOMMENDATIONS BASED ON ACTUAL DATA AND PREDICTED RAINFALL DATA

Actual Rainfall	Predicted Rainfall
27 January 2022	27 January 2022
27 February 2022	27 February 2022
30 March 2022	30 March 2022
30 April 2022	30 April 2022
31 May 2022	31 May 2022
01 July 2022	01 July 2022
01 August 2022	01 August 2022
01 September 2022	01 September 2022
02 October 2022	02 October 2022
02 November 2022	02 November 2022

The BiLSTM models demand substantially higher training times than traditional methods such as ARIMA or Random Forest. For offline forecasting or policy simulations, this cost is acceptable; however, for real-time or resource-constrained agricultural systems, model efficiency becomes a key concern. Hybrid approaches—combining pre-trained BiLSTM forecasts with lighter statistical adjustments-may offer a practical compromise. Regularization techniques, including dropout and early stopping, were applied to mitigate overfitting. Additionally, rainfall data are typically imbalanced (few heavy-rain days vs. many light-rain days), which can bias training. This imbalance was partially addressed by using MAE (less sensitive to large outliers) alongside RMSE. In operational deployments, periodic retraining with recent data is essential to maintain accuracy amid evolving climatic conditions.

Overall, the double-layer BiLSTM trained on ten years of rainfall data (Scenario 4) yielded the best predictive performance, achieving high correlation ($r = 0.95$), low MAE (11.24 mm), and realistic reproduction of official planting calendar recommendations. While these results affirm the potential of BiLSTM-based rainfall forecasting for regional agricultural planning, the study also underscores that predictive accuracy must be complemented by refined decision-making rules grounded in agronomic principles. The proposed framework demonstrates a viable pathway for integrating deep learning forecasts with local agricultural decision systems, contributing to more adaptive and data-driven planting strategies for Indonesia's climate-sensitive regions.

IV. CONCLUSION

This study successfully implemented a Bidirectional Long Short-Term Memory (BiLSTM) model to accurately predict rainfall in Deli Serdang Regency, using historical data from 2013 to 2022. The best-performing model was achieved in scenario 4, which utilized a double BiLSTM

architecture and 10 years of data, yielding an MAE of 11.2382 mm and an RMSE of 19.5650 mm.

The analysis indicates that features derived from rainfall itself (such as moving averages and lags) and time-based features have the most significant predictive influence. A key finding from the model evaluation is the trade-off between general accuracy and model robustness. Increasing the data duration (10 years) and architectural complexity (double BiLSTM) was found to decrease the MAE value, but it was accompanied by a slight increase in the RMSE value. This suggests that while the model becomes more accurate under normal weather conditions, its ability to handle anomalies or extreme rainfall events is slightly diminished.

Nevertheless, the model's performance, validated through MAE and RMSE metrics, confirms its potential as a reliable decision-support tool. When tested using the established planting criteria, the model was able to generate planting schedules predictions consistent with the actual data. However, it should be noted that these criteria have limitations; meeting the rainfall threshold in a single day does not guarantee an even distribution of rain in the following days. Therefore, adjusting the criteria based on the specific characteristics of the region will be necessary for future implementation.

From an operational perspective, the proposed BiLSTM model could be integrated into an agricultural decision-support system (DSS) that automatically retrieves meteorological data, executes rainfall forecasting, and generates dynamic planting recommendations for farmers. Collaboration with local institutions such as the Agency for Agricultural Research and Development (Balitbangtan) and the Meteorology, Climatology, and Geophysics Agency (BMKG) would facilitate real-time deployment and ensure that predictive outputs align with national planting guidelines. Developing user-friendly interfaces, such as dashboards or mobile applications, would further enhance accessibility and practical adoption among local farming communities.

For future research, the framework should be extended and validated across multiple regions in Indonesia with varying climatic conditions to assess generalizability. Moreover, integrating additional parameters—such as soil moisture, temperature extremes, and remote sensing data-could further improve model robustness and adaptability. Exploration of hybrid or ensemble approaches that combine BiLSTM with other statistical or physical models is also recommended to enhance performance under extreme weather events and improve long-term prediction reliability.

By applying this predictive capability, this research offers a data-driven framework for optimizing planting schedules, mitigating the risk of crop failure, and ultimately contributing to regional food security. Overall, this study highlights the significant potential of Artificial Neural Networks in advancing precision agriculture to address local climate challenges.

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Fandi Presly Simamora is a lecturer in the Undergraduate Informatics Study Program, Faculty of Informatics, Universitas Mikroskil. The author completed her Bachelor's degree in the Information Engineering program and continued her Master's studies in the International Master's Program in Information Technology and Applications. The author focuses on writing, which is an essential part of a lecturer's role in fulfilling the Tri Dharma of Higher Education (Education and Teaching, Research, and Community Service). (email: fandi.simamora@mikroskil.ac.id).



Khairul Hawani Rambe is a lecturer who completed her Bachelor's degree in Information Engineering and pursued a Master's degree through the International Master's Program in Information Technology and Applications. Her academic interests center on writing, which she considers an essential aspect of a lecturer's role in fulfilling the Tri Dharma of Higher Education: Education and Teaching, Research, and Community Service. (email: khairul.rambe@mikroskil.ac.id).



Sophya Hadini Marpaung is a lecturer, specializing in Information Systems with a strong interest in UI/UX, AI, and related fields. As a lecturer, my dedication focused on the three pillars of a lecturer's role: teaching, community service, and research. (email: sophya.marpaung@mikroskil.ac.id).