A Multivariate LSTM Approach for Monthly Rice Production Forecasting in East Java

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Abstract— Accurate forecasting of rice output is essential for improving regional food security planning, particularly in East Java Province, which serves as a major national rice granary. This study develops a Long Short-Term Memory (LSTM) model to predict rice production using monthly data on production and harvested area from 2018 to 2024. The methodology includes data preprocessing, normalization, sequence construction with a sliding window, training of a multivariate LSTM model, and performance evaluation using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Results show that the LSTM model achieves superior predictive accuracy, with an MAE of 95,030.16, RMSE of 120,229.01, and MAPE of 16.64%, significantly outperforming baseline Moving Average and Linear Regression models. While the model effectively captures seasonal production trends, some inaccuracies remain during periods of anomalous production values. These findings suggest that the LSTM model is effective for projecting rice production and may provide a foundation for early warning systems and regional food distribution strategies. Further improvements could be realized by integrating climate variables or adopting a hybrid model architecture to enhance predictive precision.

Keywords— Artificial Intelligence, LSTM, Rice Production Forecasting, Time Series Analysis, East Java.

I. INTRODUCTION

Rice production plays a crucial role in maintaining national food security, and East Java Province is one of Indonesia's major rice-producing regions. However, rice production exhibits substantial temporal fluctuations driven by harvested area, seasonal planting cycles, climate variability, and socio-environmental dynamics [1], [2], [3]. Under increasingly uncertain climate conditions, accurate production forecasting is essential to support food stock planning, rice distribution, and adaptive agricultural policies. These challenges are exacerbated by the non-linear and seasonal characteristics of agricultural time-series data.

Methodologically, traditional statistical approaches such as linear regression and ARIMA have been widely applied for agricultural forecasting, yet their ability to capture complex seasonal patterns and non-linear dependencies remains limited [4], [5]. Advances in artificial intelligence have enabled the adoption of deep learning models, particularly Long Short-Term Memory (LSTM) networks, which are capable of learning long-term temporal dependencies and overcoming vanishing gradient issues [6], [7], [8]. As a result, LSTM has emerged as a state-of-the-art approach for time-series forecasting in various domains, including agriculture .

Despite these advances, several research gaps remain. First, many existing studies rely on annual or aggregated data, whereas rice production is strongly influenced by monthly seasonal variability. Second, most studies employ univariate inputs, limiting the model's ability to capture inter-variable dynamics [9], [10], [11], [12]. Third, LSTM-based rice production forecasting studies focusing specifically on East Java Province remain scarce, despite its distinctive production patterns and strategic importance. This study addresses these gaps by applying a multivariate LSTM model using monthly production and harvested area data from 2018 to 2024, providing a more detailed and locally adaptive forecasting framework [13], [14], [15].

Accordingly, this study aims to develop a multivariate LSTM-based model for monthly rice production forecasting in East Java Province and evaluate its performance using RMSE, MAE, and MAPE metrics [16], [17], [18]. The research seeks to answer: (1) how monthly rice production patterns evolved in East Java during 2018–2024; (2) how accurately LSTM can forecast rice production; and (3) whether incorporating harvested area improves predictive accuracy. The proposed model contributes an AI-based forecasting approach that supports regional food security planning and enriches the literature on deep learning applications for agricultural forecasting at the provincial level.

II. METHOD

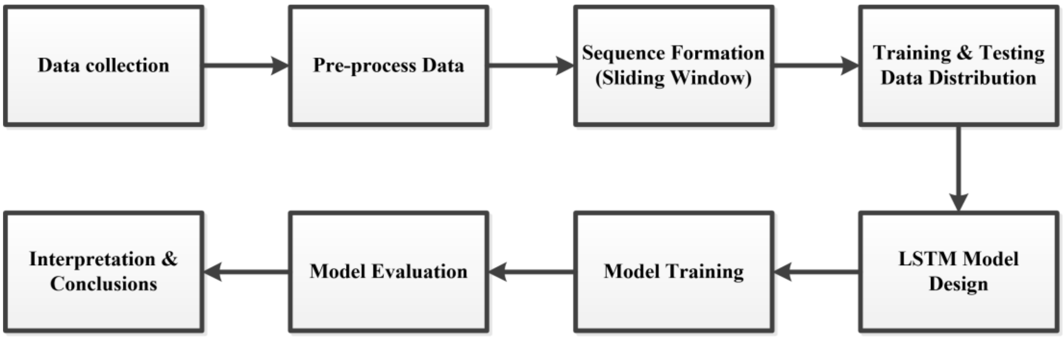

Figure 1. Research Block Diagram

A. Research Methodology

This study employs a quantitative methodology utilizing an experimental design to create a prediction model for rice production based on Long Short-Term Memory (LSTM) technology [6], [19]. The research strategy is formulated as a multivariate time series model encompassing two primary variables: rice production (tons) and harvested area (hectares). The LSTM model serves as the principal approach due to its ability to analyze long-term temporal trends in monthly data.

The study phases encompass: (1) dataset acquisition and preparation; (2) data preprocessing; (3) sequence data generation via the sliding window method; (4) creation of the LSTM model architecture; (5) model training; (6) evaluation of the model utilizing error metrics; and (7) validation of prediction results. This approach enables complete replication of the study procedure by other researchers.

B. Data Sources and Data Collection Methods

The utilized data is secondary, comprising monthly rice production (in tons) and monthly harvested area (in hectares) for East Java Province from January 2018 to December 2024. The data was sourced from the official website of the Central Statistics Agency (BPS) of East Java Province [20], [21]. Utilizing secondary data guarantees that the information has undergone administrative validation and is appropriate for scientific examination.

Data was gathered through a documentation technique, utilizing a CSV file download procedure. All data was subsequently amalgamated into a singular table with the following column configuration: date/month, production (tons), and harvested area (ha). In the event of format incompatibilities, the date format was standardized to YYYY-MM to facilitate processing as time series data.

C. Data Preprocessing

Table 1. Summary of Data Preprocessing and Model Configuration

Component	Description
Dataset	Monthly rice production and harvested area (2018–2024)
Missing value handling	Forward filling and linear interpolation
Outlier handling	Extreme values retained if verified as valid seasonal events
Normalization	Min–Max scaling (0–1)
Window size	3–6 months (sliding window)
Train–test split	80% training, 20% testing (time-based split)
Model	Multivariate LSTM
LSTM units	64
Dense layer	32 neurons (ReLU)
Optimizer	Adam (learning rate 0.001)
Loss function	Mean Squared Error
Batch size	16
Epochs	150
Software	Python, TensorFlow/Keras, NumPy, Pandas

Data preprocessing was conducted to guarantee the dataset's cleanliness and usability for the model [22], [23], [24]. The procedure encompasses:

1. Verifying the absence of values

Non-missing values were imputed using the forward filling technique or linear interpolation, where the data were sequential.

2. Identification and Management of Outliers

Irrational outliers were verified against official sources, whilst legitimate extreme values were preserved to uphold the data's integrity.

3. Outlier Handling

Extreme values were carefully examined using official statistical records. Valid extreme observations corresponding to peak or low seasonal production were retained to preserve the inherent variability of agricultural time-series data, while inconsistent or erroneous entries were corrected during preprocessing.

4. Data Standardization

All variables were normalized via MinMaxScaler within a range of 0–1 to meet the neural network's specifications.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X' : Normalization Result
X : Original Value
X_{max} : Maximum Value
X_{min} : Minimum Value

5. Formation of Data Sequences

The sliding window technique is employed to create the input sequence, utilizing window lengths (timesteps) ranging from 3 to 6 months. A window of 3 indicates that data from months 1 to 3 is used to forecast month 4.

6. Segregation of Training and Test Data

The data is allocated 80% for training and 20% for testing by a time-based split approach, owing to its temporal characteristics. A time-based split was applied to preserve temporal order and prevent information leakage from future observations, ensuring methodological rigor and reproducibility for time-series forecasting studies.

D. Development of the LSTM Model

The LSTM model architecture in this research is constructed to be reproducible with explicit parameters [25]. The model comprises:

- An input layer with dimensions of timesteps by features (2 features: production and harvested area)
- A Long Short-Term Memory (LSTM) layer comprising 64 units
- A fully connected layer including 32 neurons with ReLU activation function.
- A singular output layer (1 neuron) to produce a solitary anticipated value

The training utilized the Adam optimization algorithm with a learning rate of 0.001, a Mean Squared Error (MSE) loss function, a batch size of 16, and 150 epochs. Training data was handled in a continuous sequence without randomization to preserve temporal order. Early halting may be employed to avert overfitting.

E. Methods of Data Analysis

The data analysis was performed in three phases:

1. Descriptive analysis

Illustrating production and harvested area trends through monthly graphs to analyze seasonal patterns.

2. Analysis of modeling utilizing LSTM

Incorporating model training, validation, and the preservation of optimal weights through model checkpoints.

3. Accuracy Assessment

The evaluation was performed with the subsequent metrics:

- Mean Absolute Error (MAE)

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

- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (3)$$

- Root Mean Square Error (RMSE)

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

Where:

n : Total number of data

y_i : Actual value

$\hat{y}_i$: Predicted value

Table 2. MAPE Value Analysis [1]

MAPE Value	Description
< 10%	Very Accurate
10% - 20%	Good
20% - 50%	Fair
> 50%	Inaccurate

An actual versus expected graph is utilized to juxtapose the predicted outcomes with the exact values.

All study procedures are meticulously documented to facilitate replication. The model parameters, dataset design, and preparation phases are transparently elucidated. This research employs Python software utilizing the TensorFlow/Keras, numpy, and pandas libraries, enabling execution on various devices with analogous settings.

III. RESULT AND DISCUSSION

A. Analytical Description of Production and Cultivated Area Data

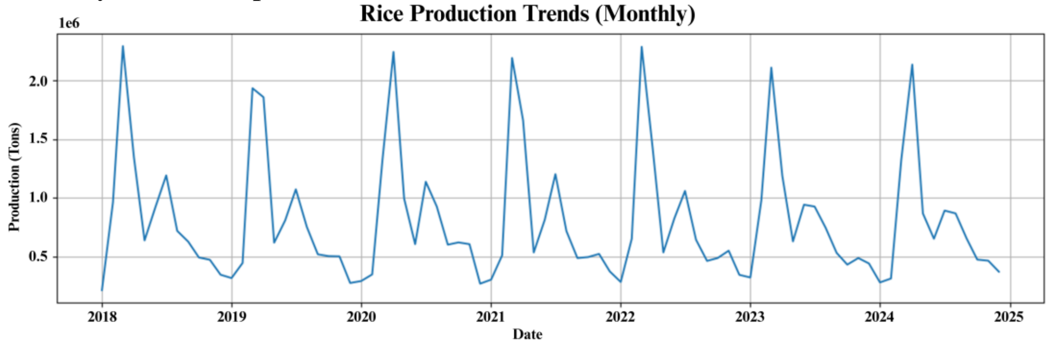

Figure 2. Monthly Trends in Rice Production in East Java Province (2018–2024)

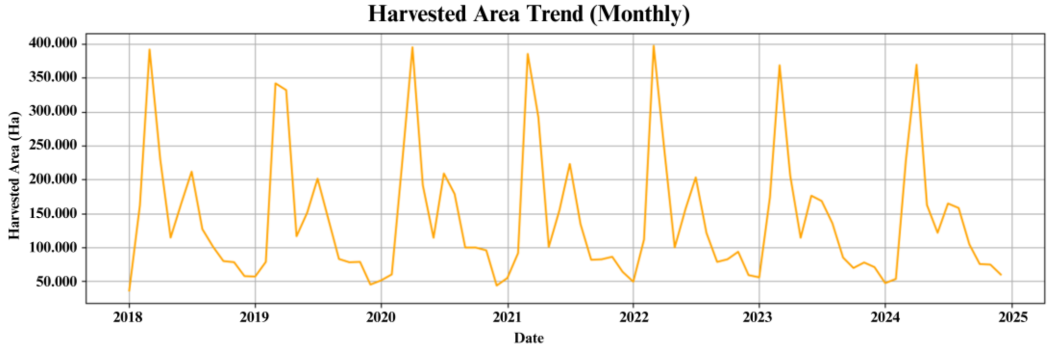

Figure 3. Trends in Monthly Rice Harvested Area in East Java Province (2018–2024)

Data regarding rice production and harvested area in East Java Province from 2018 to 2024 exhibit significant swings in both production volume and harvested area. This signifies that the rice production system in this province exhibits distinct yet intricate seasonal dynamics. The descriptive data table indicates that the mean monthly production was 809,831.97 tons, accompanied by a substantial standard deviation of 529,897.94 tons, signifying considerable variability among months.

Table 3. Descriptive Statistics of Rice Production and Harvested Area in East Java Province (2018–2024).

	Count	Mean	Std	Min	25%	50%	75%	Max
Production	84	809.832	529.898	211.337	471.491	625.716	964.980	2.293.296
Area	84	142.426	93.800	36.120	77.876	112.506	176.637	397.026

The production distribution exhibits two significant characteristics:

1. Peak production is exceptionally high, particularly during the primary harvest season (March–April), exceeding 2 million tons.
2. Minimum production transpires at the year's conclusion and commencement, specifically in January and February, when output declines to roughly 211,336 tons.

The harvested area exhibits a pattern closely aligned with production, averaging 142,425.73 hectares, with seasonal fluctuations corresponding to the cropping cycle. The coefficient of variation for harvested area is notably large, signifying a diverse distribution during the year.

The correlation heatmap illustrates a correlation value approaching 1.00, signifying an almost perfect linear relationship between the two variables. This discovery establishes a crucial basis for predictive models: the stronger the connection between input and output variables, the higher the model's capacity to utilize that signal to enhance accuracy.

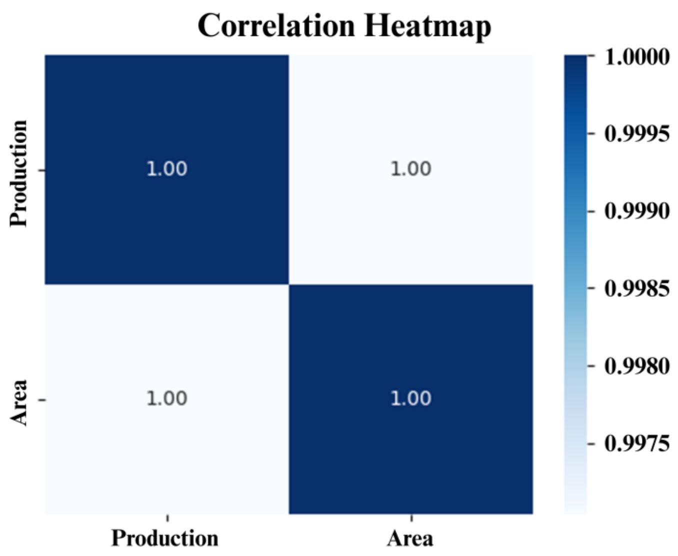

Figure 4. Correlation Heatmap of Rice Production and Harvested Area

B. Temporal Dynamics of Production and Cultivated Areas

Monthly trend visualizations indicate consistently stable seasonal patterns across the years. Production reaches its zenith in the initial three months and then has a substantial fall in the mid to late years. This pattern signifies that the farming system in East Java adheres to a traditional planting calendar, leading to repetitive planting seasons.

The patterns of harvested area demonstrate changes that closely mirror production levels. This substantiates the validity of the premise that harvested area is a crucial predictor of production and serves as a highly suitable supporting variable in multivariate models.

The consistency of temporal patterns is essential for LSTM models, as they perform more effectively when data demonstrates a recurrent seasonal pattern. This elucidates the model's attainment of comparatively constant prediction performance in this investigation, with an average error of less than 20% in the majority of months.

C. Performance of the LSTM Model and Comparison with the Baseline

Table 4. Evaluation of LSTM Model Efficacy Relative to Baseline

Model	MAE	RMSE	MAPE(%)
LSTM	95.030,16	120.229,01	16,64
Moving Average	353.682,06	517.770,56	47,09
Linear Regression	301.488,46	367.565,21	52,36

The test findings indicate that the LSTM model substantially surpasses both baselines—Moving Average and Linear Regression—across all evaluation criteria (MAE, RMSE, MAPE).

Performance of LSTM:

- MAE = 95.030,16
- RMSE = 120.229,01
- MAPE = 16,64%

A MAPE value under 20% signifies that the model is classified inside the good forecasting accuracy category, as delineated in Table 1 about MAPE value analysis.

Initial Performance:

- Moving Average: MAPE 47,09%
- Linear Regression: MAPE 52,36%

The Moving Average sometimes fails to reflect the dynamics of swift shifts, particularly during the transition from low to high output levels. Linear Regression, as a linear model, can solely represent straightforward linear correlations and fails to account for intricate seasonal variations.

The benefits of LSTM stem from various factors:

1. The capacity to capture long-term dependencies across months.
2. Managing non-linear patterns with a gating mechanism (input, forget, output).
3. The interplay of production variables and cultivated area enhances the temporal context acquired by the model.

Consequently, the application of LSTM has demonstrated a superior predictive representation compared to conventional approaches.

D. Assessment of Predictive Errors and Behavioral Patterns

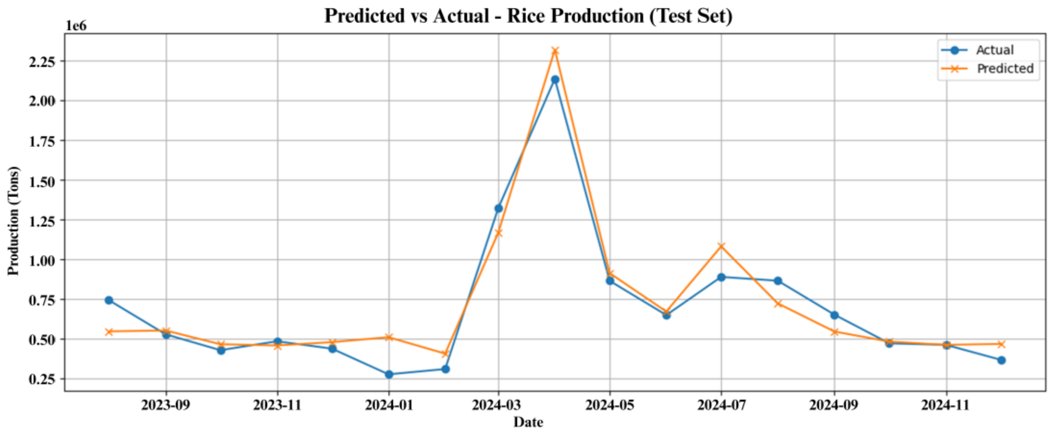

Figure 5. Comparison of Actual and Forecasted Rice Production Values (Test Set)

The graph comparing anticipated and real values indicates that the LSTM model effectively tracked production trends, particularly during peak periods like March to April 2024. During these months, despite significant production fluctuations, the model consistently predicted numbers within a range closely aligned with the actual figures.

Table 5. LSTM Model Prediction Outcomes throughout the Testing Phase (Actual versus Predicted)

date	Actual Production (ton)	Predicted Production (ton)	Error (ton)	Error (%)	MA Pred	Lr Pred
2023-08-01	743.342,68	547.234,69	196.107,98	26,38	830.357,22	897.030,94
2023-09-01	528.980,73	552.859,52	-23.878,79	-4,51	869.215,46	617.353,62
2023-10-01	428.914,00	466.292,11	-37.378,11	-8,71	732.183,97	731.536,90
2023-11-01	485.115,13	458.659,54	26.455,58	5,45	567.079,13	481.935,31
2023-12-01	438.705,74	479.594,41	-40.888,66	-9,32	481.003,28	835.811,00
2024-01-01	277.035,02	510.528,08	-233.493,06	-84,28	450.911,62	670.773,70
2024-02-01	310.234,48	407.129,68	-96.895,20	-31,23	400.285,29	635.995,52
2024-03-01	1.321.465,79	1.166.963,49	154.502,29	11,69	341.991,74	801.456,50
2024-04-01	2.135.744,25	2.319.570,42	-183.826,17	-8,60	636.245,09	1.306.781,44
2024-05-01	865.264,09	913.526,38	-48.262,29	-5,57	1.255.814,84	1.267.644,71
2024-06-01	649.671,78	671.877,12	-22.205,34	-3,41	1.440.824,71	179.179,48
2024-07-01	889.962,44	1.081.881,61	-191.919,16	-21,56	1.216.893,37	1.241.430,81
2024-08-01	866.020,53	723.196,13	142.824,39	16,49	801.632,77	851.094,16
2024-09-01	652.260,74	546.299,05	105.961,68	16,24	801.884,91	768.400,52
2024-10-01	471.937,28	482.917,47	-10.980,19	-2,32	802.747,90	726.243,29
2024-11-01	462.469,22	462.358,04	111,17	0,02	663.406,18	418.825,75
2024-12-01	368.369,67	468.192,29	-99.822,62	-27,09	528.889,08	826.875,70

Higher prediction errors were observed during extreme production months, particularly during unusually low or peak harvest periods. This behavior indicates that while LSTM effectively captures dominant seasonal trends, abrupt deviations remain challenging due to limited representation of extreme events in training data. Nevertheless, the model performs consistently during normal seasonal cycles, supporting its applicability for regional production planning and early warning purposes.

1. Precise Interval

Months like November 2024, October 2024, and May 2024 exhibited errors below 5%, signifying exceptionally precise predictions. The elevated precision during these moderate months suggests that the model exhibits optimal stability when production values are near the mean and do not encounter significant anomalies.

2. Period of Underprediction/Overprediction

The most significant miscalculation transpired in January–February 2024. During these months, actual production was very low, although the model overestimated it. This phenomenon is prevalent due to:

- the model's increased exposure to high-yielding patterns during training,
- the minority presence of low extreme values within the distribution,
- the potential suboptimality of the window size during extreme periods.

Nonetheless, despite the occurrence of outlier errors, the model exhibits commendable predictive stability overall.

E. Instruction and Assessment Analysis of Curves

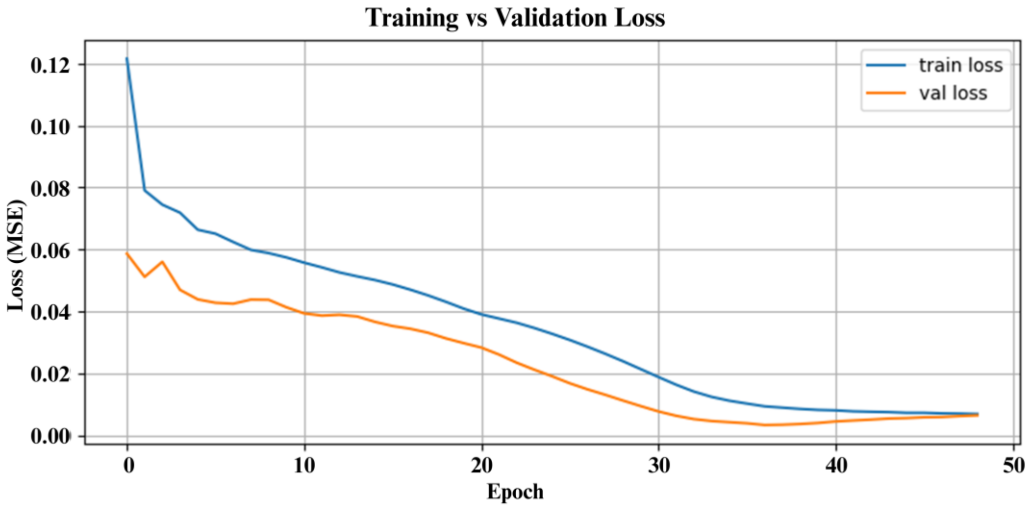

Figure 6. Curves of Training Loss and Validation Loss for the LSTM Model

The loss curve illustrates a consistent decline in training loss, accompanied by a more pronounced reduction in validation loss:

1. This signifies that the model does not exhibit overfitting.
2. The model acquires generalizable patterns.
3. Early Stopping effectively concludes training at the right juncture.
4. The 64-unit LSTM combined with a 32-unit Dense layer is adequately representational, obviating the necessity for a more complex architecture.

This stability is essential as it signifies that the dataset possesses high temporal quality for the model's learning process.

F. Analysis of Possible Seasonal Errors

According to the Prediction Results table:

– Positive errors (underpredictions) are more prevalent following the peak harvest period.
– Negative mistakes (overpredictions) are more prevalent during intervals of diminished production.

This phenomenon can be elucidated by the model's behavior:

LSTMs more readily learn ascending trends than steeply descending ones, particularly when the data distribution is biased towards elevated values.

The ramifications indicate that additional research ought to contemplate:

- Including climatic factors (precipitation, temperature),
- Including land fertility metrics (NDVI/EVI),
- Using an extended timeframe (6–12 months),
- or hybrid architectures like CNN-LSTM.

This study corroborates earlier findings that LSTM is efficacious in agricultural forecasting. Nonetheless, the particular contributions of this work are:

- Using high-resolution monthly data (84 data points) for East Java, instead of annual data.
- Using a multivariate method to enable the model to comprehend the relationships between production and harvested area.
- Establishing a model baseline to objectively assess LSTM performance.
- Examining errors in relation to seasonal dynamics, a unique yet pertinent method in agricultural forecasting.

This study's findings demonstrate that LSTM is the preeminent model for forecasting monthly rice production in East Java. This model, characterized by a low error rate and reliable performance, presents substantial prospects for:

- Regional rice inventory management,
- Logistical planning for food distribution,
- Prompt identification of possible production reductions,
- Enhancing early warning systems for food security.

This model can serve as the basis for creating an agricultural production monitoring dashboard that incorporates real-time data in the future.

IV. Conclusion

This study illustrates that the Long Short-Term Memory (LSTM) model can deliver enhanced forecast accuracy for monthly rice production in East Java Province by employing production and harvested area data from 2018 to 2024. The evaluation findings indicate an MAE of 95,030.16, an RMSE of 120,229.01, and a MAPE of 16.64%, all of which surpass the performance of the baseline Moving Average and Linear Regression approaches. The model effectively identifies seasonal trends and a robust correlation between production and harvested area, although it encounters constraints in forecasting extreme values during instances of very low production. A consistent training process devoid of overfitting signals a strong model generalization capability. These findings validate that multivariate LSTM is an effective and viable method for forecasting rice production, with potential for enhancement through the incorporation of climate factors or the use of more sophisticated model architectures to increase accuracy in the future.

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