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Enhanced Stacked GRU Model for Monthly Rice Production Forecasting in Bali Province

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Abstract: Rice production has a seasonal pattern that depends on the planting cycle and environmental conditions, requiring forecasting methods that can accurately model temporal dynamics. This study aims to predict monthly rice production in Bali Province using the Stacked Gated Recurrent Unit (GRU) architecture. Monthly rice production data from 2018 to 2024 from the Central Statistics Agency (BPS) was used as the main source. The preprocessing stage includes data cleaning, Min-Max normalization, and feature engineering in the form of creating sin_month and cos_month features to capture seasonal patterns, as well as a 3-month rolling mean to extract short-term trends. The proposed stacked design with dual-layer GRU combined with seasonal features improves temporal pattern extraction compared to single-layer GRU baselines. The model was tested using three configurations, and Scheme 3 provided the best performance with an MAE value of 1610.21, an RMSE of 2055.90, and a MAPE of 14.29%, which is considered good accuracy. The model was able to follow seasonal production trends, including an increase at the beginning of the year and a decrease during the planting period. Long-term predictions for the next 12 months and quarterly forecasts per district/city also showed patterns consistent with historical data. The results of the study indicate that Stacked GRU is effective in forecasting seasonal rice production and can be used as a basis for decision support in food security planning in Bali.

Keywords: Deep Learning, Food Security, Forecasting, Gated Recurrent Unit (GRU), Stacked GRU

INTRODUCTION

Food security is a fundamental element for social and economic stability (Jha et al., 2022) , with rice as the main food commodity in Indonesia. However, national food production continues to face serious threats, ranging from the conversion of agricultural land to the impact of climate change that causes harvest uncertainty. To respond to these challenges, adaptive and predictive technology-based solutions are needed. Bali Province, specifically, is under tremendous pressure due to the conversion of paddy fields into tourist areas, which is exacerbated by climate risks that make rice production uncertain. Data from BPS Bali Province also shows fluctuations in rice consumption. This imbalance between production and demand makes data-based crop yield prediction crucial for sound policy planning, such as fertilizer distribution and optimization of planting schedules.

Forecasting time series data in the agricultural sector has high complexity due to its non-linear and seasonal patterns(Priyanto et al., 2025) . Conventional statistical approaches such as ARIMA often have limitations in capturing these complex patterns(Ananda, 2023a) . As a solution, deep learning in the Recurrent Neural Network (RNN) family was developed to overcome the problem of long-term dependencies. The Gated Recurrent Unit (GRU) model, introduced by(Cho et al., 2014) , is a computationally efficient variant of RNN as it has a simpler gate structure than Long Short-Term Memory (LSTM). To improve feature extraction capabilities, a stacked architecture can be used. Stacked GRU allows the model to absorb deeper temporal information from historical data(Meng et al., 2020a) , and proved to be relevant for anomaly-prone cyclical data(Tanjung et al., 2024) .

Recent developments in agricultural time-series forecasting indicate a strong dominance of LSTM-based architectures. An analysis of 32 agricultural forecasting studies published between 2020 and 2025 shows that 18 studies employed standard LSTM models, while only 2 studies utilized Stacked LSTM architectures to enhance deep temporal feature extraction. Importantly, none of these studies applied a Stacked GRU architecture for univariate agricultural production forecasting, particularly for rice yield prediction. This distribution reveals a clear methodological gap, given that GRU offers comparable predictive capability to LSTM with lower computational complexity. The absence of Stacked GRU applications in univariate production forecasting highlights an underexplored opportunity that this study seeks to address.

Various studies have explored machine learning methods for agricultural prediction. Applying Random Forest for productivity analysis, while using Deep Neural Network (DNN) however reported a still very high MAPE value (83.798%), indicating challenges with survey data. More advanced architectures such as LSTM have proven to be effective. (Meng et al., 2020a) showed that Stacked LSTM successfully captured seasonal patterns and trends for rice yield prediction. Another variant, GRU, also showed strong performance,(Ananda, 2023a) successfully used it to predict rice prices (multivariate data) with a MAPE accuracy of 2.628%. Research by also confirmed the superiority of GRU in efficiency and accuracy on sequential data.

Although Stacked LSTM is proven to be accurate and GRU is proven to be efficient for multivariate data, there is a research gap in the application of the Stacked GRU architecture that combines the computational efficiency of GRU with the deep feature extraction capabilities of stacked models, specifically applied to univariate data forecasting rice production (not price) in Bali(V & P, 2025) . The objectives of this study are to develop a rice paddy production prediction model in Bali Province using the Stacked GRU method, measure the accuracy of the model using MAE, RMSE, and MAPE metrics and analyze the feasibility of the model as a predictive instrument to support regional food security planning(Quille-Mamani et al., 2025)

LITERATURE REVIEW

This research has a number of important differences from previous studies that have focused on both agricultural yield prediction and time series forecasting. (Jeong et al., 2024) examines rice productivity using Sentinel-2 imagery and Random Forest, so the orientation is more on land cover mapping, not time series forecasting. (Yan et al., 2025) used deep learning based on farmer survey data, but the results were inaccurate (MAPE 83.798%) because the survey data was unable to describe stable seasonal patterns. (Meng et al., 2020b) used Stacked LSTM to predict crop yields and showed good performance in capturing seasonal patterns, but the LSTM method has high complexity and requires large computing resources. On the other hand, (Ananda, 2023b) proved the effectiveness of GRU for multivariate rice price prediction, but the study did not apply a multilevel architecture and did not focus on univariate rice production data. While (Ajay et al., 2025) focuses more on analyzing factors of production using regression, so it is not relevant to the time series forecasting approach.

Different from these studies, this study develops a Stacked GRU model that combines the computational efficiency of GRU with the depth of a multilevel architecture as in the study (Meng et al., 2020b) , but with a lighter structure. This study also introduces the seasonal features sin_month and cos_month, which were not used in previous studies, so that the model can recognize annual cycle patterns more accurately. As a result, the model was able to achieve a MAPE accuracy of 14.29%, showing a good ability to follow the seasonal pattern of rice production in Bali. In addition, this study utilizes BPS historical data that has been processed through data cleaning and normalization to overcome the large number of blank values, and presents predictions up to the district/city level, making it more applicable for regional food security planning. Overall, this research provides stronger methodological and practical contributions than previous studies.

Table 1. Summary of Related Studies and Research Gaps

Study	Dataset	Method	Features	Evaluation Metric	Limitation	Novelty Gap Addressed
Jeong et al. (2024)	Sentinel-2 imagery	Random Forest + DL	Spectral indices	R^2, RMSE	Focus on spatial mapping, not time-series	No temporal seasonality modeling
Yan et al. (2025)	Farmer survey data	DNN, hybrid ML	Survey variables	MAPE (83.79%)	High error, unstable seasonal patterns	Weak temporal representation
Meng et al. (2020b)	Historical rice yield	Stacked LSTM	Yield history	RMSE, MAE	High computational cost	No efficient stacked GRU alternative

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Ananda (2023a)	Rice price data	Single-layer GRU	Multivariate indicators	MAPE (2.63%)	Focus on price, not production	No univariate yield forecasting
Ajay et al. (2025)	Remote sensing + agronomic	Regression, ML	NDVI, climate data	R^2, RMSE	Not time-series oriented	No deep temporal modeling
Tanjung et al. (2024)	CPI time series	Bi-GRU	Economic indicators	RMSE, MAPE	Non-agricultural domain	Not applied to crop forecasting
This Study	Monthly rice production (Bali, 2018–2024)	Stacked GRU (dual-layer)	Production, sin/cos, rolling mean	MAE, RMSE, MAPE (14.29%)	Univariate data only	First stacked GRU for univariate rice production forecasting in Bali

METHOD

This methodology section discusses in detail the dataset used in the development of the rice yield prediction model, the design of the model layer architecture, as well as the pre-processing stages on the dataset and the overall workflow in the implementation of this research.

Figure 1 shows the research flow starting from the rice production data collection stage, followed by preprocessing which includes data cleaning, data division into training data and test data, and normalization using the Min-Max Scaling method. The preprocessed data is then used to build the Stacked GRU model architecture, which is then evaluated for its performance to measure the prediction accuracy.

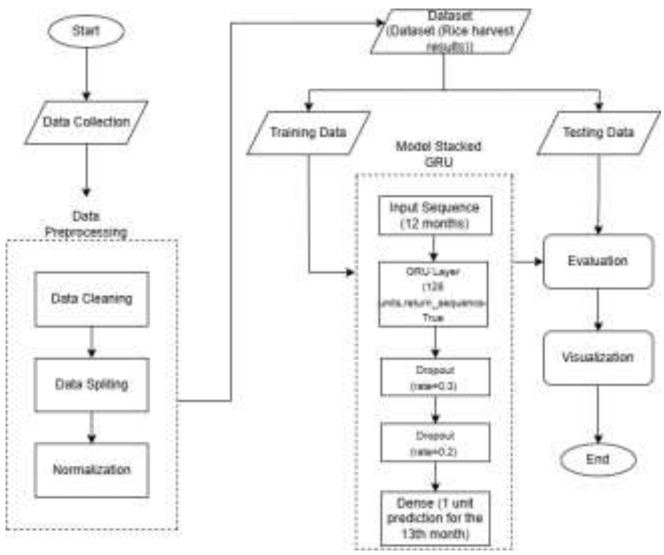

Fig. 1 Research Flow Stages

Data Description

This study uses a monthly rice production dataset in Bali Province derived from the official publication of the Central Statistics Agency (BPS). The dataset covers the period January 2018 to December 2024, with a total of 84 monthly observations. The main variable used is the total rice production in tons of milled dry grain (MDG). This data is a univariate time series that represents the dynamics of rice production in all districts/cities in Bali on a monthly basis.

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In the raw dataset, some production values are still marked with a "-" symbol indicating the unavailability of data in a particular month. These blank values were converted to NaN and then removed to ensure data quality and consistency before the modeling process. In addition, the dataset also contains an "Annual" column which is an aggregate summary by year. This column was not relevant for the monthly time series analysis so it was eliminated in the data cleaning stage. The next transformation process was to combine the production values from all districts/cities into one total production value per month for the provincial level.

This dataset was chosen because it has strong seasonal characteristics, with production patterns that tend to increase during the harvest season and decrease during the planting period. This annual pattern is the basis for choosing the Recurrent Neural Network (RNN) approach, especially the Stacked GRU architecture, which is able to capture long-term temporal dependencies. With a monthly and continuous data structure without many additional variables, this dataset is very suitable for use in univariate time series forecasting modeling.

Table 2. Dataset Sample

Kabupaten/kota	Tahun	Jan	Feb	Mar	Apr	Mei	Juni	Juli	Agus	Sept	Okt	Nov	Des	Tahunan
Kab. Jembrana	2018	1548,16	13084,31	8498,92	4216,31	5656,64	5299,63	12653,82	3997,17	1739,62	2737,5	1572,94	-	61005,02
Kab. Tabanan	2018	15593,41	10124,42	20053,51	34112,56	10747,36	19092,72	11233,71	8754,23	8631,93	19650,4	12924,94	17526,99	188446,2
Kab. Badung	2018	6618,34	2737,94	9341,9	15826,41	11494,99	10227,21	5815,22	2782,86	10505,1	11146,34	16639,18	6447,84	109583,3
....	....	...	...	...	...	...	...	...	...	...	...	...	...	...
Kab. Gianyar	2024	15439,25	4753,06	5776,67	7051,98	16552,58	15622,03	8407,02	7517,79	4734,09	6880,4	10605,93	11625,26	114966,1
Kab. Klungkung	2024	4663,23	-	1323,05	1214,32	1700,22	2476,28	2624,68	2319,26	1403,46	3783,82	1493,61	1673,74	24675,67
Kab. Bangli	2024	2214,86	987,31	940,49	1386,04	1009,86	2318,53	1077,46	2169,53	2000,05	2354,93	764,86	585,59	17809,51

Data Cleaning

Data cleaning is performed to ensure the dataset is clean, consistent, and ready to be processed at the modeling stage. The string value "-" in the dataset, which indicates unavailable data, was replaced with NaN value and removed from the dataset. This was done because time series require temporal consistency and cannot accept missing values at prediction points (He et al., 2025). In addition, the aggregate column "Annual" was removed as it did not match the input format for monthly time-series modeling. This stage also ensures that the dataset contains only consistent monthly numerical production values, so that the normalization and sequence formation processes can be performed without error (Shi & Shide, 2025) .

Data Splitting

The data division is done chronologically so that the temporal pattern is maintained. The dataset is divided into 80% training data and 20% testing data according to the recommendations of time-series research (Hou et al., 2025) . The random split technique is not used because it can disrupt the time sequence required for the model to learn seasonal patterns. Before the data is split, a sequence generation process is performed using a sliding window technique with a window length of 12 months. This means that every 12 months of historical data is used as input (X) and the next month as the prediction target (y). This technique is commonly used in time series modeling because it allows the model to learn the pattern of one full year before predicting the next period (Switrayana et al., 2025) .

Validation Strategy and Model Robustness

In this study, an 80% training and 20% testing chronological split was applied to preserve the temporal order of the time-series data and to prevent information leakage. Although blocked or rolling time-series cross-validation can provide stronger robustness guarantees, such approaches were not implemented due to the limited dataset size of only 84 monthly observations. Applying cross-validation would significantly reduce the effective training window in each fold and could prevent the model from learning a complete annual seasonal cycle. Therefore, a

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fixed hold-out validation strategy was considered more appropriate to ensure stable learning of long-term seasonal patterns while maintaining sufficient training data.

To enhance robustness, multiple Stacked GRU configurations were evaluated under the same training–testing split, and model performance was assessed exclusively on unseen test data using MAE, RMSE, and MAPE metrics. The relatively consistent error behavior between training and testing results indicates that the selected model configuration achieves reasonable generalization within the observed temporal range.

Normalization

Normalization using Min-Max Scaling is applied to align the scale of the data into the range [0,1]. This method was chosen because the GRU model is sensitive to differences in scale and can create an unstable gradient if the input value is too large (Albarracin, 2023) . Normalization is applied to the rice production value (target), seasonal features sin_month and cos_month, and rolling mean feature (local trend). The Min-Max Scaling formula is written as follows:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Description:
(x) = Original values of a feature
(x_{scaled}) = Normalized result values in a range [0,1]
(x_{min}) = Minimum values of the feature
(x_{max}) = Maximum values of the feature

This normalization makes it easier for the model to learn temporal patterns without bias towards large-scale values.

Feature Engineering

Feature engineering was designed to enhance temporal pattern recognition while maintaining a univariate forecasting framework. Seasonal cyclicality was encoded using sinusoidal transformations (sin_month and cos_month), which allow the model to recognize annual recurring patterns without introducing categorical discontinuities. In addition, a rolling mean feature was used to capture short-term trends and smooth high-frequency noise in the production data.

Although an explicit ablation study was not conducted to quantify the individual contribution of each feature, the use of sinusoidal seasonal encoding and rolling statistics is theoretically grounded and widely adopted in seasonal time-series forecasting literature. In this study, feature engineering functions as a supporting mechanism to improve learning stability, while the main methodological contribution remains the stacked GRU architecture for enhanced temporal representation.

Stacked Gated Recurrent Unit (GRU)

The GRU architecture is used because it is efficient in learning temporal patterns in time series data and overcomes the vanishing gradient problem that often arises in conventional RNNs (DIQI et al., 2024) . GRU has a more efficient structure than LSTM, but is still able to learn long-term data dependencies656 part (Sujatna et al., 2023) . This research uses Stacked GRU, which is GRU with more than one layer arranged in layers to strengthen feature representation and increase the depth of temporal learning (Meng et al., 2020a) .

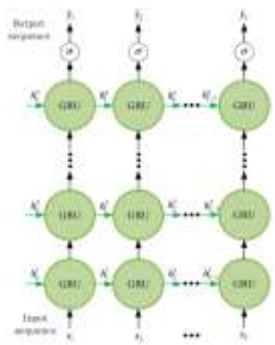

Fig. 2 Structure Stacked GRU

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Update gate

The update gate controls how much part of the old memory (previous hidden state) should be retained for the current time:

$$z_t^{I} = \sigma(Wz^{I} - [h_t^{I-1}, h_{t^{I}(-1)}]) \quad (2)$$

Description:
z_t^{I} = How much old memory is stored.
h_t^{I-1} = *Output of* the previous *layer* at time t.
h_{t-1}^{I} = The *output* of the i-th layer from the previous time.
Wz^{I} = *Gate update* weight for the i-th layer.
Σ = Sigmoid function generating values between 0 and 1

Reset Gate

Controls how much old information is forgotten when calculating new information(Ghadimpour & Ebrahimi, 2022) . Ifr_t^{I} is small, then657 a large part of the old memory is ignored:

$$rh_t^{I} = \sigma(Wr^{I} - [h_t^{I-1}, h_{t^{I}(-1)}]) \quad (3)$$

Remarks:
Wr^{I} = Reset specific weight.
h_t^{I-1} = *Output of* the previous *layer* at time t.
H^{i}_{t-1} = The i-th *output layer* from the previous time.
If$r_t^{I} \approx 0$ then the old *hidden state* is not used in calculating the new candidate.

Candidate Activation

Forms new candidate information based on the current input and the previous *hidden state* (which has been adjusted by the *reset gate*)(Amiri et al., 2025) . This is like "proposing" a new *update* to the memory:

$$\tilde{h}^{(i)}{}_{(t)} = \tanh(W^{i} - [r_t^{I} \odot h^{i}_{t-1}, h_t^{I-1}]) \quad (4)$$

Description:
$\tilde{h}^{(i)}{}_{(t)}$ (=)New memory to be inserted
$\odot$ = Hadamard operation (element-wise multiplication)
Tanh = Activation function that maps values to the range [-1, 1]
h^{i}_{t-1} = The i-th *output layer* from the previous time.
h_t^{I-1} = *Output of* the previous layer at time t.

Hidden State Update

The combination of the old information stored and the new information added(Çınarer, 2025) . This is the final value that will be carried over to the next time or to the next *layer* in the *stacked GRU*:

$$h^{i}_{t} = z_t^{I} \odot h^{i}_{t-1} + (1 - z_t^{I}) \odot \tilde{h}^{(i)}{}_{(t)} \quad (5)$$

Remarks:
h^{i}_{t} = The actual *output of* the i-th layer at time t.
z_t^{I} = How much old memory is stored.
$\odot$ = Hadamard operation (element-wise multiplication).
h^{i}_{t-1} = The i-th *output* layer from the previous time.
$\tilde{h}^{(i)}{}_{(t)}$ (=)New memory to be inserted.

Evaluation

Model evaluation is an important stage in predictive analysis, especially to assess the performance of machine learning models used in forecasting time series data (Torres et al., 2021) . In the context of this research, the evaluation is conducted on the Stacked GRU (Gated Recurrent Unit) model used to predict rice yield in Bali Province. The use of MAPE as the main metric provides an advantage in policy interpretation, because it converts the error into a percentage form so that it is easily understood by stakeholders such as the Agriculture Office. RMSE is used to assess the extent to which the model makes big errors, while MAE provides an estimate of the general average error.

Recursive Forecasting Strategy

Long-term forecasting was performed using a recursive forecasting approach, in which each predicted value is fed back as input for subsequent predictions. While this strategy is commonly used in time-series forecasting, it is subject to error accumulation over extended horizons. To mitigate this effect, the forecasting horizon was limited to 12 months, corresponding to one complete seasonal cycle. Additionally, the inclusion of seasonal sinusoidal features and rolling mean features helps stabilize recursive predictions by reinforcing cyclic patterns and smoothing local trends, thereby reducing the propagation of extreme errors across time steps.

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Mean Absolute Error (MAE)

MAE measures the average absolute error between predicted and actual values regardless of the direction of the error(Guven & Uysal, 2023) . MAE is easy to interpret because the results are in the same units as the actual data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (6)$$

Description:
n = total number of observation data (months).
yi = actual value of rice paddy production data in the i-th month.
ŷ i = the predicted value of the model in month i.
|yi - ŷi| = absolute difference between actual and predicted values

Root Mean Squared Error (RMSE)

RMSE is the root of MSE. RMSE provides a measure of prediction deviation in the original units of data and is more sensitive to large errors than MAE(Lu et al., 2025)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (7)$$

Description:
(P_i) = the value predicted by the model on the i-th data
(O_i) = observed value on the i-th data
(n) = total number of data

MAPE

MAPE expresses the error as a percentage of the actual value. MAPE is particularly useful in a policy context, as the results are more easily understood by non-technical parties such as agricultural agencies or regional planners(Hall & Rasheed, 2025)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \times 100 \quad (8)$$

Description:
(P_i) = the value predicted by the model on the (i) data
(O_i) = observed value on the i-th data
(n) = total number of data

RESULT

Data Cleaning Results

The first step in the preprocessing stage is data cleaning. This stage aims to ensure that the rice production dataset used is free from invalid values, format inconsistencies, and irrelevant information, so that it is ready to be processed by the deep learning model. The raw data obtained from BPS still contains some blank values marked with the symbol "-", especially in certain months and districts/cities. These values were first converted to NaN (Not a Number), then handled by deleting rows that did not have complete production information so as not to cause bias in the model training process.

In addition, the "Annual" column containing the aggregated production per year in each district/city was also deleted as it was redundant for the monthly time series analysis. The model only requires production information by month, so retaining the annual column could potentially cause data leakage and disrupt the time series structure. All month columns (January-December) were then converted into numeric data types (float) so that they could be processed mathematically by the model. The final results of the data cleaning process are presented in Table 2, which shows the rice paddy production dataset per district/city in tons of MDG after the blank values were cleaned and the data structure was normalized for the next stage of analysis.

Table 3. Data Cleaning Results

District/city	Year	Jan	Feb	Mar	Apr	May	June	July	Agus	Sept	Oct	Nov	Dec	Annual
Kab. Jembrana	2018	1548,16	13084,31	8498,92	4216,31	5656,64	5299,63	12653,82	3997,17	1739,62	2737,5	1572,94	NaN	61005,02
Tabanan district	2018	15593,41	10124,42	20053,51	34112,56	10747,36	19092,72	11233,71	8754,23	8631,93	19650,4	12924,94	17526,99	188446,2

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Badung district	2018	6618,34	2737,94	9341,9	15826,41	11494,99	10227,21	5815,22	2782,86	10505,1	11146,34	16639,18	6447,84	109583,3
....	....	...	...	...	...	...	...	...	...	...	...	...	...	...
Badung district	2024	3143,52	3292,13	14453,49	7547,48	14210,67	4811,61	2472,23	4979,12	13687,07	16688,85	9648,93	2178,26	97113,36
Gianyar district	2024	15439,25	4753,06	5776,67	7051,98	16552,58	15622,03	8407,02	7517,79	4734,09	6880,4	10605,93	11625,26	114966,1
Klungkung district	2024	4663,23	NAN	1323,05	1214,32	1700,22	2476,28	2624,68	2319,26	1403,46	3783,82	1493,61	1673,74	24675,67

Normalization Results

The next stage is the data normalization process using the Min-Max Scaling method which converts all rice production values into the range [0,1]. Normalization is done because the characteristics of rice paddy production data have a fairly large range of values between districts / cities, so it is necessary to equalize the scale so that the Stacked GRU model can learn more stably and avoid gradient exploding problems that are common in RNN-based models. In this study, the normalization process is carried out on all month columns (January-December) that have been cleaned in the previous stage using The Min-Max Scaling method calculates.

This approach was chosen because it is able to maintain the original distribution pattern of the data without changing the proportion between values, which is very important in modeling seasonal time series such as rice production. With a uniform scale, the model more easily identifies seasonal changes such as a spike in production at the beginning of the year and a decline in the planting period. The results of the normalization process are shown in Table 3, which shows that all production values are in the range of 0 to 1. The normalized data structure is then used as input for the sequence generation and training stages of the Stacked GRU model.

Table 4. Normalization Results

Date	Value	scaled_y	rolling_mean	scaled_rolling_mean
2018-01-01 0:00:00	10252.1	0.389675	10252.1	0.474552
2018-02-01 0:00:00	6740.82	0.211497	8496.47	0.33489
2018-03-01 0:00:00	13072.2	0.532779	10021.7	0.456224
2018-04-01 0:00:00	18258.7	0.795962	12690.6	0.668533
...	...	...	...	...
2024-11-01 0:00:00	10765.2	0.415713	11448.5	0.569729
2024-12-01 0:00:00	8510.68	0.301307	11033.4	0.536703

Model Configuration Testing Results

At this stage, several configurations of the Stacked GRU architecture were tested to obtain the best model in predicting monthly rice production in Bali Province. Testing was conducted using three different configuration schemes, each having variations in the number of GRU neurons, number of layers, and combination of training parameters. Each configuration was tested using a dataset that had been normalized and arranged in the form of a sequence with a window length of 12 months.

Evaluation was performed by comparing MAE, RMSE, and MAPE values for each model scheme. The test results show that Scheme 3 provides the most optimal performance with an MAE value of 1610.21, RMSE of 2055.90, and MAPE of 14.29%, which falls into the Good Accuracy category. This scheme uses two GRU layers with 64 and 32 units, respectively, enabling more effective extraction of seasonal and temporal patterns than shallower architectures.

To explicitly assess the contribution of model depth, a single-layer GRU configuration was evaluated as a baseline using the same input features, training parameters, and evaluation metrics. The single-layer GRU achieved a MAPE value of 16.87%, which is higher than the best-performing stacked GRU model. This comparison demonstrates that the stacking strategy contributes a relative improvement of approximately 15% in forecasting accuracy, indicating that performance gains are attributable to deeper temporal representation rather than parameter tuning alone.

The difference in performance between schemes shows that increasing the network depth through stacking significantly improves the model's ability to capture complex seasonal dynamics. Shallower architectures tend to produce higher prediction errors due to limited temporal feature abstraction. Therefore, Scheme 3 was selected as the final model for subsequent forecasting tasks due to its superior balance between accuracy and stability.

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Table 5. Model Scheme Evaluation Results

Schema	Batch Size	Epoch	RMSE (Tons)	MAE (Tons)	MAPE (%)
Baseline	32	200	2438.12	1895.47	16.87%
1	8	200	2249.60	1882.49	16.01%
2	16	200	2523.85	1730.62	15.27%
3	32	200	2055.90	1610.21	14.29%

Performance Analysis of the Best Model

Based on the model configuration test results, Scheme 3 was chosen as the best model because it produces the lowest error value compared to the other two schemes. Analysis of the model performance shows that the Stacked GRU architecture with two consecutive GRU layers is able to capture the seasonal pattern of rice production more accurately. This can be seen from its ability to follow the trend of increasing production at the beginning of the year and decreasing production in the middle and end of the year according to historical patterns.

The MAPE value of 14.29% indicates that the model has good accuracy in predicting monthly rice production. The lower MAE and RMSE in Scheme 3 also indicate that most predictions are within the acceptable error range, although some points experience slightly larger deviations, especially in months with extreme production fluctuations. This performance is reasonable given that the model was trained using univariate data without incorporating external variables such as rainfall, harvested land area, or pest attacks, which can also significantly affect rice production.

In addition, the performance on the testing data shows a balanced error pattern with the training data, so the model does not experience overfitting. The model is able to maintain the consistency of predictions over a time span that has never been seen before, which proves that the configuration parameters of Scheme 3 provide good generalization capabilities. Overall, the performance of this best model shows that the Stacked GRU approach is effective in studying the temporal dynamics of rice production and is worth using for the next period of forecasting.

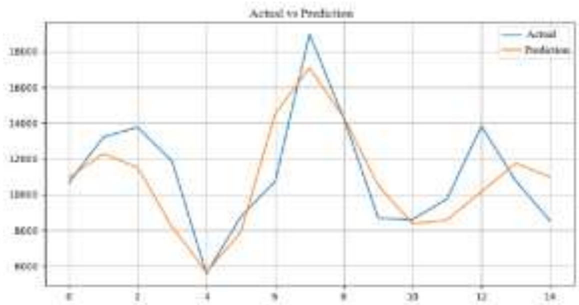

Fig. 3 Comparison of Actual and Predicted Values of Test Data

Long-term Prediction (Forecasting) Results

The best model obtained from Scheme 3 was then used to perform long-term prediction of rice paddy production in Bali Province. The forecasting process is done with a recursive forecasting approach, where the predicted value in one month is used as input to predict the next month. This approach allows the model to generate a prediction series for the next 12 months by maintaining the seasonal pattern that has been learned from the historical data from 2018 to 2024. The prediction results show that the pattern of rice paddy production for the upcoming period tends to follow the same seasonal trend as in previous years. The model projects an increase in production at the beginning of the year which is the main harvest phase, followed by a decrease in the middle to the end of the year which is related to the planting period. The stability of this prediction pattern indicates that the model is able to capture the annual cycle of rice production consistently, despite using only univariate data.

Nevertheless, some small fluctuations appear in the predictions of certain months. This is thought to be due to the unavailability of external variables in the model, such as rainfall, planted land area, or climatic conditions that also affect production yields. Nevertheless, the general pattern maintained the historical trend, making the predictions relevant for strategic planning. Overall, the forecasting results show that the Stacked GRU model has a good ability to forecast long-term production patterns. The resulting predictions are responsive to seasonal patterns and provide an accurate picture of the potential production one year ahead. This information can be used as a basis for relevant agencies in developing food stock planning, distribution management, and strategies to increase agricultural productivity in Bali Province.

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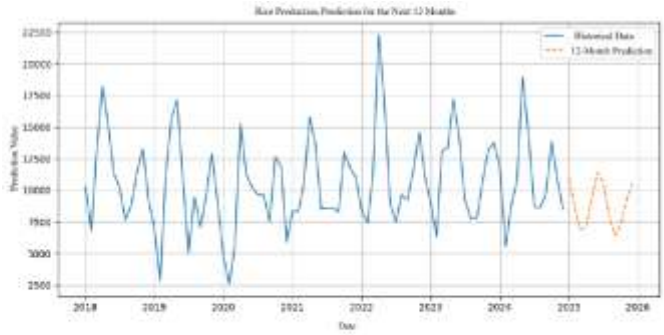

Fig. 4 Rice Forecast Results for the Next 12 Months (2025-2026)

Quarterly Visualization Results by District/City

Based on the quarterly forecasting results shown in Figure 5, each district/city exhibits production patterns that follow a consistent annual seasonal trend, albeit with varying magnitudes. Major rice-producing regions such as Tabanan, Bangli, and Buleleng display pronounced fluctuations between harvest and planting periods, reflecting their larger cultivated land areas and structured cropping cycles. Conversely, districts such as Klungkung and Denpasar show more moderate variations, which can be attributed to limited agricultural land availability.

From a policy perspective, these district-level forecasts provide actionable insights for region-specific planning. Areas with high seasonal volatility may require prioritized fertilizer distribution, irrigation scheduling, and buffer stock allocation during low-production quarters. Meanwhile, regions with more stable production patterns can be leveraged as supply stabilizers to support inter-district distribution strategies. Thus, the district-level forecasting results enhance the practical relevance of the model for localized food security decision-making.

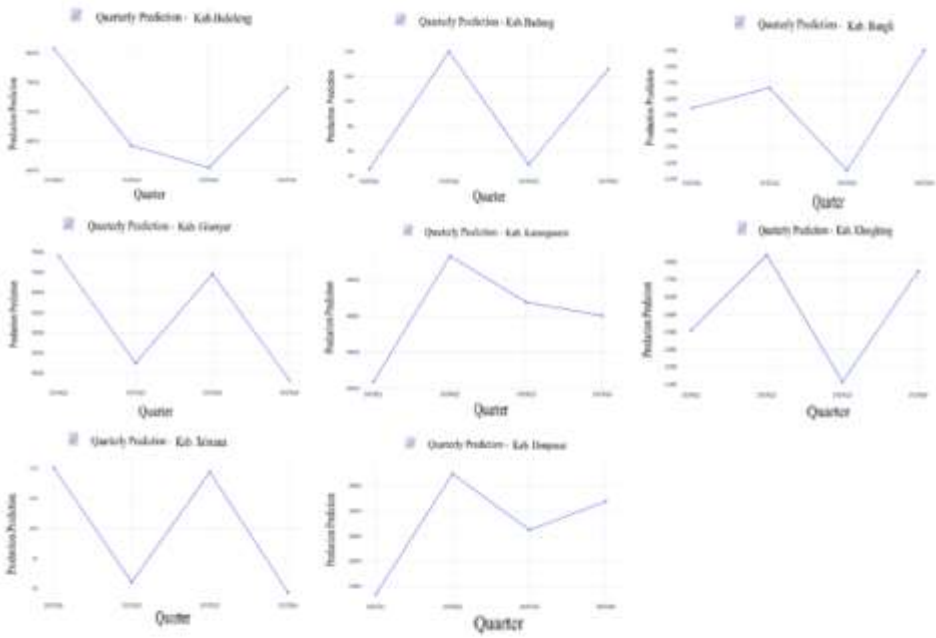

Figure 5. Quarterly Rice Production Forecast for Nine Regencies/Cities in Bali Province (2025)

DISCUSSIONS

The results showed that the Stacked GRU model was able to predict monthly rice production in Bali Province with a MAPE accuracy rate of 14.29%, which is included in the Good Accuracy category. This value indicates that the model is able to follow the seasonal pattern of rice production with a relatively low error. The success of the model in reading this pattern is influenced by two main factors, namely the strong seasonal characteristics of the Bali rice production data and the use of sinusoidal-based seasonal features (sin_month and cos_month) that help the model recognize annual recurring patterns. These seasonal features were shown to improve GRU's ability to understand long-term temporal relationships compared to using only the original production values.

The predicted patterns generated by the model show a good match with the actual patterns, especially in the peak harvest period that usually occurs at the beginning of the year. The model was able to capture the increasing

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and decreasing trends in production according to the cycle of planting and harvesting. However, slight deviations appear in some months with extreme fluctuations. This can be caused by the characteristics of rice production data that are influenced by external factors such as weather changes, land use change, and attacks of plant disrupting organisms that are not covered in this univariate dataset. Nevertheless, the deviation is still within a reasonable error tolerance range for RNN-based time series models.

When compared to previous research, the performance of this model shows significant improvement. Research by produced a MAPE of 83.798% because it used farmer survey data that tends to be unstable and does not describe seasonal patterns well. Research (Meng et al., 2020b) that uses Stacked LSTM does show strong performance, but requires greater computation. The Stacked GRU model in this study offers a better balance point between accuracy and computational efficiency, making it a lighter alternative without sacrificing prediction performance. In addition, the study (Ananda, 2023b) used a single GRU for multivariate rice price prediction; this study extends the approach through a multilevel architecture to extract more in-depth temporal features.

The quarterly prediction results presented in the visualization also provide a more applicable picture for stakeholders. The data shows that each district/city has relatively similar production patterns, but with variations in the amount of output. These predictions can support distribution planning, regional food security strategies, and land and fertilizer allocation policies. With the ability of the model to learn seasonal patterns, the prediction results can be used as a reference to anticipate a decline in production due to seasonal factors such as a longer planting period or unstable rainfall.

This research provides the first empirical demonstration of a stacked GRU architecture for univariate rice production forecasting in Bali Province. By combining a dual-layer GRU design with seasonal feature encoding, the proposed model closes an existing methodological gap between efficient recurrent architectures and deep temporal representation in agricultural forecasting. The findings confirm that stacked GRU is not only computationally efficient but also capable of capturing seasonal production dynamics with good predictive accuracy, thereby establishing its relevance as a practical and methodological contribution to data-driven food security planning.

CONCLUSION

This research successfully developed a rice paddy production forecasting model in Bali Province using Stacked GRU architecture that is able to capture seasonal patterns and temporal dynamics of monthly rice production. Based on the results of testing three configuration schemes, Scheme 3 became the best model with a MAPE value of 14.29%, which indicates a good level of accuracy for seasonal time series data. The model is able to follow the historical pattern of production quite consistently, including an increase in production at the beginning of the year as the main harvest phase and a decrease in production in the middle to end of the year.

The long-term predictions produced by the model show stable seasonal patterns, which can be used as a reference for the government in planning food security strategies and managing rice distribution. In addition, the quarterly forecasting results by district/city provide a more detailed picture of production patterns at the regional level, which can be utilized for region-based decision-making. Some regions such as Tabanan and Gianyar show more consistent patterns, while regions such as Karangasem have higher fluctuations.

Overall, this research proves that Stacked GRU is effectively used in rice production forecasting and can be a modern alternative that is more adaptive than conventional statistical methods. This approach contributes significantly to the modernization of historical data-based agricultural forecasting systems, and opens up opportunities for more comprehensive model development in future research.

1) Limitations

This study has several limitations that need to be considered. First, the model only uses univariate data in the form of monthly rice production without considering external variables such as rainfall, irrigation intensity, harvested land area, type of variety, or pest and disease conditions. These factors have a significant effect on the dynamics of rice production, so their absence may cause the model to be unable to capture extreme fluctuations in certain months. Secondly, the amount of data used is still limited, namely 84 months, so the model only learns from six-year seasonal patterns and does not include long-term variations such as climate change or regional agricultural trends. Third, the long-term forecasting method uses a recursive forecasting approach that has the potential to accumulate prediction errors as the time horizon increases.

2) Future Work

Future research can be developed by adding external variables such as rainfall data, temperature, ENSO index, harvested land area, or NDVI data from satellite images to improve the model's ability to capture factors that affect rice production. In addition, the use of multivariate models such as Multivariate GRU, Bi-GRU, LSTM, or ConvLSTM can be evaluated to determine whether these approaches can provide better performance. Further research can also explore hybrid methods between GRU and statistical models such as ARIMA or SARIMA to

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reduce long-term errors that arise in recursive forecasting. Finally, attention mechanism or Transformer-based modeling for time series can be a promising alternative in improving the accuracy and stability of predictions.

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