

Comparative Analysis of ARIMA and Prophet Methods in Forecasting Producer-Level Medium Rice Prices in East Java Province

Egar Caesario Firmansyah¹, I Kadek Dwi Nuryana²

^{1, 2}*Universitas Negeri Surabaya, Surabaya, Indonesia*

egar.22134@mhs.unesa.ac.id, dwinuryana@unesa.ac.id

ABSTRACT

Price instability of medium rice has important implications for food security and agricultural policy in Indonesia, making accurate price forecasting essential for decision-making. This study investigates the forecasting capability of the Autoregressive Integrated Moving Average (ARIMA) and Prophet models for predicting producer-level medium rice prices in East Java Province. Monthly producer price data spanning January 2020 to December 2025 were collected from the East Java Open Data Portal. The research followed the Cross-Industry Standard Process for Data Mining (CRISP-DM), covering problem identification, data exploration, preprocessing, model development, performance assessment, and forecasting deployment. Forecast accuracy was measured using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental results reveal that ARIMA (1,1,1) achieved the highest predictive accuracy, recording an MAE of 238.37, an RMSE of 293.11, and a MAPE of 1.88%, whereas Prophet produced larger prediction errors, with values of 2,062.14, 2,113.86, and 16.46%, respectively. Based on these results, the ARIMA model was selected to estimate producer-level medium rice prices for the 2026 forecasting period. Overall, the study demonstrates that ARIMA is better suited to the characteristics of the analyzed dataset and has the potential to support data-driven agricultural price monitoring and food price stabilization policies.

Keyword: ARIMA, Prophet, Time Series Forecasting, Medium Rice, Producer Price, East Java.

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Corresponding Author

Egar Caesario Firmansyah

Universitas Negeri Surabaya, Surabaya, Indonesia

egar.22134@mhs.unesa.ac.id

1. INTRODUCTION

Food security is a key factor in supporting economic stability and sustainable development, especially in agrarian countries such as Indonesia. Among various agricultural commodities, medium rice serves as the primary staple food for the population and plays an important role in maintaining food availability, improving farmers' welfare, and supporting government policies related to the agricultural sector. As a result, changes in producer-level medium rice prices have direct implications for both producers and consumers [1], [2]. East Java is recognized as one of Indonesia's major rice-producing provinces and contributes substantially to the national rice supply. Consequently, understanding and forecasting producer-level rice prices are important for improving agricultural planning and assisting policy formulation aimed at maintaining price stability [2].

Historical records of producer-level medium rice prices are accessible through the East Java Open Data Portal, providing a reliable source of information for price analysis and forecasting studies [3]. Nevertheless, historical observations alone cannot provide meaningful insights without appropriate forecasting techniques capable of identifying temporal behavior and estimating future price movements. Reliable forecasts can help policymakers anticipate potential price changes, strengthen market stability, and support evidence-based decisions related to agricultural and food security policies [4].

Forecasting based on time series analysis has been widely adopted to predict agricultural commodity prices because it enables future values to be estimated from historical observations [5]. Among the available forecasting techniques, the Autoregressive Integrated Moving Average (ARIMA) model is one of the most established statistical approaches for modeling linear time series data after stationarity has been achieved [6], [7]. Another widely used method is Prophet, an additive forecasting model that automatically captures long-term trends and seasonal patterns while requiring relatively limited parameter tuning [8]. Previous studies have shown that both ARIMA and Prophet can produce reliable forecasting results, although their predictive performance is highly dependent on the characteristics of the analyzed dataset [9], [10].

Despite numerous comparative studies involving ARIMA and Prophet, limited attention has been given to forecasting producer-level medium rice prices in East Java. To address this gap, this study evaluates and compares the forecasting accuracy of both models using monthly producer price data collected between January 2020 and December 2025 from the East Java Open Data Portal [3]. Model performance is assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to determine the forecasting approach with the highest predictive accuracy [7]. The resulting forecasts are expected to provide useful information for agricultural price monitoring and to support the East Java Agricultural and Food Security Office in developing evidence-based strategies for maintaining producer price stability.

2. METHODS

2.1 Research Framework

This study followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) as a structured guideline throughout the research process [11], [12]. Rather than treating the workflow as independent activities, each stage was performed sequentially, beginning with defining the research objectives, followed by data exploration and preprocessing, model construction and validation, and concluding with the generation of forecasting results for practical use [11].

In the Business Understanding stage, the study established its main objective, namely to compare the forecasting accuracy of the ARIMA and Prophet models for predicting producer-level medium rice prices in East Java. During Data Understanding, the historical dataset was examined to identify its temporal behavior, seasonal patterns, and potential data quality problems. The Data Preparation stage focused on preprocessing the dataset by eliminating invalid records with zero price values and aggregating the remaining observations into monthly average prices.

The Modeling stage involved constructing forecasting models using both ARIMA and Prophet based on the prepared dataset. Their predictive performance was then assessed in the Evaluation stage using multiple forecasting error metrics. Finally, the Deployment stage

generated future price forecasts using the model that demonstrated the best overall performance. The complete sequence of the research framework is presented in Figure 1.

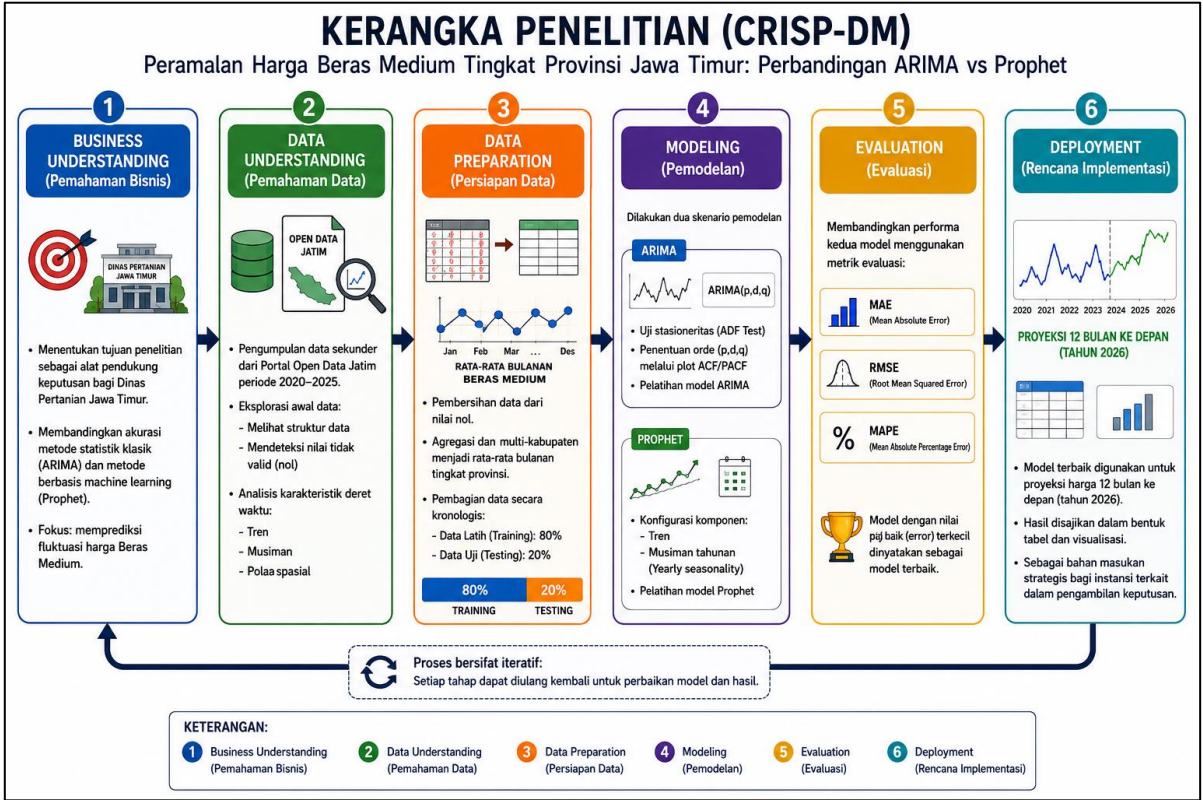


Figure 1. CRISP-DM Framework

2.2 Dataset and Data Preparation

Historical producer-level medium rice price data covering the period from January 2020 to December 2025 were obtained from the East Java Open Data Portal [3]. Preliminary exploration of the available food commodity datasets indicated that medium rice possessed the highest data quality, exhibiting the lowest proportion of invalid (zero-value) observations among all commodities. Therefore, medium rice was selected as the research object. Invalid observations were removed during preprocessing, and the remaining daily records were aggregated into monthly average prices, resulting in a final dataset of 72 monthly observations. The percentage of invalid observations for each commodity is presented in Figure 2.

	Komoditas	Jumlah Data	Rentang	Nilai Nol	Persentase Nol (%)
0	BERAS PREMIUM	2736	2020-01 s/d 2025-12	800	29.24
1	GABAH KERING GILING	2736	2020-01 s/d 2025-12	760	27.78
2	GABAH KERING PANEN	2736	2020-01 s/d 2025-12	878	32.09
3	BERAS MEDIUM	2736	2020-01 s/d 2025-12	667	24.38
4	JAGUNG PIPIL KERING	2736	2020-01 s/d 2025-12	749	27.38
5	KEDELAI	2736	2020-01 s/d 2025-12	2222	81.21

Figure 2. Percentage of Invalid Data

The dataset was subsequently divided into training and testing subsets following the standard practice in time series forecasting [7]. A total of 57 monthly observations (January 2020–September 2024) were used for model training, while the remaining 15 observations (October 2024–December 2025) were reserved for model evaluation.

2.3 Forecasting Models

The forecasting stage involved developing and comparing two prediction models, namely Autoregressive Integrated Moving Average (ARIMA) and Prophet, using the prepared monthly producer price dataset [6], [8]. For the ARIMA approach, the first step was to examine whether the time series satisfied the stationarity assumption through the Augmented Dickey-Fuller (ADF) test. Since the original data were identified as non-stationary, first-order differencing was applied before model estimation could be performed [6], [7].

Following the transformation process, several ARIMA alternatives were examined to identify the most appropriate model. Model selection relied on the Akaike Information Criterion (AIC), with the smallest AIC value indicating the preferred specification. Based on this criterion, ARIMA(1,1,1) was selected for the forecasting process [6].

Unlike ARIMA, Prophet was implemented without requiring manual differencing because the model estimates long-term trend and seasonal effects directly through its additive framework [8]. To maintain consistency during model comparison, identical training and testing datasets were used for both forecasting approaches, allowing differences in predictive performance to be attributed to the models rather than to the data [10].

2.4 Performance Evaluation

The accuracy of each forecasting model was determined by comparing the predicted producer prices with the corresponding observed values in the testing dataset. Forecasting errors were quantified using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are commonly employed to evaluate predictive performance in time series analysis [7], [10]. Because each metric emphasizes a different aspect of prediction error, the three measures were considered together to obtain a balanced evaluation of model performance [4], [7]. The forecasting approach that achieved the lowest overall error values was selected as the final model for generating future producer-level medium rice price forecasts in East Java.

3. RESULTS AND DISCUSSION

3.1. Exploratory Data Analysis

The monthly producer-level medium rice prices in East Java were first explored to identify the characteristics of the dataset prior to model development. After data preprocessing and monthly aggregation, the final dataset consisted of 72 observations covering the period from January 2020 to December 2025. As presented in Table 1, the average producer price was Rp10,364.81/kg with a standard deviation of Rp1,738.69, indicating moderate price variability throughout the observation period. The minimum and maximum prices were Rp8,388.18/kg and Rp13,255.39/kg, respectively, reflecting a gradual increase in producer prices over time.

The temporal pattern of the dataset is illustrated in Figure 3, which shows a general upward trend accompanied by recurring seasonal fluctuations. Producer prices increased noticeably from early 2023 and reached their highest levels during 2024–2025. These characteristics suggest that the dataset contains both trend and seasonal components, making it appropriate for time series forecasting [5], [7].

Table 1. Descriptive Statistics

Statistik	Nilai (Rp/Kg)
Jumlah Observasi	72 bulan
Rata-rata (Mean)	10.364,81
Standar Deviasi	1.738,69
Nilai Minimum	8.388,18
Kuartil 1 (Q1)	8.816,35
Median (Q2)	9.794,17
Kuartil 3 (Q3)	12.283,66
Nilai Maksimum	13.255,39

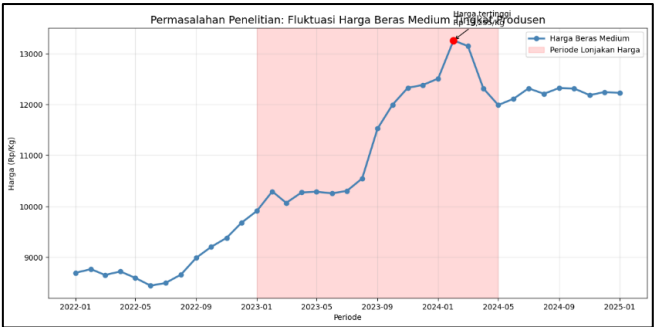


Figure 3. Monthly Price Trend

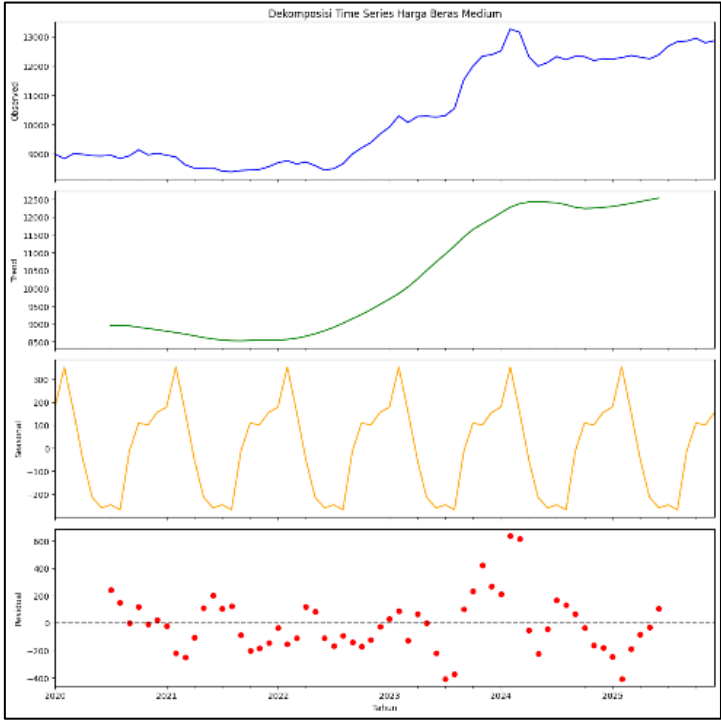


Figure 4. Time Series Decomposition

To further examine the underlying structure of the data, time series decomposition was performed [7]. As shown in Figure 4, the trend component exhibits a sustained increase throughout the observation period, while the seasonal component demonstrates recurring annual fluctuations. The residual component contains relatively random variations after removing trend and seasonality, indicating that most systematic temporal patterns were successfully separated. These findings confirm that the historical producer price series possesses clear temporal characteristics suitable for forecasting using ARIMA and Prophet.

3.2. Forecasting Model Performance

The ARIMA model was developed only after confirming that the price series satisfied the stationarity requirement. Stationarity was examined using the Augmented Dickey-Fuller (ADF) test [6], [7]. As reported in Table 2, the original monthly series did not meet this assumption. Consequently, first-order differencing was performed to eliminate the non-stationary behavior. The resulting series produced a p-value of 0.0060, indicating that the stationarity criterion had been achieved and that the data were appropriate for ARIMA modeling [6], [7].

Table 2. ADF Test Results

Kondisi Data	ADF Statistic	p-value	Kesimpulan
Data Asli (Original)	1,3705	0,9970	Tidak Stasioner (H0 gagal ditolak)
Setelah Differencing Orde 1	-3,5901	0,0060	Stasioner (H0 ditolak)

Multiple ARIMA specifications were examined to determine the most appropriate model for the dataset. Model selection was based on the Akaike Information Criterion (AIC), where a lower AIC indicates a better balance between model fit and complexity [6]. Among the evaluated candidates, ARIMA(1,1,1) produced the smallest AIC value and was therefore selected for forecasting.

The predictive capability of ARIMA and Prophet was subsequently assessed using the same testing dataset to ensure a consistent comparison. The results summarized in Table 3 demonstrate that ARIMA(1,1,1) delivered superior performance for every evaluation metric. Specifically, the ARIMA model achieved an MAE of 238.37, an RMSE of 293.11, and a MAPE of 1.88%. In comparison, Prophet yielded considerably higher errors, with MAE, RMSE, and MAPE values of 2,062.14, 2,113.86, and 16.46%, respectively.

Table 3. Performance Comparison

Model	MAE (Rp/Kg)	RMSE (Rp/Kg)	MAPE (%)	Status Model
ARIMA(1,1,1)	238,37	293,11	1,88%	Terbaik
Prophet	2.062,14	2.113,86	16,46%	Alternatif

The forecasting results obtained from the ARIMA model are presented in Figure 5. The comparison between the forecasted and observed producer prices during the testing period indicates that the model was able to reproduce the overall movement of the historical series with only minor deviations. Although the actual prices showed a modest upward trend toward the end of the testing period, the forecasts remained relatively stable while maintaining a high level of accuracy, as demonstrated by the low MAPE value.

Model adequacy was further assessed through the Ljung-Box test. The test results indicate that the residuals exhibit white-noise characteristics, suggesting that no significant autocorrelation

remained after model fitting. This finding implies that the ARIMA model successfully captured the underlying temporal structure contained in the historical producer price series [6], [7].

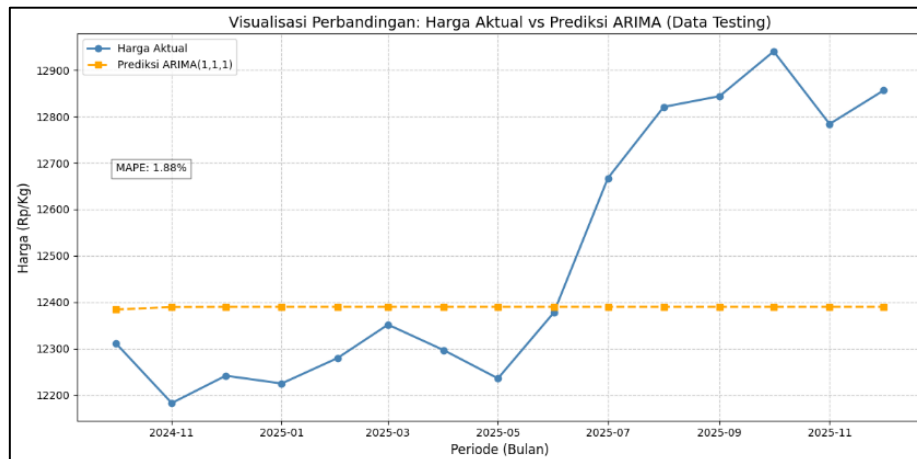


Figure 5. Actual vs Predicted (ARIMA)

3.3. Forecasting Results

Based on its superior forecasting performance, ARIMA(1,1,1) was selected to generate future producer-level medium rice price forecasts. The forecasting results are presented in Figure 6 and Table 4, showing projected monthly prices for the period January–December 2026. The forecasts indicate a slight increase at the beginning of the year, followed by relatively stable producer prices throughout the remaining months. This suggests that no substantial price fluctuations are expected under historical market conditions.

Table 4. Forecast Values for 2026

No	Periode (Bulan)	Prediksi Harga (Rp/Kg)
1	Januari 2026	12.908,98
2	Februari 2026	12.912,43
3	Maret 2026	12.912,66
4	April 2026	12.912,67
5	Mei 2026	12.912,67
6	Juni 2026	12.912,67
7	Juli 2026	12.912,67
8	Agustus 2026	12.912,67
9	September 2026	12.912,67
10	Oktober 2026	12.912,67
11	November 2026	12.912,67
12	Desember 2026	12.912,67

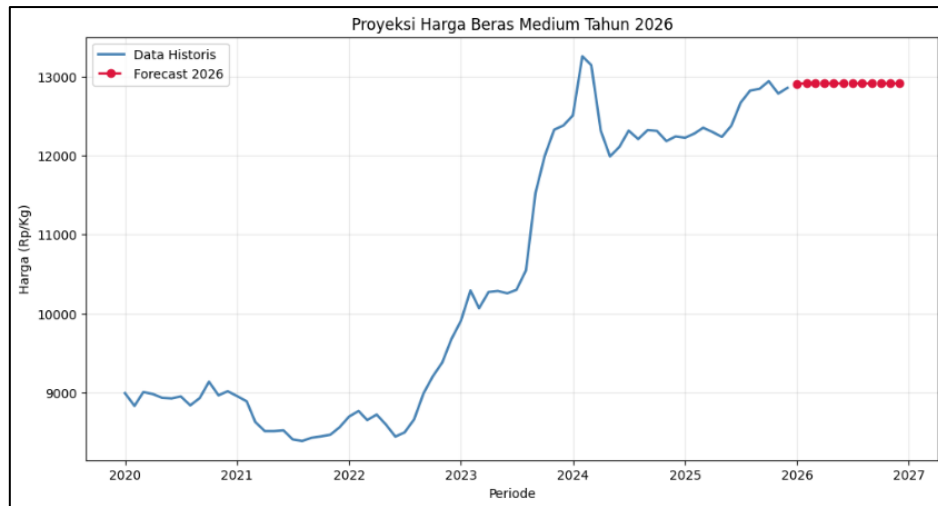


Figure 6. Forecast for 2026

3.4. Discussion

The comparison results indicate that ARIMA provided more accurate forecasts than Prophet for predicting producer-level medium rice prices in East Java. This is evidenced by the consistently lower MAE, RMSE, and MAPE values obtained by ARIMA. The historical price series displays a gradual upward movement together with recurring seasonal fluctuations, making its temporal characteristics well suited to the assumptions underlying the ARIMA model [6], [7].

Although Prophet was able to represent the overall trend and seasonal pattern of the dataset, its prediction errors remained substantially higher than those of ARIMA. These results suggest that the greater flexibility of Prophet's additive modeling framework did not provide additional benefits for the relatively stable price behavior observed in this study. Instead, the statistical characteristics of the dataset were more effectively represented by the ARIMA approach [8].

The outcomes of this research are in agreement with previous studies. Menculini et al. found that ARIMA generated more accurate forecasts than Prophet for wholesale food price prediction [9]. Likewise, Chen et al. emphasized that forecasting performance is strongly influenced by the characteristics of the dataset being analyzed rather than by the forecasting algorithm alone [13]. The present findings further support the view that model selection should be guided by the underlying properties of the data instead of assuming that one forecasting method consistently outperforms others across different applications.

From an application standpoint, the results indicate that ARIMA can be utilized as a practical decision-support tool for monitoring producer-level rice prices in East Java. Reliable price forecasts enable the East Java Agricultural and Food Security Office to anticipate future market movements, prepare appropriate intervention strategies, and support data-driven policies aimed at preserving food price stability.

CONCLUSION

This study compared the forecasting performance of the Autoregressive Integrated Moving Average (ARIMA) and Prophet models for predicting producer-level medium rice prices in East Java Province using monthly data from January 2020 to December 2025. The

results showed that the ARIMA(1,1,1) model consistently outperformed the Prophet model across all evaluation metrics, achieving an MAE of 238.37, an RMSE of 293.11, and a MAPE of 1.88%, compared with the Prophet model, which produced an MAE of 2,062.14, an RMSE of 2,113.86, and a MAPE of 16.46%. These findings indicate that ARIMA provides higher forecasting accuracy and is more suitable for modeling producer-level medium rice prices in East Java.

The superior performance of ARIMA suggests that it is a reliable forecasting model for supporting agricultural price monitoring and evidence-based policy formulation. Accurate price forecasts can assist government agencies in anticipating price fluctuations, maintaining market stability, and developing timely strategies to support food security and agricultural commodity management.

Future research is recommended to investigate hybrid forecasting approaches by combining statistical and machine learning methods, as well as incorporating external variables such as weather conditions, inflation, production levels, and other socioeconomic factors. These improvements may enhance forecasting accuracy and provide more comprehensive decision-support tools for agricultural commodity price forecasting.

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