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Utilizin Sarima for Seasonal Forecasting of Coffee Production in Aceh Province, Indonesia

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Abstract
In this paper, we forecast coffee production in Aceh Province, Indonesia, using the Seasonal Autoregressive Integrated Moving Average (SARIMA) method. Coffee is a critical commodity for the region's economy, contributing significantly to both local income and export revenues. Accurate forecasting of coffee production is essential for economic planning, supply chain management, and strategic development in the coffee sector. Using secondary data from the Indonesian Central Bureau of Statistics, we identified the SARIMA (2,0,1)(1,1,1)12 model as the best fit, with a Mean Absolute Percentage Error (MAPE) of 12.94%. The forecasting results for the period of 2023 to 2024 reveal a consistent seasonal pattern in line with historical data, though a slight decline in production is projected. Notably, the lowest production of 22 tons occurred in February 2019, while the highest, 21,408 tons, was recorded in July 2019. These findings provide valuable insights for policymakers and stakeholders in the coffee industry, offering a robust basis for developing targeted interventions to enhance production and manage fluctuations. The results underscore the importance of reliable forecasting models like SARIMA in supporting sustainable growth and decision-making in regional agricultural sectors.
Keywords: Coffee, Data Mining, Forecasting, SARIMA, MAPE.

Introduction
The Directorate General of Plantations has made coffee a leading commodity of Indonesian plantations that has great potential and role to support economic growth. Aceh Province is known as the best arabica coffee and robusta coffee producing area in the world, such as gayo coffee which is an arabica coffee variety which is one of the leading commodities originating from the Gayo Plateau, Central Aceh, Indonesia. Coffee is one of the main commodities in Aceh's economy. Forecasting coffee production can assist in regional economic planning, predicting revenue generated from coffee exports, as well as identifying potential economic development in the coffee sector. Therefore, forecasting coffee production is required, which can serve as the basis for policy development and development programs in the coffee sector. Local governments and related organizations can use forecasting information to design supporting programs, such as farmer training, infrastructure development, and market promotion[1].

Sourced from (BPS (Badan Pusat Statistika), 2023), data showing the state of coffee production in Indonesia in 2023/2024 is still very minimal and only estimated figures. Then, for the availability of data per province, according to (Statistics Indonesia, 2022) only recorded the development of coffee production in Aceh from 2016 to 2022 in monthly form [2]. One way to obtain data on the amount of coffee production in 2023-2024 in Aceh Province is to use forecasting techniques. Forecasting Aceh coffee production can be done using the Seasonal Autoregressive Integrated Moving Average (SARIMA) time series method. SARIMA has similarities with the ARIMA Box Jenkins method, except that there is the addition of the term Seasonal in front of the word ARIMA. This is interpreted as an explanation of the seasonal pattern in the data. Data identification certainly needs to be done at the beginning of the sarima analysis to find out whether the data contains trends or seasonality. ARIMA and SARIMA both have the same requirements regarding data distribution [3].

This research was conducted to predict the coffee production of Aceh province using the SARIMA forecasting method.

In addition to knowing the ability of the SARIMA method to predict coffee production in Aceh province, the forecasting results will be tested using the Mean Absolute Percentage Error (MAPE) method formula in order to determine the percentage error of the use of the Seasonal Autoregressive Integrated Moving Average (SARIMA) method in this study.

Related Works

1. Coffee

Coffee is one of the plantation commodities in Indonesia, this can be seen from the number of coffee plants cultivated in each province in Indonesia. In general, there are several types of coffee commodities in Indonesia. Of the many types of coffee that are most in demand, there are only two main types of variations, namely arabica coffee (Coffea Arabica) and robusta coffee (Coffea Robusta). Of the two types of coffee, the most popular type of coffee in Indonesia is arabica coffee, because the coffee has a more diverse variety of flavors, sweet, soft, strong and sharp flavors while robusta coffee has a neutral variety of flavors, a taste similar to wheat and before roasting the aroma of nuts is more pronounced [4].

There are two types of coffee grown in the Aceh area, namely Robusta and Arabica types. The famous Robusta coffee is produced from the Ulee Kareng District area, in Banda Aceh itself Ulee Kareng coffee is very popular. Almost all coffee shops in the city serve this type of coffee, while the Arabica type is produced from the Gayo highlands. In this region, the average farmer grows Arabica coffee. This type of coffee has a distinctive taste with the main characteristics including complex aromas and flavors and strong viscosity. Coffee plants in this area have long been planted, which according to records, coffee plantations in Tanah Gayo, have been developed since 1908. Coffee plants are very suitable and thrive in areas that are at an altitude of 1200 above sea level, so Gayo coffee is a coffee that has its own distinctive taste [5].

One of the coffee species, arabica (Coffee arabica), was first described by Linnaeus in 1753. Arabica coffee entered Indonesia in 1696 which was brought by the Dutch East India Co. trading company from Ceylo. Arabica coffee is the most widely developed coffee in the world and in Indonesia in particular. This coffee is grown in the highlands which have a dry climate around 1350-1850 meters above sea level. While in Indonesia itself this coffee can thrive in high areas up to an altitude of 1200 meters above sea level. This type of coffee tends not to withstand the attack of leaf rust disease (Hemileia vastatrix), but this coffee has a strong level of aroma and taste. Arabica coffee naturally has a variety of flavors, depending on the growing location, including flavors of fruit, spice, and others. This type of coffee bean has been made as the majority product. Naturally, the flavor of arabica coffee provides a mild coffee taste that does not cause disturbances to sleep, while arabica coffee does have low caffeine levels in the range of 1.2%, in addition, arabica coffee has a distinctive aroma [6].

Robusta coffee or Coffea canephora, was originally only known as a shrub or wild plant that can grow up to several meters in height. Until finally robusta coffee was first discovered in Congo in 1898 by Emil Laurent. But apart from that, there are those who claim that this type of robusta coffee was discovered earlier by two British travelers named Richard and John Speake in 1862. Robusta coffee is known to have a slightly sour taste, more bitter, and higher caffeine content than Arabica coffee, which can cause sleep disturbances. In addition, robusta coffee has a wider range of growing areas than arabica coffee, which must be grown at a certain altitude. It can be grown in the lowlands up to 1,000 meters above sea level. This type of coffee is more resistant to pests and diseases. This makes robusta coffee cheaper[7].

Coffee production in Indonesia from 2020 to 2022 has fluctuated. In 2020 coffee production amounted to 762.38 thousand tons, increasing to 786.19 thousand tons in 2021 or an increase of 3.12 percent. In 2022 coffee production fell to 774.96 thousand tons or decreased by 1.43 percent. When viewed by province, the largest coffee production produced by Large Companies (PB) in 2022 came from East Java Province with a production of 3.39 thousand tons or 85.15 percent of the total production from PB in Indonesia. The largest production of People's Plantation Coffee (PR) by province in 2022 came from South Sumatra province which reached 208.04 thousand tons or around 26.98 percent of the total national PR production. Aceh Province is the province with the fifth coffee production by province in Indonesia, which is 9.08 percent in 2022. According to the Indonesia Statistics 2022 report from the Central Statistics Agency (BPS), Aceh Province's coffee production has increased where in 2020 it reached 73.4 thousand tons and in 2021 it reached 74.2 thousand tons.

2. Forecasting

Forecasting is a calculating process used for the projection of future products or services, based on the analysis of historical data within a certain time span. In the business world, forecasting plays a central role as the main basis for decision making. The implementation of forecasting can extend to all aspects of the business process, with the aim of planning demand requirements for future periods. This becomes crucial due to rapid changes in environmental conditions and consumer preferences. Basically, forecasting is an attempt to project certain variables, such as the demand for a product or set of products in a future period. Although its essence is projection or prediction, the use of certain techniques can improve the quality of forecasting beyond mere estimation. Accurate forecasting results allow a product to plan its strategy and make informed business decisions. Some of the most commonly used forecasting models include timeseries models, such as moving averages, smoothing methods, linear regression, and ARIMA [8].

3. SARIMA

A model commonly used to predict variables according to the behavior of observed variable data without including independent variables in the model is the Autoregressive Integrated Moving Average (ARIMA) model discovered and studied by Box-Jenkin. The Box-Jenkin forecasting technique is slightly different from most forecasting methods, because modeling does not require certain assumptions about the historical time series data, but rather an iterative method is used to determine the best model. The best models that have been selected will be rechecked whether they can describe/reflect the data appropriately. In addition, the selection of the best model in Box-Jenkin can be determined through the residual value between the forecasting data and the past data is small. If the selected model has not been able to describe the data correctly, it is necessary to determine that the model needs to be repeated. The Box-Jenkin model can be classified into several models, namely: Autoregressive (AR), Moving Average (MA), Autoregressive-Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) [9].

As explained about ARIMA, SARIMA has similarities with the Box Jenkins ARIMA method, except that there is the addition of the term Seasonal in front of the word ARIMA. This is interpreted as an explanation of the seasonal pattern in the data. Data identification certainly needs to be done at the beginning of the sarima analysis to find out whether the data contains trends or seasonality. ARIMA and SARIMA both have the same requirements regarding data distribution. Stationary can be interpreted as data fluctuations within a certain value or can be said to show no upward or downward trend. If in practice the data experiences a certain trend then it is necessary to make a difference or difference [10].

Seasonal Autoregressive Integrated Moving Average generally contains a model that is suitable in seasonal situations, this model is also a development of the previous ARIMA model. This Seasonal ARIMA model is denoted by (p,d,q)(P,D,Q)s. With p, d, q are non-seasonal ARIMA parameters that regulate the non-seasonal component of the time series data. P, D, Q are seasonal ARIMA parameters that govern the seasonal component of the time series data. And s is the seasonal period [11].

Table 1. SARIMA model components and parameters

Components	Parameters	Description
Autoregressive (AR)	p	The amount of use of previous data values to perform forecasting
Integration (I)	d	The number of differencing processes performed so that the data becomes stationary
Moving Average (MA)	q	The number of error terms used for forecasting
Seasonal Autoregressive (SAR)	P	The amount of use of previous data values to perform forecasting in seasonal periods
Seasonal Integration	D	The number of data differencing processes in the seasonal period
Seasonal Moving Average (SMA)	Q	The number of error terms used to forecast the seasonal period
Seasonality	s	the length of the seasonal period

Table 1 describes each parameter used in the SARIMA model. These parameters formed in a SARIMA(p, d, q)(P, D, Q)s model.

Materials & Methods

1. Data Collection

The dataset or historical data used is taken from one of Indonesia's statistical data provider sites, bps.go.id. The data obtained is sourced from the publication of Indonesian Coffee Statistics covering the last 6 years, namely from Indonesian Coffee Statistics 2017 to Indonesian Coffee Statistics 2022. The dataset or historical data used is Aceh Province coffee production data starting from the period January 2016 to December 2022. In the data analysis stage, the coffee production results of Aceh Province obtained in Indonesian Coffee Statistics from the period January 2016 to December 2022. Then the following presentation of Aceh Province coffee production data is as follows.

Table 2. Coffee Production Data of Aceh Province

Month	2016	2017	2018	2019	2020	2021	2022
January	95	62	65	29	671	680	643
February	47	275	284	22	582	589	558
March	71	99	102	43	722	731	692
April	4127	1603	1657	166	478	484	458
May	3605	6470	6685	1367	604	612	579
June	6737	13422	13869	6229	4809	4868	4608
July	10722	15999	16530	21408	16040	16239	15370
August	13236	13130	13567	19794	18459	18687	17688
September	10769	7503	7753	12871	21129	21391	20246
October	10176	5856	6051	8161	7820	7917	7493
November	4436	3496	3613	1613	1241	1256	1189
December	1210	579	598	948	864	875	828

The table above shows data on coffee production in Aceh Province in the form of monthly in the period of seven years 2016-2022. In analyzing time series data, of course, an identification stage is needed so that the characteristics of the data can be known. A simple thing that can be done is to make a visual of the time series data of the amount of coffee production in Aceh Province using a line chart starting from the period January 2016 to December 2022.

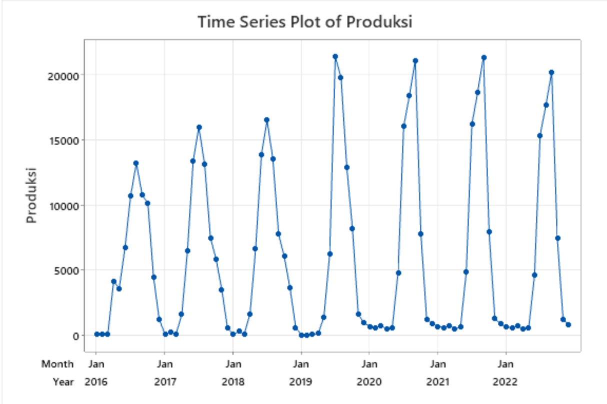

Figure 3. Plot of Coffee Production Data of Aceh Province

The following plot shows that coffee production in Aceh Province from 2016-2022 follows a seasonal pattern. The highest peak of coffee production per year is always from June to October.

2. Methods

The first step in this research is data collection. Information on Aceh Province's coffee production data was obtained through the Indonesian Coffee Statistics publication published by the Indonesian Central Bureau of Statistics website. This dataset covers the coffee production of Aceh Province during a certain period. This historical data is the basis for the analysis and predictions that will be carried out in this study. The scheme for the Aceh Province coffee production forecasting system using the SARIMA method is as shown below.

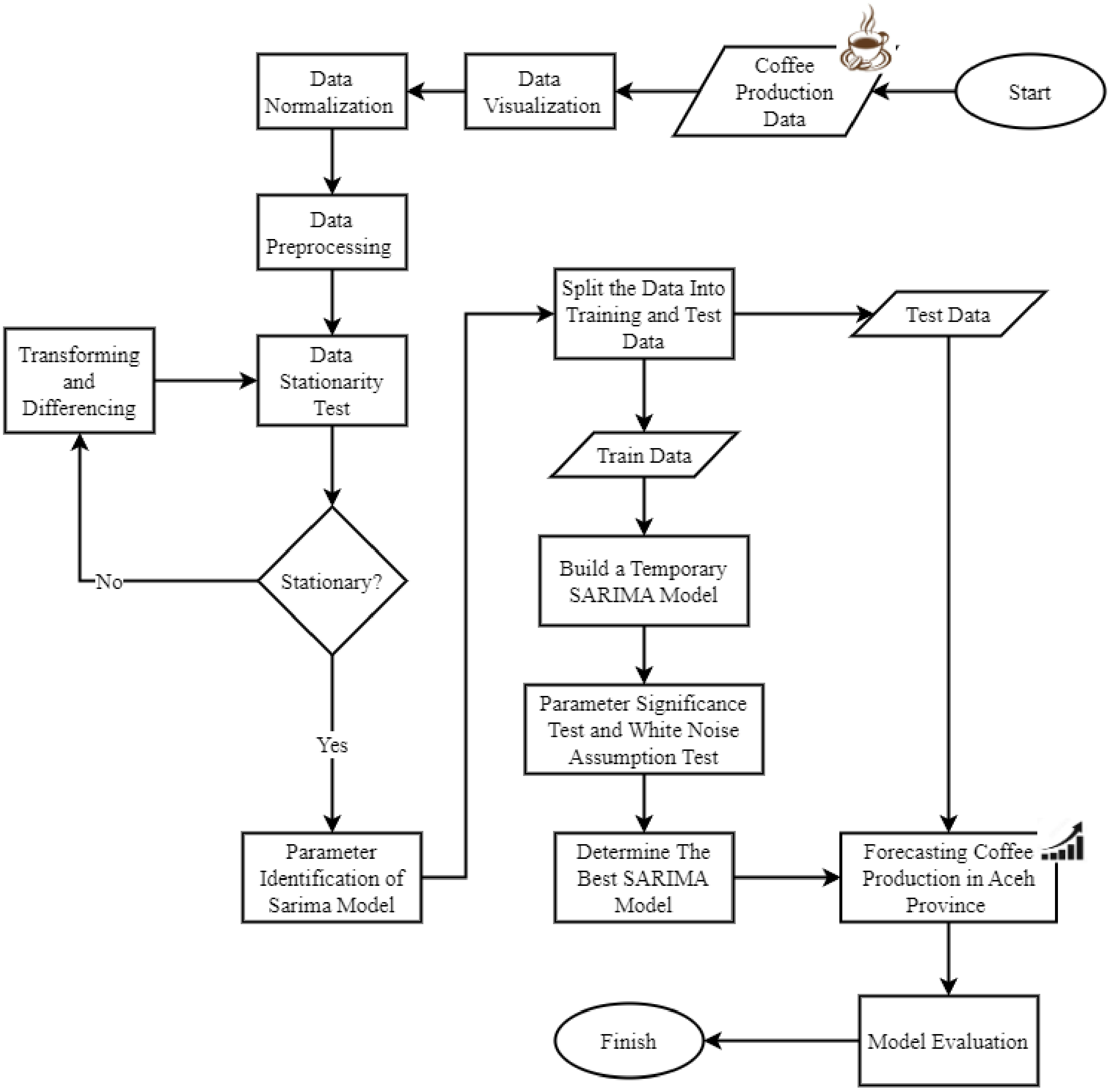

Figure 1. Design System

The data is then subjected to several steps such as cleaning, transforming, and normalizing the data to make it suitable for use in the process of making predictions by the model. These steps aim to improve data quality, overcome problems that may arise, and prepare the data so that it can be interpreted properly by the predictive model. At the SARIMA model building stage, stages such as determining autoregressive parameters (p), differencing (d), moving average (q), seasonal autoregressive (P), seasonal differencing (D), seasonal moving average (Q), and seasonal period (s) are carried out. The SARIMA model equation is as follows.

$$\Phi(B^\wedge s)\Phi p(B)(1-B)^\wedge d(1-B^\wedge s)^\wedge DZt = \Theta q(B)\Theta Q(B^\wedge s)at \qquad (1)$$

Where Φ(B^s) is Autoregressive (AR), Φp (B) is Seasonal Autoregressive (SAR), (1 - B)d is differencing, (1 – B^s) D is Seasonal differencing, Θq (B) is Moving Average (MA), and ΘQ (B^s) is Seasonal Moving Average (SMA).

After training, the SARIMA model is evaluated using test data. The evaluation is done by calculating the Mean Absolute Percentage Error (MAPE) metric. This metric helps assess the extent to which the model can accurately predict crypto prices. The output is in the form of coffee production prediction results of Aceh Province predicted by the SARIMA method used in this study, which then these results are denormalized to obtain forecasting results according to the original scale.

3. Evaluation

Mean Absolute Percentage Error (MAPE) is the average absolute difference between the forecasting and actual values, expressed as a percentage of the actual value. MAPE is calculated as the average of the absolute value of the percentage difference between the actual and predicted values divided by the actual value, which is then multiplied by 100 to get the percentage [12].

$$MAPE = \frac{\sum_{t=1}^{n} \left|\left(\frac{A_t - F_t}{A_t}\right)100\right|}{n} \qquad (2)$$

Where At is Actual demand to t, Ft is the result of forecasting to t, and n is the amount of forecasting data.

Results and Discussion

The identification of the SARIMA forecasting model aims to determine future data estimates based on historical data in the past. In addition, the identification of the SARIMA model is also based on the form of seasonal or trend patterns contained in the data. When creating a SARIMA model, the first step is to perform data transformation or data normalization, cross validation, data stationarity test, SARIMA model identification, model parameter estimation, diagnostic checks, SARIMA model forecasting, and model validation.

In this research, data normalization or transformation aims to reduce redundancy, improve data integrity, and facilitate analysis. This process usually involves grouping data into smaller tables and connecting those tables with appropriate relationships. Perform data scaling or data normalization to change the data scale to a range between 0 and 1, with the min max scaling method. Furthermore, in this study, the dataset that has been transformed is divided into two parts, namely training data (train) and test data (test) using cross validation techniques. Cross Validation is a technique that utilizes limited data.

The most widely used data stationarity test at this time is the unit root test with the Augmented Dickey Fuller Test (ADF test) on the grounds that the ADF Test has considered the possibility of autocorrelation in the error term if the series used is nonstationary.

Augmented Dickey-Fuller Test

Null hypothesis: Data are non-stationary
Alternative hypothesis: Data are stationary

Test Statistic	P-Value	Recommendation
-3.14601	0.023	Test statistic <= critical value of -2.90261. Significance level = 0.05 Reject null hypothesis. Data appears to be stationary, not supporting differencing.

Figure 4. Augmented Dickey Fuller Test (ADF Test)

Based on the figure above, it can be seen that in the Augmented Dickey-Fuller (ADF) test, the statistical value generated from the calculation is -3.14601 and the resulting P-Value is 0.023, which means that the data that has been tested can be considered stationary because the P-Value (0.023) is smaller than the commonly used significance level (usually 0.05), this indicates that the data is stationary on average and variance and is not required to be repeated differencing.

Before determining the best SARIMA model and its forecasting value, it is necessary to identify the stationarity pattern in the data. This identification is done using ACF and PACF plots. The ACF plot shows the correlation between an observation and the previous observation at various lags. If there is a seasonal pattern, the ACF plot will show a peak at the lag corresponding to the seasonal period. Whereas the PACF plot shows the direct correlation between an observation and the previous observation at a particular lag, after the effect of the previous lag has been removed. The PACF plot is useful for identifying the autoregressive order (p) in the model. Identifying the stationarity of the ACF and PACF plots helps us determine whether the data is stationary or not. Stationary data has a constant mean, variance, and covariance over time. Determining the model order based on the shape of the ACF and PACF plots, we can determine the parameters p, d, q for the non-seasonal component and P, D, Q, s for the seasonal component in the SARIMA model.

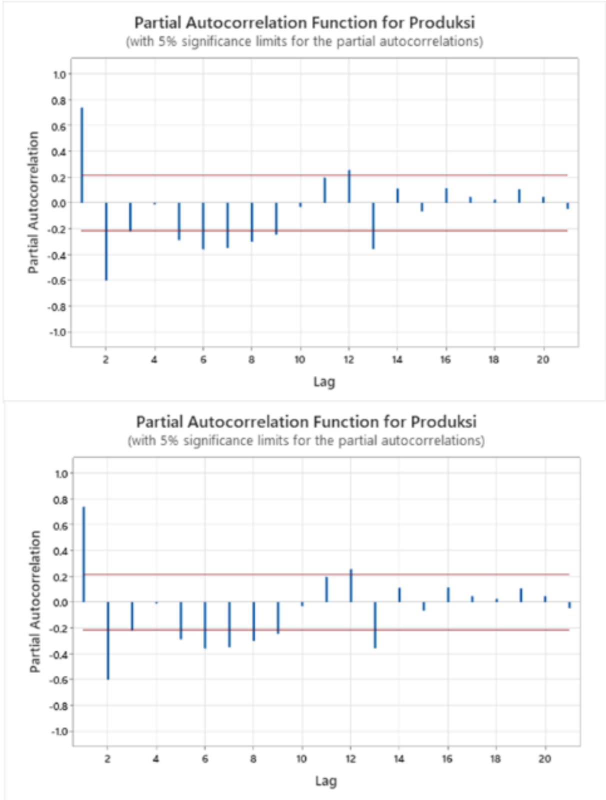

Figure 5. ACF and PACF Plots

Based on the table and figure above, it can be seen that in the ACF plot, a high and significant autocorrelation value at lag 1 indicates that production data in a period is strongly influenced by production data in the previous period. This indicates a trend or seasonal pattern in the production data. It can also be seen in the ACF plot that the repeated up and down pattern in the autocorrelation value indicates a strong seasonal component in the production data. The autocorrelation value generally decreases as the lag increases, but the decrease is quite slow. This indicates that the influence of previous production values on current production is quite long.

While on the PACF plot it can be seen that there are significant spikes at certain lags, there are some spikes (very high or low PACF values) that cross the significance limit at certain lags. This indicates that there is a significant direct correlation between the production value at that lag and the current production value, after the effect of the previous lag is removed. Rapid decay After a significant spike at a certain lag, the PACF values tend to decline rapidly and fall within the significance limit. This indicates that the direct influence of more distant lags is getting smaller. Based on the ACF and PACF plots of the data, the SARIMA (2,1,1)(1,1,1)^{12} model and the SARIMA (2,0,1)(1,1,1)^{12} model are suitable SARIMA models to be estimated.

In determining the initial model, in addition to looking at significant lags, it is also necessary to consider the principle of parsimony to use as few parameters as possible so that the model is more stable. There are results from the identification of the temporary conjecture model for the SARIMA model based on the results of the previous parameter estimation, namely the SARIMA (2,1,1)(1,1,1)^{12} model and the SARIMA (2,0,1)(1,1,1)^{12} model. The following results are presented:

Table 3. Model Parameter Estimation

No	Model	Parameter	Coef	SE Coef	T-Value	P-Value
1	SARIMA (2,1,1)(1,1,1)^{12}	AR 1	0.521	0.119	4.37	0.000
		AR 2	-0.406	0.117	-3.48	0.001
		SAR 12	0.561	0.502	1.12	0.268
		MA 1	0.9668	0.0622	15.53	0.000
		SMA 12	0.776	0.48	1.62	0.111
		Constant	-3.38	4.80	-0.7	0.484
2	SARIMA (2,0,1)(1,1,1)^{12}	AR 1	1.188	0.104	11.45	0.000
		AR 2	-0.569	0.103	-5.54	0.000
		SAR 12	-0.4	90.0	0.000	0.997
		MA 1	1.0166	0.035	29.02	0.000
		SMA 12	-0.4	90.0	0.000	0.997
		Constant	44.15	2.70	16.34	0.000

In the table above is a comparison of parameter estimates for each SARIMA model. Based on the SARIMA (2,1,1)(1,1,1)^{12} model, this model has 2 AR components (AR 1 and AR 2), 1 MA component (MA1), and 1 SAR and SMA component each with a seasonal period of 12. There is 1 differencing (D=1) which indicates that the data needs to be differenced once to become stationary. While the SARIMA $(2,0,1)(1,1,1)^{12}$ model has 2 AR components (AR1 and AR2), 1 MA component (MA1), and 1 SAR and SMA component each with a seasonal period of 12. There is no differencing (d=0) which indicates that the data is stationary or enough with one seasonal differencing.

After the best model parameter estimation results are obtained, it is necessary to perform calculations using the forecasting results. Forecasting can be done using the system and the resulting forecasting results for Aceh Province coffee production in the period 2023-2024 can be obtained based on the resulting time series model, namely the SARIMA $(2,1,1)(1,1,1)^{12}$ model.

Table 4. Future Forcasting Of Coffee Production

Period	Future Forcasting
1	660.7
2	502.3
3	511.4
4	522.5
5	890.0
6	5078.5
7	15354.3
8	17300.8
9	18951.5
10	7399.3
11	1252.2
12	635.8
13	408.4
14	263.5
15	266.7
16	423.2
17	903.7
18	5161.9
19	15161.5
20	16902.4
21	18043.3
22	7160.2
23	1095.5
24	331.3

The following table illustrates that forecasting for the next 24 periods will experience the same seasonal pattern as the amount of coffee production from 2016 to 2022. Then, a combined plot between the actual data, predictions, and also forecasting in the period January 2023 - December 2024.

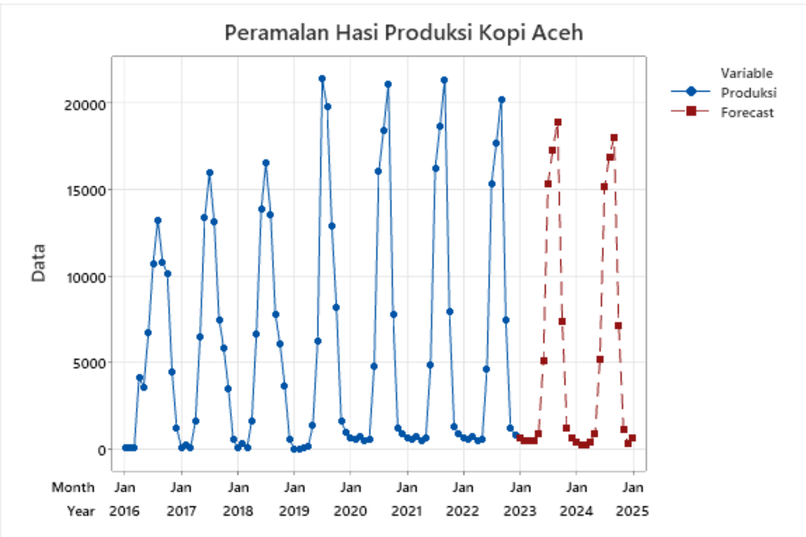

Figure 6. Future Forcasting Of Coffee Production Plots

In the following figure, it can be seen that the actual data is depicted in blue, and forecasting for the next 24 periods is depicted in red. The forecasting data follows the pattern in the actual data of the amount of coffee production in Aceh in 2016-2022.

After obtaining predictions from the SARIMA model, the next step is to continue calculating the recurrence matrix, to calculate how accurate the model has been calculated with an evaluation matrix in the form of MAPE. Mean Absolute Percentage Error or MAPE, or often abbreviated as MAPE, is a statistical indicator that shows how accurate forecasting estimates are in forecasting techniques.

Table 5. MAPE Value Range

Range MAPE	Description
<10%	Excellent forecasting model capability
10-20%	Good forecasting model capability
20-50%	Fair forecasting model capability
>50%	Poor forecasting model capability
<10%	Excellent forecasting model capability

For the results of the accuracy of forecasting the coffee production results of Aceh Province as measured by MAPE obtained a result of 12.94%, this shows that the SARIMA model has good modeling capabilities.

Conclusions

This study successfully applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast coffee production in Aceh Province, Indonesia, using historical data obtained from the Indonesian Central Bureau of Statistics. The SARIMA $(2,0,1)(1,1,1)^{12}$ model was identified as the best fit for the time series data, providing accurate predictions with a Mean Absolute Percentage Error (MAPE) of 12.94%. This level of accuracy falls within the "Good Forecasting Ability" category, demonstrating the effectiveness of the model for predicting coffee production patterns. The results highlight the potential of SARIMA models in accurately capturing the seasonal dynamics of agricultural production.

The forecast for the period from 2023 to 2024 reveals a consistent seasonal pattern with previous years, indicating that Aceh's coffee production follows a predictable trend. However, the projections also suggest a slight decline in overall production, which raises concerns about future yield sustainability. This finding is critical for policymakers, as it emphasizes the need for targeted interventions to counter potential production challenges. Such measures could involve improving agricultural practices, addressing climate-related factors, or providing additional support to local farmers.

This research demonstrates that the SARIMA model is a valuable tool for agricultural forecasting, particularly in regions where seasonal production cycles play a significant role. The insights provided by this study are vital for regional planning, export revenue forecasting, and the development of the coffee sector in Aceh Province. Future research could explore additional factors affecting coffee production, such as climate change or market volatility, to further refine forecasting models and ensure the long-term growth of Aceh's coffee industry.

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