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A SARIMA APPROACH WITH PARAMETER OPTIMIZATION FOR ENHANCING FORECAST ACCURACY FOR NATIVE CHICKEN EGG PRODUCTION

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ABSTRACT

This study aims to accurately forecast monthly native chicken egg production using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model with parameter optimization. The optimization process was conducted through a combination of auto.arima() initialization and an exhaustive grid search across the parameter space, evaluated using multiple performance metrics. The dataset comprised monthly production data from Magelang City, Indonesia, spanning the period from 2016 to 2022. The best-performing model, SARIMA (2,1,2)(1,0,1,12), achieved an R^2 of 0.89, MAE of 82.13, RMSE of 92.92, MAPE of 7.21%, and MASE of 0.67 on the testing set, indicating satisfactory forecasting performance. Compared with the non-optimized SARIMA baseline, the optimized model showed improved predictive accuracy. However, the residuals did not follow a normal distribution, suggesting potential limitations in model assumptions. Moreover, the study is limited by its focus on a single geographic location and native chicken production data, which may restrict its generalizability. Despite these limitations, the findings demonstrate that parameter optimization in SARIMA enhances forecast accuracy and can support better planning for food security initiatives.

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1. INTRODUCTION

Chicken egg production is pivotal in the poultry industry, contributing to global food security and economic development, and aligning with Sustainable Development Goal (SDG) 2. The production process demonstrates clear seasonal patterns and long-term trends, which necessitate the development of robust forecasting models to accommodate these variations. Effective forecasting of chicken egg production enables the poultry industry, particularly farmers, to make informed decisions regarding feed management, cage conditions, and production planning. Given the cyclical nature of egg production, precise forecasting techniques are crucial for maintaining efficiency and sustainability. However, few studies have systematically optimized SARIMA parameters for medium-term agricultural forecasting, creating a gap that this study aims to address.

Various time series forecasting models have been proposed in recent years to improve the accuracy of predictions by minimizing forecast errors. In the field of Machine Learning, models such as XGBoost [1], Non-linear/Logistic Regression [2]-[4], Neural Networks (NN) [5], [6], Random Forest (RF) [1], and Least Squares Support Vector Machines (LSSVM) [7] have been utilized with varying degrees of success. These methods demonstrate strengths in handling complex nonlinearities and large datasets. Additionally, Long Short-Term Memory (LSTM), Deep Learning, and Recurrent Neural Networks (RNN) [8], [9] are widely employed within the scope of Deep Learning models. Mathematical modeling approaches have also been explored [10], [11], though most studies focus on short-term (weekly) forecasting or small-scale data. However, traditional statistical models such as the SARIMA remain widely adopted due to their interpretability, robustness in handling seasonal time series, and ability to provide actionable insights in agricultural decision-making.

Recent studies, such as those by Noor *et al*. [12], Reyes-Radilla *et al*. [13], and Saputra [14], have applied the SARIMA model to forecast seasonal time series data. The SARIMA method is designed to handle seasonality in time series data effectively, and it has been shown to require relatively less data to produce accurate results. Noor *et al*. [12] demonstrated that SARIMA outperformed models like Linear Regression, XGBoost, and RF in the context of forecasting across diverse applications. This general strength makes it a suitable selection for forecasting native chicken egg production, where seasonality is a prominent feature of the data. However, while SARIMA shows promise, it faces limitations in optimizing results and selecting the best parameter values, which may affect forecasting accuracy [15]. This study addresses this limitation by incorporating a systematic parameter optimization process using a combination of grid search and the auto.arima function. Differs from prior SARIMA works, which often rely solely on auto.arima() or manual trial-and-error. Our method explicitly defines a broader search space, applies multi-metric evaluation, and targets medium-term forecasting of native chicken egg production. We selected the SARIMA model because of its proven performance in modeling seasonal agricultural outputs, particularly when datasets are moderate in size, such as those related to native chicken egg production.

The novelty of this work is twofold. First, it introduces a structured parameter optimization process to enhance the accuracy of the SARIMA model. Second, it applies this enhanced modeling framework to the forecasting of native chicken egg production in Magelang City, Indonesia, an area where reliable production forecasts can directly support local agricultural policy and farmer decision-making.

Forecasting is generally divided into short-term, medium-term, and long-term categories, with medium-term forecasting covering six months to two years [16]. This study falls under medium-term forecasting and aims to forecast monthly chicken egg production using the SARIMA model with parameter tuning to enhance accuracy. This approach also builds on prior work by Yulianti *et al*. [17], who examined medium-term forecasting of chicken egg production. While their study relied on a shorter data span and conventional SARIMA modeling, the present study utilizes a longer dataset (2016–2022) and incorporates parameter optimization strategies, thereby enhancing both methodological rigor and the forecasting horizon. The anticipated outcomes of this research will offer valuable insights to the poultry industry, supporting more informed decisions regarding feed management, cage and warehouse conditions, and overall production planning.

2. RESEARCH METHODS

A comprehensive methodology is proposed to forecast native chicken egg production using the SARIMA method in R Programming. The main workflow of this study is illustrated in Fig. 1.

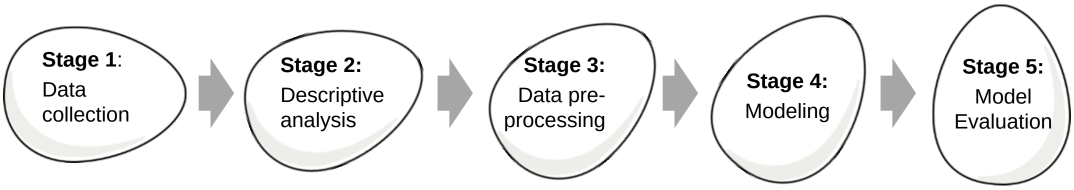

Figure 1. The Five Stages of the Research Workflow

2.1 Data Collection

The forecasting modeling process begins with collecting data on native chicken egg production for 84 months, starting January 2016 to December 2022. This data comprises a summary of time-series data on native chicken egg production per month. This research data was sourced from BPS Magelang City, representing official agricultural production statistics from backyard/native poultry farms.

2.2 Descriptive Analysis

Descriptive Analysis is a data analysis type that assists in describing, displaying, or constructively summarizing data points so that patterns emerge from the data. It provides conclusions about the data distribution and also identifies outliers. This stage includes descriptive statistics, outlier detection using boxplot diagrams, and identifying time series data patterns such as trends and seasons using decomposition diagrams and ACF/PACF inspection. SARIMA modeling can be utilized if the data shows seasonal patterns and random white noise. The white noise property of residuals was examined using the Ljung–Box test.

2.3 Data Pre-Processing

2.3.1 Data Splitting

At this stage, the dataset is divided into 72 months of training data (2016–2021) and 12 months of testing data (2022), which are used to train the model and evaluate its performance. Model training involves using historical data and tuning parameters for the best performance. The model that produces the smallest and most significant deviation will be the best forecasting model. Furthermore, the performance of the best model is evaluated using test data.

2.3.2 Stationarity Test

The SARIMA method can be modeled after time-series data achieves stationarity (constant mean and variance values over time) for the variables predicted by different transformation methods. Non-stationary time-series data can lead to autocorrelation and heteroscedasticity, which may have an unfavorable impact on the estimation model. Data can be considered stationary if the data pattern revolves around a constant mean value and the variance around the mean is continuous over a certain period. To identify stationarity, the Augmented Dickey-Fuller (ADF) test can be applied as in Eq. (1) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) as stated in Eq. (2) [18]. If the p-value resulting from the ADF test is less than the significance level (alpha value) of 0.05, then the time-series data is likely stationary, and vice versa. Conversely, if the p-value resulting from the KPSS test is less than the significance level of 0.05, then the time-series data is non-stationary, or vice versa.

$$\Delta y_t = \delta + \alpha y_t - 1 + \varepsilon_t, \tag{1}$$

where y_t represents the value at time t, δ and α denote parameters to be estimated, and ε_t is supposed to be white noise.

$$y_t = \delta_t + r_t + \varepsilon_t, \tag{2}$$

where y_t is the observed time series, δ_t denotes a deterministic trend, r_t represents a random walk, and ε_t is a stationary error.

2.3.3 Data Transformation

If the time series data is non-stationary, the series must be transformed (by differentiating the data in the mean and taking the natural logarithm of the variance) to make it stationary. However, if the series is already stationary, there's no need to apply differencing (d) to the model again. First-order differencing ($d = 1$) and seasonal differencing ($D = 0$) were applied to achieve stationarity, confirmed by ADF and KPSS tests. No variance-stabilizing transformation was needed, as visual inspection confirmed stable variance. Data transformation in this study is facilitated by using the auto.arima() function from the forecast package in R Programming so that model selection becomes more effective.

2.4 Modeling: Seasonal Autoregressive Integrated Moving Average

The SARIMA model is an advanced version of the ARIMA model that incorporates a seasonal component [19]. This model is utilized when a time series is not stationary, meaning that all moment data (median, variance, and covariance) are not constant within a certain period. Non-stationary time series data can be transformed into a stationary time series by differencing (d), which means replacing the original time series with a different time series. The SARIMA model can be represented by ARIMA $(p, d, q)(P, D, Q, s)$, where p implies the autoregressive (AR) lag number, d denotes the differential passes number, q indicates the moving average (MA) order, P is the AR seasonal lags number, D is the seasonal differences number, Q is the MA seasonal lags number, and s is the seasonal periods number.

The SARIMA model with the order $(p, d, q)(P, D, Q, s)$ can be mathematically expressed as in Eq. (3).

$$\left(1 - \sum_{i=1}^{p} \phi_i\, y_{t-i} + \sum_{i=1}^{P} \Phi_i\, y_{t-si}\right)(1 - y_t)^d (1 - y_{t-s})^D y_t = \left(\sum_{j=1}^{q} \theta_j y_{t-j} + \sum_{j=1}^{Q} \Theta_j y_{t-sj}\right)\epsilon_t, \tag{3}$$

where y_t denotes the forecast value or dependent variable at time t, s represents the seasonal period, ε_t represents the white noise time series at time t, ϕ_i is the AR(p) parameter for $i = 1, 2, \ldots, p$, Φ_i is the seasonal parameter AR(P) for $j = 1, 2, \ldots, P$. Furthermore, θ_j is the MA(q) parameter for $j = 1, 2, \ldots, q$. Θ_j is the MA(Q) parameter for $j = 1, 2, \ldots, Q$.

2.4.1 Parameter Tuning

When training models, tuning parameters is essential to optimize performance and maximize forecasting accuracy. The parameters p, d, q, P, D, and Q are typically tuned. A combination of the grid search technique and the auto.arima() function from the forecast package in R programming is used for efficient and optimal parameter tuning. The search space covers $p, q, P, Q \in [0-3]$, $d, D \in [0-1]$, with the seasonal period $s = 12$, and step size $= 1$. Each candidate model is evaluated using AIC, R^2, MAE, RMSE, MAPE, and MASE to select the configuration with the smallest deviation. The grid search is exhaustive within the defined range, and auto.arima() is used to identify initial promising candidates. During this process, metrics such as R-squared (R^2), Akaike Information Criterion (AIC), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE) are utilized to select the model with the minimum deviation value.

2.4.2 Residual Normality Test

The normality test is a method used to decide whether the data is from a population that follows a normal distribution. This type of data is considered reliable for research purposes. If the p-value is less than the alpha value (0.05), the data distribution is abnormal. In such cases, data transformation techniques such as logarithms, square roots, or certain inverses can make the distribution closer to normal. In this study, the Jarque Bera (JB) test in Eq. (4) [20] and the Kolmogorov-Smirnov (KS) test in Eq. (5) [21] were employed for normality assessment since the data set consisted of more than 50 observations.

$$JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right), \tag{4}$$

where n represents the sample size, s denotes skewness, and k is kurtosis.

$$KS = \max|F(x) - G(x)|, \tag{5}$$

where $F(x)$ denotes the observed cumulative frequency distribution of a random sample of n observations, and $G(x)$ represents the theoretical frequency distribution (k/n).

2.4.3 Autocorrelation Test

The autocorrelation test is a method used to decide the residual correlation between a period and the previous period. If the significance value is more than 0.05, it means there is no autocorrelation in the model, and vice versa. The Ljung-Box test (LB) in Eq. (6) is utilized in this study to identify residual autocorrelation. A good model does not exhibit autocorrelation. If there are no lags outside the interval limits of the correlogram, the residual non-autocorrelation assumption is also satisfied.

$$LB = n(n+2)\sum_{k=1}^{K}\frac{(\rho_k)^2}{n-k}, \tag{6}$$

with n being the number of observations in the time series data, K representing the number of lags tested, k as the lag difference, and ρ_k as the autocorrelation coefficient at lag-k.

2.4.4 Homoscedasticity Test

The homoscedasticity test is a method used to decide whether the residual variance tends to be constant. It was assessed using the Breusch–Pagan (BP) test and the White test. Both tests regress the squared residuals on fitted values (and squared terms in the White test) to detect systematic variance patterns. The test statistic is expressed as in Eq. (7).

$$LM = nR^2, \tag{7}$$

where n is the number of observations and R^2 is from the auxiliary regression. Under H_0, residuals are homoscedastic, and LM with degrees of freedom equal to the number of regressors. If H_0 is rejected, heteroscedasticity is present, and remedies such as logarithmic transformation or robust standard errors may be applied. In this study, the BP and White tests did not reject H_0 at the 5% level, confirming the assumption of homoscedasticity.

2.5 Model Evaluation

Evaluating model performance involves measuring the deviation of forecasting results from actual data. The model's accuracy improves with a smaller deviation value. This research utilizes AIC, R^2, MAE, RMSE, MAPE, and MASE as metrics to measure forecasting performance. Table 1 lists the details of each metric from Eqs. (8) to (13)

Table 1. Metrics for Measuring Deviations from Forecast Results [22]-[24]

Metric	Equation	
AIC	$2k - 2\ln(log - likelihood)$	(8)
R^2	$1 - \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - \bar{A}_t)^2}$	(9)
MAE	$\frac{1}{n}\sum_{t=1}^{n}\lvert A_t - F_t\rvert$	(10)
RMSE	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2}$	(11)
MAPE	$\frac{100}{n}\sum_{t=1}^{n}\frac{\lvert A_t - F_t\rvert}{A_t}$	(12)
MASE	$\frac{MAE}{\frac{1}{n-1}\sum_{t=2}^{n}\lvert A_t - A_{t-1}\rvert}$	(13)

where k is the number of estimated variables, n being the number of observations in the time series data, A_t represents the actual value at time t, $\bar{A}_t$ represents the mean of actual values, and F_t is forecasted value at time t.

When evaluating model performance, it is critical to determine the detailed aspects of the data and the context of the forecasting task. Therefore, visualizing results through distribution plots or residuals can provide further insight into model performance. Overall, using a combination of these metrics can offer a comprehensive evaluation of a forecasting model, aiding in assessing its accuracy and potentially enhancing its generalizability.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

The Central Statistics Agency for Magelang City reported that the average egg production by native chickens from January 2016 to December 2022 was 990.2 kg. The lowest production amount was 754 kg in August 2018, and the highest was 1,223 kg in April 2020. The standard deviation (SD) of egg production was 148.1 kg. A small SD compared to the mean and a mean close to the median suggest a normal distribution. Fig. 2 illustrates monthly native chicken egg production. Although the data are recorded monthly, the X-axis labels are presented at quarterly intervals (January, April, July, and October) to improve readability while maintaining the full monthly resolution of the series.

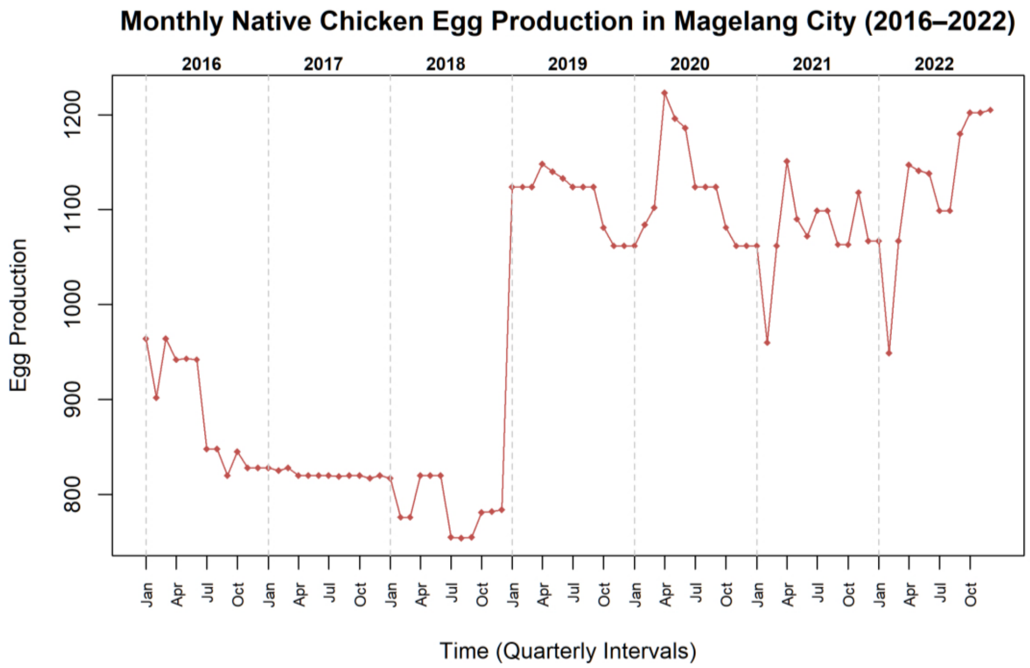

Figure 2. Monthly Native Chicken Egg Production in Magelang City, 2016–2022 (with quarterly labels on the X-axis for clarity)
(Source: processed using R Programming)

To detect outliers, a boxplot diagram is used as shown in Fig. 3.

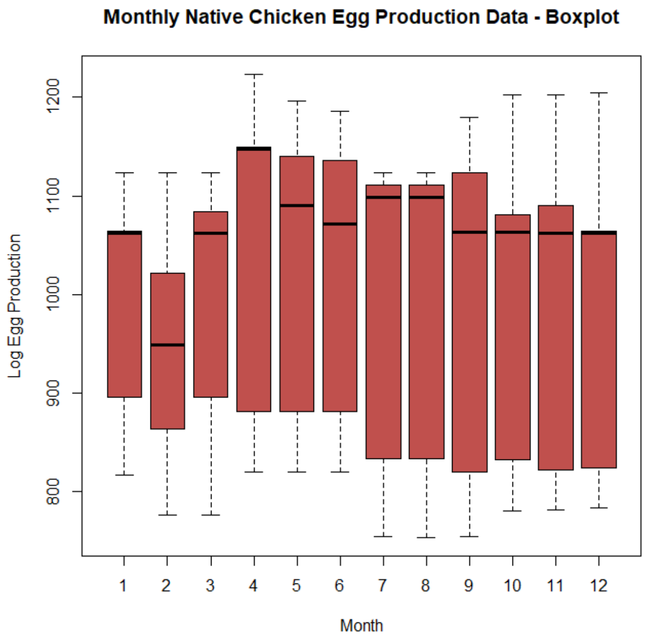

Figure 3. Boxplot Diagram Illustrating the Number of Chicken Egg Production from January 2016 to December 2022
(Source: processed using R Programming)

The boxplot diagram shows the size of the data variance (box length), which tends to be the same. However, the median size of the data tends to vary for each month. There were no outliers in the dataset, and egg production was highest in April, May, and June. Meanwhile, it was lowest in February.

In addition, the time series plot has been decomposed to reveal the data pattern, as illustrated in Fig. 4. The multiplicative decomposition of the identified time series data pattern exhibits a mixed trend, with a downtrend initially followed by an upward trend, followed by a relatively constant trend, and then another upward trend. The data pattern also indicates non-stationarity and a long-term positive trend over time. Furthermore, the time series plot in Fig. 4 exhibits non-linear and seasonal data patterns that repeat yearly with peaks in April-June. The residual component captures irregular fluctuations of Total Egg Production from January 2016 to December 2022, making the SARIMA method the most suitable approach for this research.

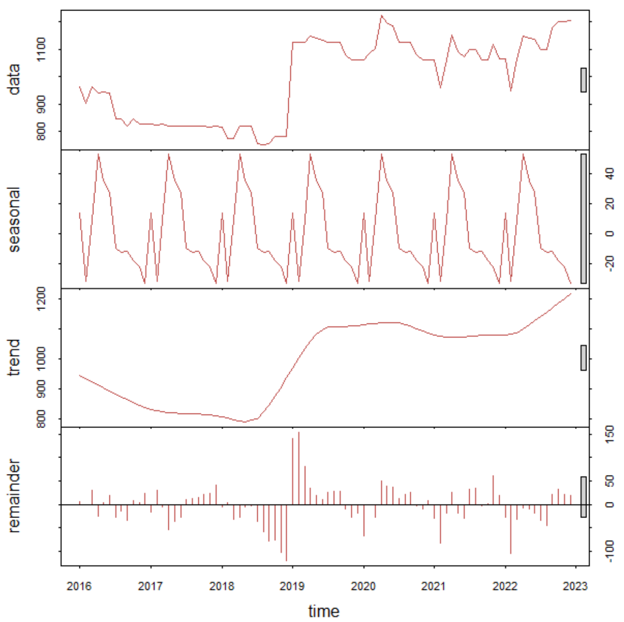

Figure 4. Decomposition Plot: Total Egg Production from January 2016 to December 2022
(Source: processed using R Programming)

3.2 Data Preprocessing

The data preprocessing process begins by splitting the dataset into 72 months (6 years) of training data for model training and 12 months (1 year) of testing data to assess the model's performance. The SARIMA method can be modeled after the training data reaches stationarity. Therefore, the stationarity level of the time series data is determined using the ADF and KPSS tests with a significance level (alpha) of 5% (0.05). Based on the ADF and KPSS test results presented in Table 2, it is evident that the time series is non-stationary. Therefore, time series data is transformed to achieve stationarity.

Table 2. Time Series Stationarity Level for Alpha = 0.05

Test	Lag	P-value	Interpretation
ADF	4	0.2836	non-stationary
KPSS	3	0.0100	non-stationary

This data transformation produces several SARIMA models as presented in Table 3.

Table 3. SARIMA Models for 12 Months

Model	Order (p, d, q)	Seasonal (P, D, Q, s)
1	(1,1,0)	(1,0,0,12)
2	(0,1,0)	(1,0,0,12)
3	(0,1,0)	(1,0,1,12)
4	(0,1,0)	(0,0,1,12)
5	(0,1,1)	(0,0,1,12)
6	(2,1,2)	(1,0,1,12)

3.3 SARIMA and Parameter Tuning

Multiple SARIMA models are recommended based on data transformation and parameter tuning results. The best model is determined by the lowest AIC value and the highest $\boldsymbol{R^2}$. To further validate the selection, MAE, RMSE, and MAPE metrics are used with the training data, as shown in Table 4. Model 6, with the order (2,1,2) and Seasonal (1,0,1,12), is identified as the best model due to its highest $\boldsymbol{R^2}$ value (0.8869) and the smallest values for all evaluation metrics. However, this model has a higher AIC value compared to the other models. Model 6 offers the best compromise among evaluated models. While its AIC is slightly higher than Model 2, its predictive accuracy across MAE, RMSE, and MAPE is superior, which is prioritized for the forecasting objective. Additionally, model 2 with the order (0,1,0) and seasonal order (1,0,0,12) has the lowest AIC value (772.0568) and can also be an alternative to evaluate its performance in forecasting.

Table 4. SARIMA Model with Evaluation Metrics for 12 Months

Model	Order (p, d, q)	Seasonal (P, D, Q, s)	AIC	R^2	MAE	RMSE	MAPE	MASE
1	(1,1,0)	(1,0,0,12)	773.7869	0.8631	26.1207	53.5390	2.5816	1.0129
2	(0,1,0)	(1,0,0,12)	**772.0568**	0.8625	25.7281	53.6426	2.5412	0.9976
3	(0,1,0)	(1,0,1,12)	773.1537	0.8692	25.8480	52.3303	2.5470	1.0023
4	(0,1,0)	(0,0,1,12)	772.1224	0.8624	25.6898	53.6761	2.5364	0.9962
5	(0,1,1)	(0,0,1,12)	773.8008	0.8630	26.1648	53.5515	2.5853	1.0146
6	**(2,1,2)**	**(1,0,1,12)**	775.6467	**0.8869**	**24.5289**	**48.6605**	**2.4392**	**0.9511**

The z-test results in Table 5 also show the significance of the parameters AR(2) and MA(2) for Order (2,1,2), as well as SAR(1) and SMA(1) for Seasonal (1,0,1,12) for 12 months.

Table 5. Optimal Parameters of the SARIMA$(2,1,2)(1,0,1,12)$ Model to Forecast

Parameter	Estimate	Std. Error	Z value	Significance	
AR(1)	-0.07945	0.055303	-1.4365	0.1508	
AR(2)	-0.98158	0.023555	-41.672	< 2.2e-16	***
MA(1)	0.01614	0.063135	0.2556	0.7983	
MA(2)	0.99986	0.059757	16.7322	< 2.2e-16	***
SAR(1)	0.99513	0.046250	21.5164	< 2.2e-16	***
SMA(1)	-0.96164	0.182572	-5.2672	1.385e-07	***

Note: *** (significance)

3.4 Model Diagnostic Test

Fig. 5 shows the residual and ACF plots of the SARIMA(2,1,2)(1,0,1,12) model. This graph shows that no specific information appears in the data, where all points are irregularly distributed around zero (no systematic pattern), which means that the selected model is adequate. In addition, the residual ACF data plot shows a white noise model characterized by all lags being within the threshold.

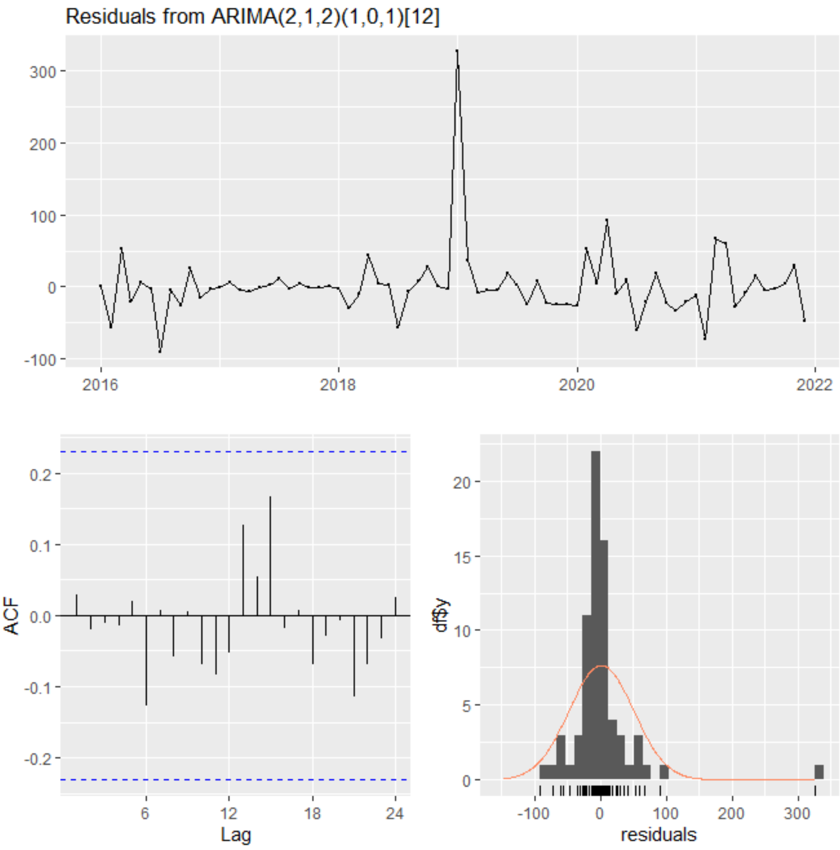

Figure 5. Residual Plot of the Best SARIMA Model and ACF
(Source: processed using R Programming)

Based on the JB and KS tests with a significance level (alpha) = 5%, the model's residual normality is not satisfied because the p-value < alpha is presented in Table 6.

Table 6. Residual Normality Test Results for Significance = 0.05

Test	p-value	Interpretation
JB	2.2e-16	non-normally distributed
KS	4.4e-16	non-normally distributed

Besides, the Ljung-Box test for the SARIMA(2,1,2)(1,0,1,12) model produces a statistical value of 9.94 at $df = 23$ and a p-value of 0.9916 (greater than $\alpha = 0.05$). It indicates no autocorrelation or heteroscedasticity in the time series data, satisfying the assumptions of non-autocorrelation and homoscedasticity. The correlogram in Fig. 6 further supports this conclusion, as it shows no lags outside the interval limits. Therefore, it can be inferred that the model does not exhibit autocorrelation or heteroscedasticity. Although residuals are non-normally distributed, this does not invalidate the SARIMA model for forecasting purposes, though it may limit certain inference tasks. Potential improvements could be made by adding exogenous variables or exploring nonlinear models.

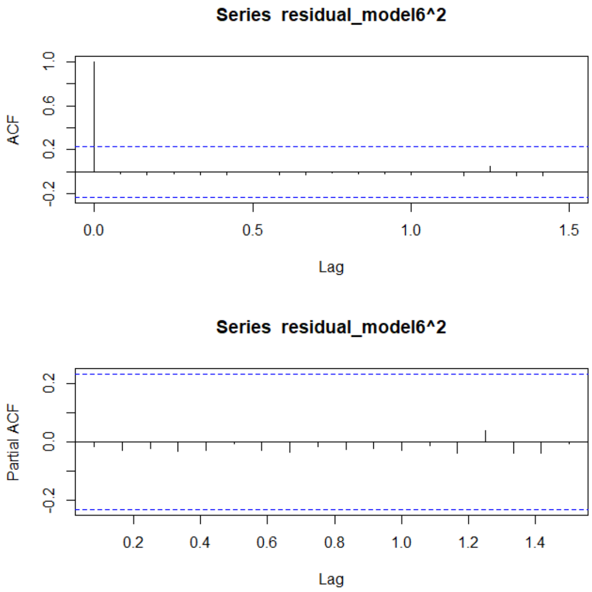

Figure 6. Correlogram Plot of SARIMA$(2,1,2)(1,0,1,12)$ Model
(Source: processed using R Programming)

3.5 Model Evaluation

Retrospective forecasting is used to measure model performance. This forecast compares forecast data with actual data using a test dataset. The predicted and actual egg production numbers are listed in Table 7 and illustrated in Fig. 7.

Table 7. Total Egg Production Results Forecasted and Actual for the 2022 Period

Period	Forecasting	Actual
Jan	1070.45	1067
Feb	1058.88	949
Mar	1099.19	1067
Apr	1113.89	1147
May	1081.49	1141
Jun	1085.79	1138
Jul	1093.67	1099
Aug	1084.48	1099
Sep	1056.90	1180
Oct	1064.78	1202
Nov	1086.16	1202
Dec	1070.06	1205

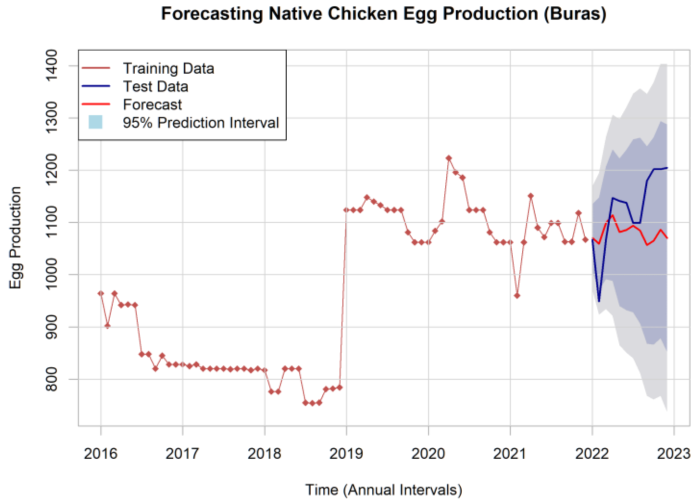

Figure 7. Plot of Actual and Forecast Egg Production
(Source: processed using R Programming)

The red plot in Fig. 7 shows the training data. The navy plot represents the actual values of the test data, and the red plot represents the forecasted values, with the highest 95% confidence interval shown as the shaded area. This model appears to have captured the potential variability in the sample but still lacks the central tendency of the time series data. It is not surprising, considering that SARIMA models are often better suited to time series data with trends or seasonality, which this time series seems to show.

The results presented in Table 8 demonstrate that the proposed model for forecasting native chicken egg production is highly accurate. The SARIMA(2,1,2)(1,0,1,12) model produced promising results in estimating the number of egg production with an MAPE of 7.21%, corresponding to approximately 92.79% forecast accuracy (defined as 100% – MAPE). The model effectively captures temporal and seasonal patterns in the data, making it reliable for medium-term forecasting purposes. Notably, the model slightly overestimates production in September-December, which may be linked to unmodeled seasonal factors such as feed changes or weather anomalies.

Table 8. Evaluation Results from the Forecasting Model

Metric	MAE	RMSE	MAPE	MASE
Value	82.1285	92.9163	7.2097	0.6712

3.6 Discussion

In many forecasting scenarios, selecting a forecasting model is often based on minimizing deviation or maximizing accuracy. In addition to AIC and R^2 metrics, it is valuable to consider metrics such as MAE, RMSE, MAPE, and MASE to assist in selecting a forecasting model. The modeling results indicate that the SARIMA(2,1,2)(1,0,1,12) model performs better than other SARIMA models in forecasting native chicken egg production. The model demonstrates high accuracy, with the highest R^2 value among other models at 0.89. The lowest MAE, RMSE, MAPE, and MASE values were 24.53, 48.66, 2.44, and 0.95, respectively.

Meanwhile, the SARIMA model evaluation results show that the model has excellent performance, with an accuracy rate of over 92.7% (defined as 100% – MAPE). Although the evaluation results decreased by about 4.8% compared with the modeling performance, the overall model performance is still excellent. The drop in accuracy is likely due to seasonal shifts and unobserved external factors such as feed quality, weather changes, and economic conditions, which were not included in the model. Comparatively, it is an improvement over the accuracy rate of 88.26% reported in the study by [10]. A baseline comparison with the default auto.arima() model showed that our optimized SARIMA reduced MAPE by 1.32 percentage points, confirming the benefit of systematic parameter optimization.

The findings of this research have several practical implications for stakeholders in the poultry industry. Accurate egg production forecasting enables farmers to optimize production schedules, manage inventory efficiently, and meet consumer demand effectively. It also helps farmers plan logistics, pricing strategies, and promotional activities. Policymakers can utilize forecasting models to anticipate market trends, support decision-making, and implement interventions to ensure food safety and stability in poultry markets. These implications are anticipated benefits based on improved forecasting accuracy, not directly tested in this study.

This study has some limitations. Firstly, the scope of egg production only covers native chickens, which means that the findings may not be widely applicable. Although they do represent the overall context of poultry egg production forecasting, these patterns may generalize to other poultry types (e.g., broiler or layer) under similar seasonal and production conditions. To enhance generalizability, future research should validate this approach using multi-regional and multi-breed datasets. Future research could validate this approach on different platforms to enhance its generalizability. Secondly, the forecasting model exclusively focuses on production quantity and does not consider other external factors, such as feed type, weather, economic indicators, and other potential influences that could improve the model's performance. Lastly, it's worth exploring deep learning and reinforcement learning methods by incorporating various criteria and comparing them with existing benchmarks. Therefore, suitable models are crucial for understanding the relationship between production periods.

4. CONCLUSION

This study presents a comprehensive analysis to forecast native chicken egg production using the SARIMA method with systematic parameter optimization (auto.arima + exhaustive grid search). The SARIMA(2,1,2)(1,0,1,12) model is identified as the most effective model due to its high accuracy, as evidenced by the low values of MAE (82.13), RMSE (92.92), MAPE (7.21%), and MASE (0.67). By utilizing this SARIMA model, egg production forecasting with high accuracy can be achieved, thereby providing valuable insight into the decision-making process regarding future egg production in the poultry industry. By utilizing this model, the poultry industry can plan feed management and housing conditions, thereby increasing productivity, distribution, and marketing, and ultimately potentially contributing to the long-term sustainability and profitability of the poultry market.

Author Contributions

Rendra Gustriansyah: Writing - Original Draft. Deshinta Arrova Dewi: Writing - Review and Editing. Shinta Puspasari: Formal Analysis. Ahmad Sanmorino: Data Curation. All authors provided critical feedback, revised earlier versions of the manuscript, and approved the final version for submission.

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Declarations

The authors declare that they have no competing interests.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors.

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