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Forecasting chicken meat and egg in Indonesia using ARIMA and SARIMA

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ABSTRACT

Chicken meat and eggs are part of the main commodities in Indonesia. Indonesian people's consumption of chicken meat per capita per year continues to increase. Indonesian government is trying to lure investments to help fund these growing needs. However, inflation has never been positively affected investments. Furthermore, the price of chicken meat and eggs in Indonesia are vulnerable to such a fluctuation. This price hike causes losses to society, due to higher costs, and to the country: inflation affects the future of investment. So, if ones can forecast both commodities, could help decision makers optimizing their policies. This research forecasts the price of chicken meat and egg using the ARIMA and SARIMA methods. Price forecasting is done on chicken meat and egg because they are interrelated, as seen from the Pearson Correlation Test of 0.92 in the datasets and 0.87 in the forecasting results. The selection of the best model is based on the smallest MSE, MAE, and MAPE. The best chicken meat price forecasting results using the ARIMA(3, 1, 2) with MAPE value of 2.31%, while the best chicken egg price forecasting results is the SARIMA[(2, 1, 1)(2, 0, 2, 0), n] with MAPE value of 3.44%.

KEYWORDS
Chicken meat
Chicken egg
Forecasting
Arima
Sarima

1. Introduction

Chicken meat and chicken egg are part of the main commodities in Indonesia based on the Decree of the Minister of Trade and Industry No. 115/MPP/KEP/2/1998. Chicken meat is one of the main sources of animal protein consumed by Indonesians besides fish and eggs. Director General of Livestock and Animal Health state that total consumption of chicken meat of Indonesian reaches 84.07% of the total consumption of other livestock meat [1]. According to the Central Statistics Agency (BPS), the consumption of chicken meat per capita per year of Indonesians continues to increase. The consumption of purebred chicken meat per capita per year in 2017 increased by 11.2%, while the consumption of free-range chicken meat increased by 24.9% from the previous year. In addition, the level of consumption of animal protein in Indonesian society in 2018 for chicken meat and chicken egg was higher compared to beef.

Indonesia as a developing country realize the importance of economic development for a prosperous society. In carrying out economic development, Indonesia experiences various problems. One of these problems is the lack of funds from within the country [2]. Indonesia's domestic savings are not sufficient to fulfill the investment needs in Indonesia. Therefore, the government is trying to get funds from abroad in the form of investment. Inflation has a significant effect on foreign direct investment entering Indonesia [3]. Inflation affects foreign direct investment indirectly through its effect on domestic interest. Based on this statement, if inflation in a country is high, it will be followed by an increase in domestic interest rates. This condition will encourage a decline in a country's investment income [4]. This is as stated in classical theory that there is an inverse relationship between domestic interest rates and the amount of investment received by a country [5].

On the other hand, the price of chicken meat and chicken egg in Indonesia is vulnerable to fluctuation. The price of chicken egg in 2018 has increased from the previous 4 years with high fluctuations [6]. This price hike causes losses to society, due to higher costs, and also to the country, because inflation affects the future of investment. Reporting from the official website of Bank Indonesia, low and stable inflation is a prerequisite for sustainable economic growth. It is important to control inflation, because high and unstable inflation has a negative impact on economic growth and the social and economic conditions of the community.

Previous research on commodity price forecasting conducted by Febrian Sugiharta stated that of the 30 time series method tested, the Box Jenkins or ARIMA method is the most suitable method for forecasting red chili commodity prices [7]. Ďurka Peter and Pastoreková Silvia have conducted research in forecasting time series data, the ARIMA model is more accurate than ARIMAX with smaller MAPE and RMSE values [8]. Research by F.N. Hadiansyah said that the ARIMA model has the best performance in forecasting chili prices compared to the AR, ARI, and IMA methods, with an RMSE value of 964.005 and MAPE value of 1.479% [9]. Another study that compared ARIMA with the Backpropagation Artificial Neural Network (ANN) method for stock price forecasting states that the ARIMA method has an MSE value of 0.001145 while Backpropagation ANN has an MSE value of 0.00140 [10].

Research on time series data by comparing the SARIMA method and the Poisson Regression method states that the SARIMA model has better performance with an RMSE value of 0.40 while the Poisson Regression model has an RMSE value of 0.54 [11]. Research using the SARIMA method has been conducted to predict dust fall levels in the city of Quetta, Pakistan [12]. Research to compare the performance of the SARIMA method with the Dynamic Linear Model (DLM) method in forecasting epidemiology has been carried out. This study concludes that both the SARIMA and DLM methods have good performance, none is superior because each has its own advantages [13].

In this study, the algorithms used for forecasting are ARIMA for forecasting the price of chicken meat, and SARIMA for forecasting the price of the chicken egg. The chicken meat price dataset successfully passed the stationary test after log and differencing transformations, which means that it is free from the seasonality component, so the suitable method is ARIMA. Meanwhile, the chicken egg price dataset did not pass the stationary test even after log and differencing transformations, which means that the seasonality component was too high and was not successfully removed from the dataset, so the suitable method is SARIMA. Parameter optimization of the model is done using the Grid Search method. The best model is selected based on the MSE, MAE, and MAPE. The hyperparameter used in the Grid Search are determined based on ACF and PACF plot. Then, the model will be tested using the Ljung-Box method to check whether the model is suitable for use or not. After the model is declared feasible, then forecasts and calculates the error in the model assessment and evaluation phase.

2. Method

This research is divided into 7 main phases shown in Figure 1 : data collection, preprocessing, model candidate determination, best model determination, diagnostic test, model assessment and evaluation, and analysis.

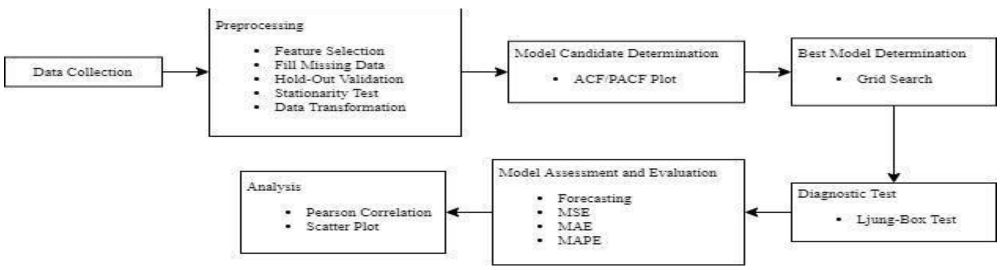

Fig. 1. Research design

2.1. Data Collections

In this study, the dataset was obtained from the official website wfp.org. The dataset contains the prices of basic commodities in Indonesia from January 2007 to April 2019 in a monthly period with 1553 instances. World Food Programme (WFP) is the leading humanitarian organization that saves lives and changes lives, delivers food assistance in emergencies, and works with communities to improve nutrition and build resilience. The main commodities listed in the WFP dataset include rice, wheat, chicken meat, beef, green chilies, red chilies, chicken eggs, milk, vegetable oil, sugar, and kerosene.

2.2. Preprocessing

2.2.1. Feature Selection

Feature selection is a trivial process by eliminating features for the forecasting process. The original data consists of time series occasions of main commodities in Indonesia. However, price forecasting in this research only requires the date feature as the independent variable, and commodity prices as the target output, the remaining features were removed from the dataset. The removal process was done with python. The dataset used in this study is only the dataset of chicken meat price and chicken egg price. Price data for chicken meat and chicken egg are separated into separate dataset. There are 147 instances in the dataset of chicken meat price and 146 instances in the dataset of chicken egg price, because there is a missing value in April 2013.

2.2.2. Fill Missing Data

Handling missing data is one part of preprocessing data. In dealing with missing data, the simplest solution is to delete instances with the missing data. In a time series dataset, it is better to keep data than to delete data. Because every data in the time series depends on previous data. One method to fill the missing data is forward fill method. This method fills the missing data with the principle of Last Observation Carried Forward (LOCF). This means that the missing data will be filled with the value in the previous instance.

2.2.3. Hold-Out Validation

Hold-Out Validation is a method to split a dataset into training data and testing data. Training data is the data used by the model for the training process, and testing data is the data used to measure how well the model is performing on new data that the model has never seen before. The split in this study uses 80% for training data and the remaining 20% for testing data. This split ratio was created based on 80 20 rules or Pareto rules created in 1895 by an economist from Italy named Vilfredo Pareto. Vilfredo Pareto noticed that people in society naturally divide the vital few in the top 20% and the trivial ones in the bottom 80%.

2.2.4. Stationarity Test

A very concept in the time series model development is stationarity, which means that the probability structure of a time series does not change with time [13]. Before the dataset is used to forecast using ARIMA, it must be ensured that the dataset is stationary. However, very often an economic time series data has a trend component, where the time series data do not have a constant mean [13]. If the time series is not stationary, it must be changed to stationary first. If the time series cannot be changed to stationary, then the time series may have a high seasonality component.

The stationarity test in this study was done in two ways. The first way is to visualize the data, then see the rolling mean and standard deviation. If the rolling mean and standard deviation are relatively constant, the dataset is stationary. However, the results of the stationary test by visualizing the rolling mean and standard deviation are subjective, therefore a second method is needed. The second way is to do a Dickey-Fuller test to find out the stationary value. The Dickey-Fuller test determines whether a process has a unit root or not. The unit root determines how strongly a time series is influenced by trends. The test results are interpreted using a p-value with a threshold value of 0.05. Time series is stated to be stationary if the p-value is below 0.05.

2.2.5. Data Transformation

In time series forecasting, time series data that are not stationary can be converted into stationary with data transformation such as logarithm and differencing. Equation (1) shows a formula for the logarithm process.

$$\hat{y}_t = \log(y_t) \tag{1}$$

Equation (2) shows a formula for the differencing process.

$$\hat{y}_t = y_t - y_{t-1} \tag{2}$$

The amount of time series data that has been differencing will be reduced by one instance, because it is impossible to perform differencing in the first instance. If a time series has been differencing but still not stationary, differencing can be done again up to two times. Because differencing operations performed more than twice are often make the data not reliable.

2.3. ARIMA

Analysis of time series data has received a lot of attention, especially in the use of the Box-Jenkins ARIMA method [13]. ARIMA is a method developed by George Box and Gwilym Jenkins in 1970 and is also known as Box-Jenkins [14]. ARIMA is a method for forecasting time series data which is only based on the observed variable data behavior. ARIMA makes full use of past and present data to make forecasts. ARIMA in general can be formulated as ARIMA(p, d, q). Order p represents the degree of autoregressive (AR), order d represents the number of differencing operations performed, order q represents the degree of moving average (MA).

$$\varphi_p(B)\Delta^d y_t = \theta_q(B)e_t \tag{3}$$

Where Δ^d is a non-seasonal difference operator and the order d is the amount of differencing needed to convert the time series into stationary. This equation is known as general non-seasonal ARIMA(p, d, q) model. ARIMA is flexible (follow data patterns) and has high accuracy [15].

2.4. SARIMA

The SARIMA method has been widely used in forecasting in the economic field and has maturely been used in industry [11]. SARIMA is a development of the ARIMA method which is designed for data with seasonal factor (seasonality). A data is said to have a seasonal factor if the data has a tendency to repeat the pattern in a certain period, such as weekly, monthly, quarterly, yearly and so on. SARIMA allows a seasonality component in the time series. This leads to the general model SARIMA(p, d, q)(P, D, Q, S), where P, D, and Q are the component of the seasonal AR, seasonal I, and seasonal MA of the model, and S is the number of seasonal periods.

$$\varphi_p(B)\Phi_p(B^S)\Delta^d \Delta_S{}^D y_t = \theta_q(B)\Theta_Q(B^S)e_t \tag{4}$$

Where $\Phi_p(B^S)$ is the seasonal operator of AR, $\Delta_S{}^D$ is the seasonal operator of I, $\Theta_Q(B^S)$ is the seasonal operator of MA, and *S* is the seasonal period (for example 4 for quarterly data or 12 for monthly data).

2.5. Model Candidate Determination

If the time series dataset passes the stationary test, then the dataset is free from the seasonality component. Time series datasets that do not contain seasonality components can use the ARIMA method for forecasting. If the time series dataset does not pass the stationary test even though log and differencing transformations have been carried out, the seasonality component is likely too high, so the seasonality component cannot be removed by log transformation differencing. Seasonal ARIMA method or SARIMA can be used for forecasting using this dataset.

The identification of the initial ARIMA model can be done by using the ACF and PACF plots on the dataset to determine the AR and MA orders. Identification of the initial SARIMA model can be done by plotting ACF and PACF on the dataset to determine the non-seasonal AR and non-seasonal MA orders, and plotting ACF and PACF on the differenced datasets to determine the seasonal AR and seasonal MA orders. Order d is the number of differencing operations performed to make dataset stationary.

2.6. Best Model Determination

In this study, parameter optimization was done using the Grid Search method. This method will build models using every combination of parameter that have been predefined in the hyperparameter. Then the forecasting error will be calculated on each model and the best model with the smallest forecast error will be selected based on MSE, MAE, and MAPE. The hyperparameter determination is based on the ACF and PACF plots of the time series data.

2.7. Diagnostic Test

Diagnostic test is performed to check the feasibility of a model. The model needs to be tested for diagnostics before used. One method that is commonly used to perform diagnostic test is the Ljung-Box Test. If there is on autocorrelation, the model is appropriate to use. The Ljung-Box Test is defined as follows:

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$H0$: There is no autocorrelation

$H1$: There is autocorrelation

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \tag{5}$$

Where n is the number of samples, $\hat{\rho}_k$ is the autocorrelation sample on the lag k, and h is the amount of lag used in the test. The decision criterion ($H0$) is rejected if $Q > X^2_{1-\alpha,h}$ or p-value < α [15]. Where $X^2_{1-\alpha,h}$ is the chi-square distribution with h is the degrees of freedom and significance level of α = 0.05

2.8. Model Assessment and Evaluation

After obtaining the best model through parameter optimization and diagnostic test, the next is to forecast using the best model. Forecasting is a decision making technique based on past events to predict future events. Forecasting can also be interpreted as the use of past data to determine future trends [16]. Evaluation is the process where the calculation of errors in the forecasting results is carried out. The level of accuracy and performance of the model can be seen through this process. There are many ways to calculate errors in time series forecasting, such as MSE, MAE, and MAPE.

2.9. Analysis

The final process of this research is to analyze the results of the research that has been done. To see the correlation value of two datasets, Pearson Correlation analysis can be performed.

3. Result and Discussion

3.1. Preprocessing

3.1.1. Feature Selection

There are many features in the dataset. However, none of the features affect the price. Therefore, it is necessary to select features in the dataset. The feature selection process leaves price and date features as index, thus making this dataset a univariate time series. At this stage, only two out of 17 features are used: the date and the price.

3.1.2. Fill Missing Data

The next step is handling missing data. The chicken egg price dataset has a missing data in April 2013. This missing data will be filled in using the forward fill method. For instance, the data in April 2013 will be filled with data in March 2013.

3.1.3. Hold-Out Validation

The distribution of training data and testing data using Hold-Out validation are 80% for training data and 20% for testing data. The dataset will be divided by 118 instances for training data and 29 instances for testing data. This distribution applies to the chicken meat prices dataset and chicken egg prices dataset. Training data consist of price data from January 2007 to October 2016. Testing data consist of price data from November 2016 to April 2019. Data distribution detail are show in Table 1

Table 1. Data distribution detail

Object	*Date*	*Total*	*Percentage*
Training Dataset	January 2007 to October 2016	118 instance	80%
Testing Dataset	November 2016 to April 2019	29 instance	20%

3.1.4 Stationarity Test

In this study, the stationary test was done by observing the rolling mean and standard deviation, then performing the Dickey-Fuller test. Chicken meat price dataset was successfully converted into stationary after log transformation and differencing twice. It can be seen on Figure 2 that this dataset is stationary, because the rolling mean and standard deviation are relatively constant. In addition, the Dickey-Fuller Test results show a p-value < 0.05 and a Statistical Test value < Critical Value (1%), which means that this dataset is 99% stationary.

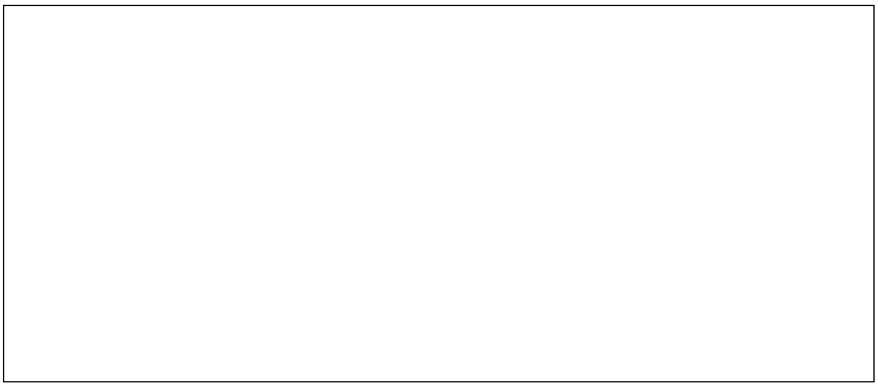

Fig. 2. Stationarity test results of chicken meat dataset after log transformation and differencing Twice

Chicken egg price dataset was not successfully converted into stationary even though log transformation had been done and differencing had been done twice. It can be seen on Figure 3 that even though rolling mean and standard deviation are relatively constant, the Dickey-Fuller Test results show the p-value > 0.05, which means that this dataset is still not stationary. This dataset is no longer possible to differencing, since differencing more than twice will make the data not reliable.

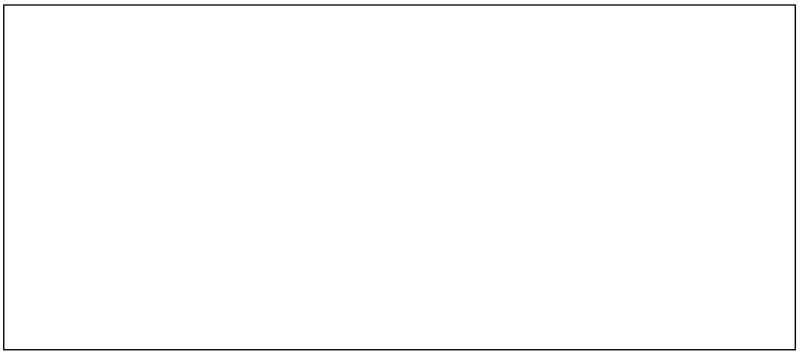

Fig. 3. Stationarity test results of chicken egg dataset after log transformation and differencing twice

3.2. Model

The chicken meat price dataset successfully passed the stationary test after log transformation and differencing twice. Because it is stationary, the seasonality and trend component in the chicken meat dataset have been removed. Since the chicken meat price dataset does not contain seasonality, the model

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that is suitable for forecasting is the ARIMA model. To identify the initial model, it is necessary to plot ACF and PACF. The p and q orders will be determined based of the ACF and PACF plots. The order d will be determined based on the number of differencing operations to make the dataset stationary. It can be seen on Figure 4 that the ACF plot decreases exponentially while the PACF plot shows a cut-off at lag 2. In addition, the chicken meat price dataset requires two differencing process to make it stationary. Thus, the initial model for this dataset is ARIMA(2, 2, 0).

Fig. 4.ACF and PACF plot of chicken meat dataset

The chicken egg price dataset cannot be converted into stationary even though log transformation had been done and differencing had been done twice. This means that the seasonality component in the chicken egg price dataset cannot be removed with log transformation and differencing. Since the chicken egg price dataset contains seasonality, a suitable model is the SARIMA model. In order to identify the initial model, it is necessary to plot ACF and PACF. ACF and PACF plots on the chicken egg price dataset to determine non-seasonal parameters (p, d, q). ACF and PACF plots on the differenced chicken egg price dataset to determine seasonal parameters (P, D, Q).

It can be seen on Figure 5 that the ACF plot decreases exponentially while the PACF plot shows cut-off at lag 2. In addition, the dataset of chicken eggs price cannot be converted into stationary even though the differencing has been done twice. Thus, the value of non-seasonal parameters is (2, 0, 0). Next, look for seasonal parameter values based on ACF and PACF plots on differenced datasets. It can be seen on Figure 6 in the ACF plot that there is cut-off at lag 2, and in the PACF plot shows a cut-off at lag 2. Since this is a monthly dataset, the order S value is 12. The SARIMA model in the statsmodels library that used in this study requires one more parameter, namely the type of trend, can be specified as a string where "c" indicates a constant, "t" indicates a linear trend with time, and "ct" is both. Since the trend continues to increase over time, the last parameter is "t". thus, the initial model for this dataset is SARIMA[(2, 0, 0)(2, 1, 2, 12), t].

Fig. 5. ACF and PACF plot of chicken egg dataset

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Fig. 6. ACF and PACF plot of chicken egg dataset after differencing

3.3. Best Model Determination

To get the best model, it is necessary to try and tuning the parameters contained in the model, so that the model with the smallest forecast error is obtained. In this study, parameter optimization was done using the Grid Search method. the Grid Search process for ARIMA model using hyperparameter produces 72 models. The best model for chicken meat prices dataset with the smallest forecast error is ARIMA(3, 1, 2).

The Grid Search process for SARIMA model using hyperparameter produces 3888 models. The best model for chicken eggs price dataset with the smallest forecast error is SARIMA[(2, 1, 1)(2, 0, 2, 0), “n”].

3.4. Diagnostic Test

The result of the Ljung-Box test on ARIMA(3, 1, 2). It can be seen that all the p-value in the second array is nothing less than the significance level of 0.05 Figure 7 and Figure 8. This means that the residuals in the ARIMA model do not contain autocorrelation and the model can be used for forecasting.

Fig. 7. Ljung-Box test result of ARIMA(3, 1, 2)
Fig. 8. Ljung-Box test result of SARIMA[(2, 1, 1)(2, 0, 2, 0), n]

3.5. Model Assessment and Evaluation

Testing was conducted with the training and testing data specified in Table 4. Forecasting is conducted to obtain forecasting of chicken meat and chicken eggs price in several periods. Then calculate the forecast error with the actual value using MSE, MAE, and MAPE. The results of forecasting and the forecast error calculation of ARIMA(3, 1, 2) can be seen in Figure 9. Forecasting Figure 10

Fig. 9. Data visualization of chicken meat price and chicken egg price dataset

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Fig. 10. Pearson correlation of the four scenarios

The evaluation results of chicken meat prices forecasting with ARIMA(3, 1, 2) shows that the MSE value is 1304316.907, the MAE value is 956.760, and the MAPE value is 2.31%. The evaluation results of chicken eggs prices forecasting with SARIMA[(2, 1, 1)(2, 0, 2, 0), n] shows that the MSE value is 966898.580, the MAE value is 764.890, and the MAPE value is 3.44%. The evaluation results shows that both model, ARIMA(3, 1, 2) and SARIMA[(2, 1, 1)(2, 0, 2, 0), n] have a fairly good performance, because the MAPE value is below 10.

3.6. Analysis

Researchers used both datasets of chicken meat prices and chicken eggs prices in Indonesia because the data visualization shows that the trends of both datasets are similar and affect each other. Data visualization of chicken meat price and chicken egg price can be seen on Figure 9. It shows that chicken meat price and chicken egg price dataset have a similar pattern. Both commodities tend to increase their price in the same period. The pattern of two commodities become clearer after log transformation to reduce the range. In addition, the pattern of forecasting results of chicken meat price and chicken egg price are similar as well. Meanwhile, the Pearson Correlation test result between chicken meat price and chicken egg price is 0.920913. This means that both datasets have a strong correlation and positive relationship, because the correlation value is very close to 1.

After that, calculate the correlation value with four scenarios (chicken meat actual price with chicken eggs actual price, chicken meat forecasting price with chicken eggs forecasting price, chicken meat forecasting price with chicken eggs actual price, chicken meat actual price with chicken eggs forecasting price). It can be seen in Figure 10 that the results of the correlation value calculation of the four scenarios are all very close to 1. This means, all four scenarios have a strong and positive relationship. In addition, scatter plots of the four scenarios in Figure 11 indicates a positive relationship, because they show an uphill pattern as they move from left to right. This means that if one variable has increased, the other variable tends to increase as well.

Fig. 11. Scatter plots of the four scenarios

4. Conclusion

Chicken meat price forecasting is done using ARIMA method, because chicken meat price dataset is successfully converted into stationary and free from seasonality. Chicken eggs price forecasting is done using SARIMA method, because chicken egg price dataset cannot be converted into stationary and is not free from seasonality. Model optimization using Grid Search on the ARIMA model produces 72 models, the best model is ARIMA(3, 1, 2) for chicken meat price forecasting with an MSE value of 1304316.907, an MAE value of 956.760, and a MAPE value of 2.31%. Grid Search process on the SARIMA model produces 3888 models, the best model is SARIMA[(2, 1, 1)(2, 0, 2, 0), "n"] for chicken eggs price forecasting with an MSE value of 966898.580, an MAE value of 764.890, and a MAPE value of 3.44%. The results of the analysis in four scenarios (chicken meat actual price with chicken eggs actual price, chicken meat forecasting price with chicken eggs forecasting price, chicken meat forecasting price with chicken eggs actual price, chicken meat actual price with chicken eggs forecasting price), all of them show a strong correlation and positive relationship, seen in the results of the Pearson Correlation test, respectively 0.920913, 0.880603, 0.807627, and 0.877754. In addition, the results of the scatter plots from the four scenarios also show a positive relationship, because they show an uphill pattern as they move from left to right. This means that if one variable has increased, the other variable tends to increase as well.

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References

[1] "Indonesia: beef consumption per capita 2031 | Statista." https://www.statista.com/statistics/757351/indonesia-beef-consumption-per-capita/ (accessed Dec. 08, 2020).

[2] T. M. Dewi and H. Cahyono, "Pengaruh Pertumbuhan Ekonomi, Bi Rate, Dan Inlfasi Terhadap Investasi Asing Langsung Di Indonesia," *J. Pendidik. Ekon.*, vol. 4, no. 3, pp. 1–7, 2016.

[3] A. T. Septifany, R. R. Hidayat, and S. Sulasmiyati, "PENANAMAN MODAL ASING DI INDONESIA (Studi Pada Bank Indonesia Periode Tahun 2006-2014)," *J. Adm. Bisnis*, vol. 25, no. 2, pp. 1–7, 2015.

[4] S. Sugiartiningsih, "Pengaruh Inflasi Indonesia Terhadap Penerimaan Penanaman Modal Asing Langsung Korea Selatan Di Indonesia Periode 2000-2014," *J. Manaj. Maranatha*, vol. 17, no. 1, p. 33, 2017, doi: 10.28932/jmm.v17i1.416.

[5] S. Sukirno, *Pengantar Teori Makroekonomi Edisi Kedua*, Ke 14. Jakarta: PT.Raja Grafindo Persada, 2002.

[6] N. Ilham and nFN Saptana, "Fluktuasi Harga Telur Ayam Ras dan Faktor Penyebabnya," *Anal. Kebijak. Pertan.*, vol. 17, no. 1, pp. 27–38, Jun. 2019, doi: 10.21082/AKP.V17N1.2019.27-38.

[7] F. Sugiharta, "Aplikasi Metode Peramalan Terhadap Harga Komoditas Cabai Merah Sebagai Dasar Pengambilan Keputusan Para Pelaku Perdagangan," 2002, Accessed: Dec. 08, 2020. [Online]. Available: http://repository.ipb.ac.id/handle/123456789/17047.

[8] D. Peter and P. Silvia, "ARIMA vs. ARIMAX – which approach is better to analyze and forecast macroeconomic time series?," *Int. Conf. Math. Methods Econ.*, no. 2, pp. 136–140, 2012.

[9] F. N. Hadiansyah, "Prediksi Harga Cabai dengan Pemodelan," vol. 2, no. 2010, pp. 71–78, 2017, doi: 10.21108/indojc.2017.21.144.

[10] D. P. Anggriningrum, P. Hendikawati, and Z. Abidin, "PERBANDINGAN PREDIKSI HARGA SAHAM DENGAN MENGGUNAKAN JARINGAN SYARAF TIRUAN BACKPROPAGATION DAN ARIMA," *Unnes J. Math.*, vol. 2, no. 2, Nov. 2013, doi: 10.15294/UJM.V2I2.3249.

[11] W. Hu, S. Tong, K. Mengersen, and D. Connell, "Weather Variability and the Incidence of Cryptosporidiosis: Comparison of Time Series Poisson Regression and SARIMA Models," *Ann. Epidemiol.*, vol. 17, no. 9, pp. 679–688, Sep. 2007, doi: 10.1016/J.ANNEPIDEM.2007.03.020.

[12] M. Sami *et al.*, "Prediction of the rate of dust fall in Quetta city, Pakistan using seasonal ARIMA (SARIMA) modeling," *undefined*, vol. 7, no. 10, Mar. 2012, doi: 10.5897/IJPS11.1357.

[13] F. F. Nobre, A. B. S. Monteiro, P. R. Telles, and G. David Williamson, "Dynamic linear model and SARIMA: a

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comparison of their forecasting performance in epidemiology," *Stat. Med.*, vol. 20, no. 20, pp. 3051–3069, Oct. 2001, doi: 10.1002/SIM.963.

[14] E. B. Dagum, "The X-II-ARIMA seasonal adjustment method," no. January 1980, p. 119, 1980, [Online]. Available: https://publications.gc.ca/site/eng/9.845219/publication.html.

[15] S. C. Hillmer and W. W. S. Wei, "Time Series Analysis: Univariate and Multivariate Methods.," *Journal of the American Statistical Association*, vol. 86, no. 413. p. 245, 1991, doi: 10.2307/2289741.

[16] F. Pakaja, A. Naba, and P. Purwanto, "Peramalan Penjualan Mobil Menggunakan Jaringan Syaraf Tiruan dan Certainty Factor," *J. EECCIS (Electrics, Electron. Commun. Control. Informatics, Syst.*, vol. 6, no. 1, pp. 23–28, 2012, doi: 10.21776/JEECCIS.V6I1.162.