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Vol. 04, No. 05, May 2024
e-ISSN: 2807-8691 | p-ISSN: 2807-839X

FORECASTING PALM OIL PRODUCTION USING LONG SHORT-TERM MEMORY (LSTM) WITH TIME SERIES CROSS VALIDATION (TSCV)

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Keywords
Oil palm; Short-Term Memory; With Time Series Cross Validation

ABSTRACT
Oil palm plant (*Elaeis guineensis Jacq.*) is a plantation crop that has a high economic value for Indonesia, because the results of oil palm plantations can increase the country's foreign exchange. Oil palm plantations can create jobs for the people of Indonesia, thus reducing unemployment in Indonesia. Oil palm plantations in Indonesia have spread to various regions, besides being found on the islands of Sumatra and Kalimantan, now oil palm plantations are almost found in various regions in Indonesia both small-scale plantations and large-scale plantations. This research uses historical data in the form of monthly palm oil production to predict the price of strategic food commodities. The period of palm oil production used is from January 1997 to December 2023 obtained from the website of PT. X or documentation data at PT. X. In this study the data was divided into 4 data scenarios using the Time Series Cross Validation (TSCV) method. The results of palm oil production modeling with LSTM that have been carried out show that palm oil production data shows differences in forecasting values and accuracy in the number of neurons and epochs used. The conclusion of this study is that from data processing and analysis in the previous chapter, it can be concluded that forecasting the amount of palm oil production in PT X can be modeled with LTSM and SARIMA method using Time Series Cross Validation (TSCV) data.

INTRODUCTION

Oil palm plant (*Elaeis guineensis Jacq.*) is a plantation crop that has a high economic value for Indonesia, because the results of oil palm plantations can increase the country's foreign exchange. Oil palm plantations can create jobs for the people of Indonesia, thus reducing unemployment in Indonesia. Oil palm plantations in Indonesia have spread to various regions, besides being found on the islands of Sumatra and Kalimantan, now oil palm plantations are almost found in various regions in Indonesia both small-scale plantations and large-scale plantations. Indonesia is the second largest palm oil producer in the world after Malaysia (Marpaung *et al.,* 2020). Indonesia and Malaysia control more than 85% of the world palm oil market where until 2016 as much as 22.76 million tons of palm oil have been exported to other countries despite fluctuations in world demand (Ditjenbun, 2021).

Oil palm is currently one type of plantation crop that occupies an important position in the agricultural sector in general, and the plantation sector in particular. This is because of the many crops

https://doi.org/10.XXXXX/ijssr.xxxx.xx

that produce oil or fat, oil palm produces the largest economic value per hectare in the world (Rusmilawati &; Prasetyaningrum, 2021). Besides being used in various consumer products such as margarine, soap, skin care products and cosmetics, palm oil has also become a feedstock in biodiesel production in Indonesia. The use of palm oil as biodiesel fuel has proven efficient in terms of energy savings and carbon emission reduction. According to Lukman as Secretary General *of the Council of Palm Oil Producing Countries* (CPOPC) that Indonesia can save up to the equivalent of IDR 161.55 trillion through the use of palm oil-based biodiesel (Baskoro, 2023). So that it has a positive impact on market demand (Puspitasari, 2017). Currently, the use of palm oil is used to meet domestic needs and is no longer focused on export activities to consumer countries such as being an environmentally friendly fuel. With the support of the B30 and B50 programs by the government as biodiesel, the need for palm oil will increase and be able to reduce the cost of diesel imports (GAPKI, 2018).

According to data from the United States Department of Agriculture (USDA), Indonesia ranks first with total production reaching 45.5 million metric tons in 2022. This high production is an important indicator for the palm oil industry, which has a major role in the Indonesian economy. However, common problems faced in oil palm cultivation include low productivity and production quality (Wahyudi, 2021). Therefore, forecasting becomes very important because the preparation of a plan is based on a projection or forecast (Setyamidjaja, 2013). In the production process of oil palm plantations , forecasting is one of the important factors to support operations to be more effective and run well. Prediction of palm oil production is very important so that all activities can be carried out planned effectively and efficiently (Syarovy *et al.,* 2023).

This study has differences with research conducted by Syarovy et al., (2023) which uses Recurrent Neural Network-Long Short-Term Memory (RNN-LSTM). RNN-LSTM is a Deep Learning Model (DNN) that can be used to predict based on sequential data. Recurrent Neural Network (RNN) algorithm is one of the deep learning algorithms that can be used to recognize patterns and make predictions on numerical data in the form of time series. While the current study uses Time Series Cross Validation (TSCV) data. Cross validation is a statistical technique used in machine learning and other predictive modeling to assess the performance and generalizability of a model. The characteristic of Time Series Cross Validation (TSCV) data or time series-based data is that the validation sample consists of successive observations (Deng, 2023). In addition, the difference in the current study is using monthly data (1999-2023), while Syarovy et al.'s (2023) study uses annual data (2011-2021).

The problem in this study is that it occurs in the palm oil production of PT. X, i.e. in the last five years, PT. X experienced instability in the amount of palm oil production. Production instability can be caused by several factors such as climate fluctuations, pest and disease attacks, ineffective garden management, and changes in government policies related to the plantation sector. Production evaluation is also carried out every month to see the production performance in that month has reached the production target or vice versa. However, problems arise because the planned and targeted production results are different from the realization of the production results. In addition, increasing palm oil production is only done through land expansion and there is still a gap between actual and potential production. Therefore, an intensification approach is needed in increasing palm oil production by applying the principles of sustainability, protecting land resources, and minimizing production costs.

The formulation of the problem in this study is how the forecasting performance of LSTM and SARIMA models when forecasting palm oil production using TSCV data. How accurate are the forecasting results of LSTM and SARIMA methods when forecasting palm oil production using TSCV data based on MAPE values. The purpose of this study describes the forecasting performance of LSTM and SARIMA models in forecasting palm oil production using TSCV data. Comparing the accuracy of LSTM and SARIMA results in forecasting palm oil production using TSCV data.

This research is expected to provide benefits and is expected to contribute to the development of production forecasting science by providing knowledge about Long Short-Term Memory (LSTM) model forecasting in forecasting palm oil production in PT X using Time Series Cross Validation (TSCV) data.

The results of this research are expected to contribute to PT. X as a palm oil business player related to the accuracy of the Long Short-Term Memory (LSTM) model forecasting results in forecasting palm oil production using Time Series Cross Validation (TSCV) data.

METHODS

In the research to be carried out, the research process will be carried out based on the design of exploratory predictive research data. The purpose of exploring palm oil production data is to explore information and also understanding using palm oil production data at PT X. With the purpose of this study, the design in this study is predictive-exploratory (Kwakkel, 2017). Predictive-exploratory was chosen because this study will predict the data to be used and process it for a certain focus where in this study the main focus is to compare the performance and accuracy of the forecasting results of the Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models in forecasting palm oil production at PT. X uses Time Series Cross Validation (TSCV) data.

This research uses historical data in the form of monthly palm oil production to predict the price of strategic food commodities. The period of palm oil production used is from January 1997 to December 2023 obtained from the website of PT. X or documentation data at PT. X. In this study the data was divided into 4 data scenarios using the Time Series Cross Validation (TSCV) method. Descriptive analysis in this study describes (describes) the mean, minimum, maximum, and standard deviation values of each research variable (Widarjono, 2015). The descriptive statistics of the data are shown in the following Table:

Table 1. Descriptive Statistics of Monthly Production for the Period January 1997 – December 2023

Statistics Descriptive	Value
Mean	320359.2371
Standard Error	6969.516842
Median	332683.8685
Standard Deviation	125451.3032
Sample Variance	15738029465
Range	530278.55
Minimum	63773.49
Maximum	594052.04
Sum	103796392.8
Count	324

Based on the table above, it can be explained as follows: The average palm oil production from 1997 to 2023 is 320,359 tons, the minimum value is 63,773 tons, the maximum value is 594,052 tons, and the standard deviation is 125,451 tons with the number of observations (n) of 324.

RESULTS

Results of forecasting palm oil production using LSTM

The results of palm oil production modeling with LSTM that have been carried out show that palm oil production data shows differences in forecasting values and accuracy in the number of neurons and epochs used. Training data built with the LSTM model with the number of neurons used of 32 gave an increase in average accuracy compared to the model built with the number of neurons used 64. Where the accuracy methods used are RMSE and MAPE. The difference in the accuracy of modeling results with training data is presented in the following table:

Table 2. Accuracy of Data Modeling and Forecasting Results Train with LSTM

Scenario Data	Number of Neurons	Epoch	RMSE	MAP
1	32	50	72212.48	62.71
		100	49658.00	67.21
	64	50	62393.67	64.34

		100	45066.17	68.55
2	32	50	72795.13	56.76
		100	56099.03	58.15
	64	50	68585.49	56.77
		100	40533.24	60.96
3	32	50	58629.83	44.88
		100	49782.73	49.31
	64	50	50987.22	49.89
		100	39913.40	50.83
4	32	50	48364.38	29.07
		100	30955.93	32.08
	64	50	42122.47	28.32
		100	29934.22	34.61
Average			51127.09	50.90

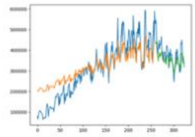
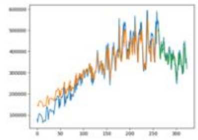
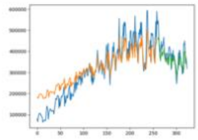
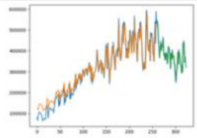
The model obtained is continued analysis to be modeled on test data and then for forecasting. The criteria for comparison of the parameters of the results of empirical data forecasts proposed in this study are RMSE and MAPE. This criterion is a bias or error from the results of forecasting carried out based on the average value of MAPE. The best parameter based on a predefined scenario is selected based on the smallest average value of forecasting bias or error.

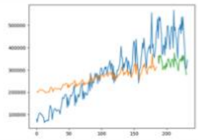
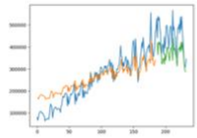
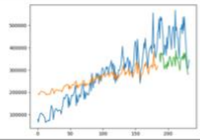
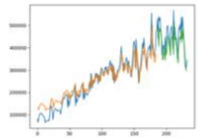
Table 3. Accuracy of Test Data Modeling and Forecasting Results with LSTM

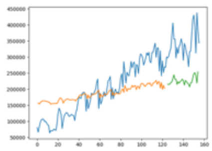
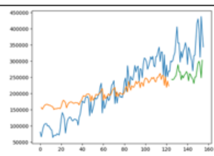
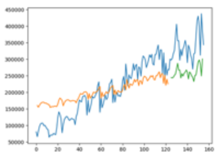
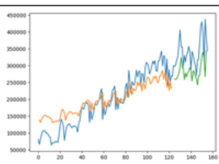
Data Scenarios	Number of Neurons	Epoch	RMSE	MAP
1	32	50	45645.51	14.09
		100	35842.73	15.47
	64	50	39805.29	14.30
		100	36632.29	16.29
2	32	50	125738.46	24.90
		100	91368.86	18.93
	64	50	118883.34	23.59
		100	62089.47	15.72
3	32	50	121843.18	32.93
		100	89569.44	22.94
	64	50	89417.49	22.86
		100	68970.07	17.40
4	32	50	89399.58	43.63
		100	50289.77	22.49
	64	50	78387.99	37.80
		100	41319.69	17.52
Average			75970.51	22.55

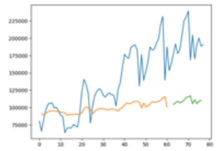
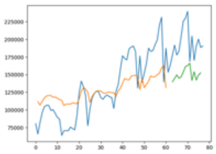
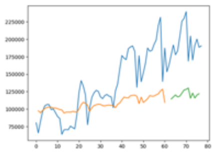
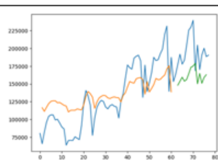
The table above shows the results of LSTM model forecasting evaluation from 4 data scenarios with parameter initialization trials on the number of neurons and epochs. From all parameter trials that have been carried out, the best model is a combination that produces a MAPE value of 14.09 where the smallest MAPE value in the other data scenario is in data scenario 1 with the initialization of epoch parameter 50 with the number of neurons 32.

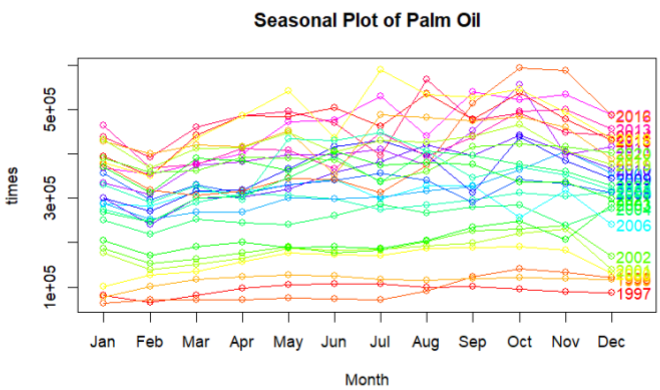
Table 4. Accuracy of Test Data Modeling and Forecasting Results with LSTM

Data	Jumlah Neuron	Epoch	Plot Ramalan
1	32	50	
		100	
	64	50	
		100	

Data	Jumlah Neuron	Epoch	Plot Ramalan
2	32	50	
		100	
	64	50	
		100	

Data	Jumlah Neuron	Epoch	Plot Ramalan
3	32	50	
		100	
	64	50	
		100	

Data	Jumlah Neuron	Epoch	Plot Ramalan
4	32	50	
		100	
	64	50	
		100	

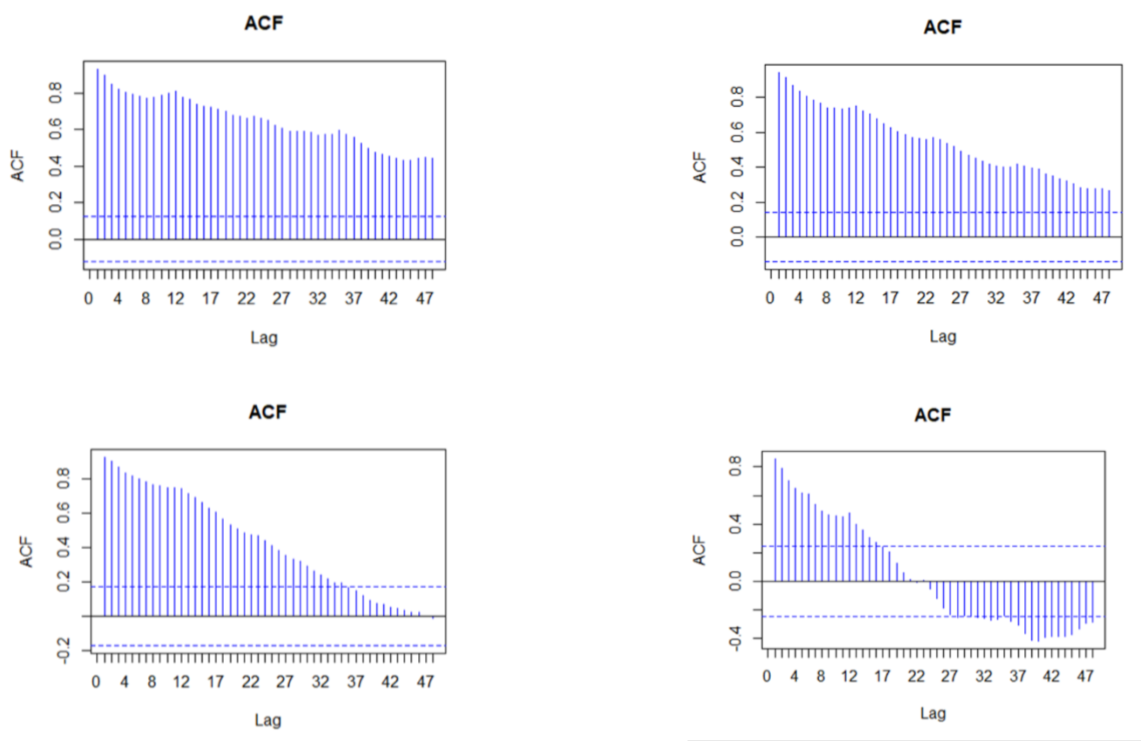


The data that will be used to determine the best model based on the candidate model will be split the data first, namely by dividing the data into two parts, the first part is as training data and the second part as testing data, this data uses the Time Series Cross Validation (TSCV) subset function. This data train is what will be used to build the model.

```
{r}
train.ts1 <- subset(data.ts[,"Sawit"],start=1,end=259)
train.ts2 <- subset(data.ts[,"Sawit"],start=1,end=194)
train.ts3 <- subset(data.ts[,"Sawit"],start=1,end=130)
train.ts4 <- subset(data.ts[,"Sawit"],start=1,end=65)
test.ts1 <- subset(data.ts[,"Sawit"],start=260,end=324)
test.ts2 <- subset(data.ts[,"Sawit"],start=195,end=233)
test.ts3 <- subset(data.ts[,"Sawit"],start=131,end=156)
test.ts4 <- subset(data.ts[,"Sawit"],start=66,end=78)
```

Figure 1. Coding R for splitting data

Furthermore, stationary checks on palm oil production data are carried out by formal exploration and testing. Stationary in the mean was observed using the ACF plot. The ACF plot in the figure can be seen from 4 data scenarios showing a slowly downward trend which shows the data is not yet stationary in the mean.



Graph 1. ACF plot of palm oil production is not yet stationary

```
```{r}
library(car)
fligner.test(Sawit~Tahun, data=data.ts)
```

        Fligner-Killeen test of homogeneity of variances

data: Sawit by Tahun
Fligner-Killeen:med chi-squared = 80.912, df = 26, p-value = 1.516e-07
```

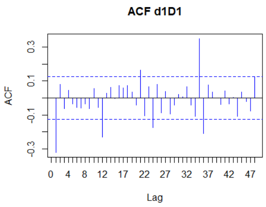
Figure 2. Coding and Output of Fligner-Killen Test results

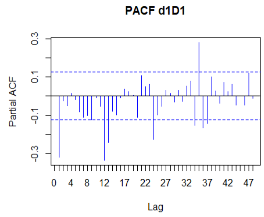
Stationary examination in the mean is also performed by formal assumption test (homogeneity of variety) with the Fligner-Killen test. Fligner-Killeen test using significance level α=5, the p-value obtained is 0.000000151, then p-value<α so it fails to reject H_0 or in other words the variety of data is not stationary, so differencing needs to be done to overcome it. From the candidate parameters that have been obtained in the previous stage, these parameters are combined to form model candidates. Each model has a differencing parameter d = 1, and seasonal differencing D = 1. The following chorelogram plots (ACF and PACF plots) of each data after differencing.

Table 5. chorelogram plots (ACF and PACF plots) of each data after differentiation

Data	ACF	PACF	EACF

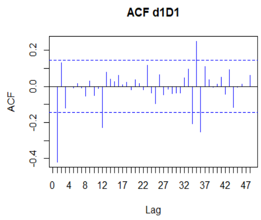
1

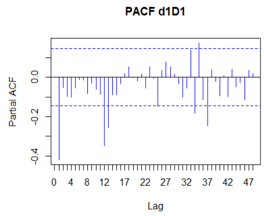





```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x o o o o o o o o o o  x  o  o
1 o x o o o o o o o o o  x  o  o
2 x x o o o o o o o o o  x  o  x
3 x x o o o o o o o o o  x  o  x
4 x o x o o o o o o o o  o  o  o
5 x x o o o o o o o o o  o  o  x
6 x x x o o o o o o o o  o  o  o
7 x x o x o x o o o o o  o  o  o
```

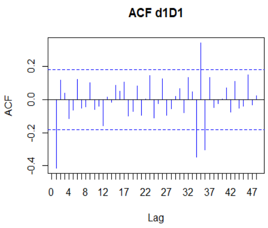
2

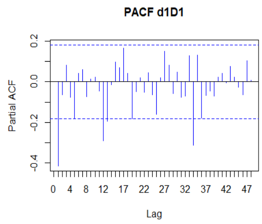





```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x o o o o o o o o o o  x  o  o
1 o x o o o o o o o o o  x  o  o
2 x o o o o o o o o o o  x  o  o
3 x o o o o o o o o o o  x  o  o
4 x o x o o o o o o o o  x  o  o
5 x x x o o o o o o o o  x  o  o
6 x o x o o o o o o o o  x  o  o
7 x o x x o o o o o o o  x  o  o
```

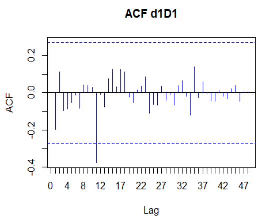
3

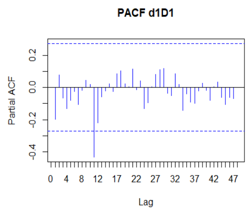





```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x o o o o o o o o o o  o  o  o
1 x x o o o o o o o o o  x  o  o
2 x o x o o o o o o o o  x  o  o
3 x o x o o o o o o o o  o  o  o
4 x x x x o o o o o o o  o  o  o
5 o x x x x o o o o o x  o  o  o
6 o o o o o o o o o o o  o  o  o
7 x x x o o o o o o o o  o  o  o
```

4






```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 o o o o o o o o o o x  o  o  o
1 x o o o o o o o o o x  o  o  o
2 x o o o o o o o o o x  o  o  o
3 x x o o o o o o o o x  o  o  o
4 x o o o o o o o o o x  o  o  o
5 x o x o o o o o o o x  o  o  o
6 o x x o o o o o o o x  o  o  o
7 o x o o o o o o o o o  o  o  o
```

Plots of ACF, PACF, and EACF values from each of these data scenarios are used to determine the values of each order on the model. The SARIMA model is a suitable model to model palm oil production data because the data contains seasonal patterns. The SARIMA model was identified based on ACF and PACF plots from already stationary data. The determination of the order p and q in the regular ARIMA model is done by taking into account the overall lag in the ACF and PACF plots, while for seasonal ARIMA because the seasonal period is annual (s = 12), the determination of the P and Q orders is done by taking into account the lags 12, 24, 36 and so on in the ACF and PACF plots. The figures above all 4 data scenarios show that regular lag on the ACF plot drops dramatically to zero after lag 1 and drops slowly after the seasonal lag, whereas in the PACF plot, regular lag drops dramatically after lag 1 and on seasonal lag drops dramatically after the 12th lag. Based on this, the possible tentative models of each data scenario are: :

Table 6. Tentative model candidate and Auto Arima

Data	Kandidat Model	Kandidat Model Auto Arima
Data Scenario 1	ARIMA (0,1,1,1) × ARIMA (2,1,2) ×(1,1,1) ARIMA (1,1,1,0) ×	ARIMA(3,1,2)(1,0,0)$_{12}$
Data Scenario 2	ARIMA (0,1,1,1) × ARIMA (2,1,1,1) × ARIMA (1,1,1,0) ×	ARIMA(0,1,1)(1,0,0)$_{12}$
Data Scenario 3	ARIMA (0,1,1,1) × ARIMA (2,1,1,1) × ARIMA (1,1,1,2) ×	ARIMA(1,1,0)(1,0,0)$_{12}$
Data Scenario 4	ARIMA (0,1,1,1) × ARIMA (2,1,1,1) × ARIMA (1,1,1,1) ×	ARIMA(1,1,0)(0,0,1)$_{12}$

Then each tentative model of each data scenario is carried out estimation or parameter estimation. The table is a tentative model of each data and its estimated values. And after that the estimated value obtained will be carried out a significance test to prove whether a parameter has meaning in the model. Based on the results obtained and testing the parameters that have been obtained, there are several conjecture models whose parameters are significant as follows.

Table 7. Parameter estimation value of each tentative model candidate

Data	Model 1	Parameter Estimation
1	$ARIMA(0,1,1) \times (1,1,1)12$	MA1: 0.3746 SAR1: 0.2179 SMA1: 0.8787
	$ARIMA(2,1,2) \times (1,1,1)12$	AR1: 0.2575 AR2: 0.3732* MA1: 0.7416* MA2: 0.2348 SAR1: 0.2392* SMA1: 0.8848*
	$ARIMA(1,1,0) \times (1,1,1)12$	AR1: -0.3731 SAR1: 0.2161 SMA1: 0.8747
2	$ARIMA(0,1,1) \times (1,1,1)12$	MA1: 0.5023 SAR1: 0.2770 SMA1: 0.8481
	$ARIMA(2,1,1) \times (1,1,1)12$	AR1: 0.3813* AR2: 0.2773* MA1: 1.000* SAR1: 0.3044* SMA1: 0.8663*
	$ARIMA(1,1,0) \times (1,1,1)12$	AR1: -0.4487 SAR1: 0.3082 SMA1: 0.8685
3	$ARIMA(0,1,1) \times (1,1,1)12$	MA1: 0.5503

		SAR1: 0.1367 SMA1: 1.000
	$ARIMA(2,1,1) \times (1,1,1)12$	AR1: -0.9408* AR2: -0.3737* MA1: -0.2925 SAR1: 0.0876 SMA1: 1.000*
	$ARIMA(1,1,2) \times (1,1,1)12$	AR1: -0.1996 MA1: 0.4279 MA2: -0.1661 SAR1: 0.1019 SMA1: 1.000
4	$ARIMA(0,1,1) \times (1,1,1)12$	MA1: 0.2610 SAR1: 0.6340 SMA1: 0.9981
	$ARIMA(2,1,1) \times (1,1,1)12$	AR1: -0.2843 AR2: 0.0549 MA1: 0.0072 SAR1: 0.5995 SMA1: 0.9990
	$ARIMA(1,1,1) \times (1,1,1)12$	AR1: -0.4325 MA1: -0.1370 SAR1: 0.5982 SMA1: 0.9987

*significant on α=5%.

Table 8. Parameter estimation value of each candidate Auto Arima model

Data	Model Auto Arima	Parameter Estimation
1	ARIMA(3,1,2)$(1,0,0)_{12}$	AR1:1.2940 AR2: -0.1749 AR3:-0.2611 MA1:-1.7430 MA2:0.7560 SAR1:0.4357
2	ARIMA(0,1,1)$(1,0,0)_{12}$	AR1: -0.4100 SMA1:0.4909
3	ARIMA(1,1,0)$(1,0,0)_{12}$	AR1: -0.4696 SMA1:0.2884
4	ARIMA(1,1,0)$(0,0,1)_{12}$	AR1: -0.2071 SMA1:0.6545

There are several SARIMA models that can be used to forecast palm oil production in PT X. The best model will be selected based on the criteria of the smallest AIC (Akaike Information Criterion), Corrected AIC (AICc) and Bayesian Information Criterion (BIC) values.

Table 9. AIC ACCc and BIC Values of Each Candidate Tentative and Auto Arima Model

Data	Model 1	AIC	AICc	BIC
1	$ARIMA(0,1,1) \times (1,1,1)12$	5896.22	5896.38	5910.24
	$ARIMA(2,1,2) \times (1,1,1)12$	5881.18	5881.65	5905.72
	$ARIMA(2,1,2) \times (1,1,0)12$	5895.36	5895.52	5909.38
	$ARIMA(3,1,2) \times (1,0,0)12$	6154.99	6155.57	6183.41
2	$ARIMA(0,1,1) \times (1,1,1)12$	4260.62712331632	4260.8543960436	4273.42111144139
	$ARIMA(2,1,1) \times (1,1,1)12$	4248.41428230623	4248.89704092692	4267.60526449383
	$ARIMA(1,1,0) \times (1,1,1)12$	4261.86535249485	4262.09262522213	4274.65934061992
	$ARIMA(0,1,1) \times (1,0,0)12$	4538.4	4538.53	4548.19
3	$ARIMA(0,1,1) \times (1,1,1)12$	2693.85855367835	2694.21569653549	2704.90724941754
	$ARIMA(2,1,1) \times (1,1,1)12$	2690.7879206477	2691.55155701133	2707.36096425648
	$ARIMA(1,1,2) \times (1,1,1)12$	2692.57596087572	2693.33959723935	2709.1490044845
	$ARIMA(1,1,0) \times (1,0,0)12$	2954.37	2954.57	2962.95
4	$ARIMA(0,1,1) \times (1,1,1)12$	1180.14944662447	1181.00051045425	1187.95442149879
	$ARIMA(2,1,1) \times (1,1,1)12$	1183.26735282762	1185.13401949429	1194.97481513911
	$ARIMA(1,1,1) \times (1,1,1)12$	1181.28863405725	1182.59298188333	1191.04485265015
	$ARIMA(1,1,0) \times (0,0,1)12$	1438.49	1438.89	1444.97

Data scenarios	Best models
1	$ARIMA(2,1,2)\times(1,1,1)_{12}$
2	$ARIMA(2,1,1)\times(1,1,1)_{12}$
3	$ARIMA(2,1,1)\times(1,1,1)_{12}$
4	$ARIMA(0,1,1)\times(1,1,1)_{12}$

After obtaining the best model from each data scenario, then the model parameter testing will be carried out using the User Defined Function printstatarima.

Table 10. User Defined Function test Results

Scenario	Model parameter test results
Data 1 Model $ARIMA(2,1,2)\times(1,1,1)_{12}$	Coefficients: s.e. t sign. ar1 0.2575 0.2338 1.1014 0.2718 ar2 0.3732 0.1427 2.6153 0.0094 ma1 -0.7416 0.2477 -2.9939 0.0030 ma2 -0.2348 0.2383 -0.9853 0.3254 sar1 0.2392 0.0836 2.8612 0.0046 sma1 -0.8848 0.0595 -14.8706 0.0000
Data 2 Model $ARIMA(2,1,1)\times(1,1,1)_{12}$	Coefficients: s.e. t sign. ar1 0.3813 0.0730 5.2233 0.0000 ar2 0.2773 0.0738 3.7575 0.0002 ma1 -1.0000 0.0265 -37.7358 0.0000 sar1 0.3044 0.1070 2.8449 0.0049 sma1 -0.8663 0.0897 -9.6577 0.0000

Data 3 Model ARIMA(2,1,1)×(1,1,1)$_{12}$	Coefficients: s.e. t sign. ar1 -0.9408 0.2464 -3.8182 0.0002 ar2 -0.3737 0.1418 -2.6354 0.0094 ma1 0.2925 0.2554 1.1453 0.2542 sar1 0.0876 0.1039 0.8431 0.4007 sma1 -1.0000 0.1021 -9.7943 0.0000
Data 4 Model ARIMA(0,1,1)×(1,1,1)$_{12}$	Coefficients: s.e. t sign. ma1 -0.2610 0.1476 -1.7683 0.0818 sar1 0.6340 0.2409 2.6318 0.0106 sma1 -0.9981 0.5858 -1.7038 0.0933

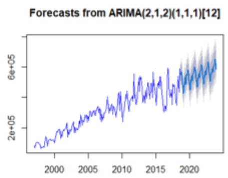
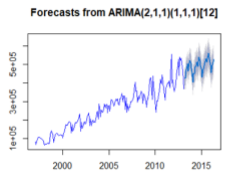
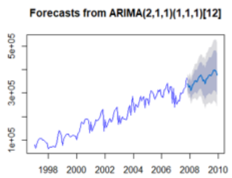
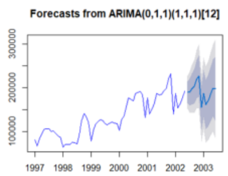
Based on the table above, the model is significant at p-value < α = 0.05. So, it was found that there was 1 significant model all the model coefficients, namely the 2nd data scenario with the ARIMA(2,1,1)×(1,1,1)$_{12}$ model. Furthermore, the Residual Correlation Test (LjungBox Test) and Normality Test (Jarque Bera Test) were carried out. The following output to determine the residual correlation of white noise and normality test output can be seen in the Table below.

Table 11. LjungBox and Jarque Bera test Results

Skenario Data	Nilai *LjungBox Test*	Nilai Jarque Bera Test
Data 1 Model ARIMA(2,1,2)×(1,1,1)$_{12}$	lags statistic df p-value 5 0.8084575 5 0.97649076 10 7.8488233 10 0.64360084 15 12.3897716 15 0.64931892 20 24.0007936 20 0.24235750 25 34.8895094 25 0.09022142 30 40.0713929 30 0.10348891	Jarque Bera Test data: residuals(tmodel2) X-squared = 90.338, df = 2, p-value < 2.2e-16
Data 2 Model ARIMA(2,1,1)×(1,1,1)$_{12}$	lags statistic df p-value 5 0.3216881 5 0.9972152 10 6.1804317 10 0.7998831 15 11.6811465 15 0.7029858 20 12.9993779 20 0.8774107 25 23.2660617 25 0.5620303 30 29.1638450 30 0.5090020	Jarque Bera Test data: residuals(tmodel2) X-squared = 64.354, df = 2, p-value = 1.066e-14
Data 3 Model ARIMA(2,1,1)×(1,1,1)$_{12}$	lags statistic df p-value 5 4.209054 5 0.51972676 10 11.076840 10 0.35156289 15 21.469303 15 0.12249307 20 32.228325 20 0.04092533 25 41.183582 25 0.02195737 30 45.781216 30 0.03259940	Jarque Bera Test data: residuals(tmodel2) X-squared = 100.67, df = 2, p-value < 2.2e-16
Data 4 Model ARIMA(0,1,1)×(1,1,1)$_{12}$	lags statistic df p-value 5 2.619352 5 0.7584228 10 3.592723 10 0.9638558 15 21.203127 15 0.1304639 20 26.310279 20 0.1558071 25 29.186815 25 0.2561822 30 30.321619 30 0.4492734	Jarque Bera Test data: residuals(tmodel1) X-squared = 12.732, df = 2, p-value = 0.001719

The table above shows the results of the Ljung – Box p-value test for time lag 5, time lag 10 time, lag 15, lag 20, lag 25 and time lag 30 is greater than α = 0.05. It can be concluded that the model of each data scenario meets the requirements of white noise or is random. Furthermore, the results of the Normality Test (Jarque Bera Test) found that the value of all models from 4 data scenarios was smaller than alpha 5% (0.05). Thus, it can be concluded that the data involved in the study is not normally distributed. The results of the formal assumption test above on all data are not met, so this study focuses on the significance of the modeling results on the parameter values. Furthermore, the best model obtained is data forecasting. The best model obtained is then carried out both on the training data and validated by being used to forecast the test data. The results of the accuracy of the problem in this study were seen based on the RMSE, MSE, and MAPE values.

Table 12. Best Model Forecasting plot of 4 Data Scenarios

Data	Plot Peramalan	Akurasi					
		Data Latih			Data Uji		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE
1		34418.6	23360.5	7.61513	180937.6	165877.8	46.52791
2		27022.6	18164.3	**0.483**	78438.06	61377.4	**1.631**
3		19159.38	13365.33	7.182571	41589.2	35204.72	10.537551
4		15713.95	10022.9	8.080656	13303.17	12424.16	6.272402

Each model from 4 data scenarios obtained the best SARIMA model, namely SARIMA$(2,1,1)\times(1,1,1)_{12}$ with a MAPE value of 1.63% with an accuracy rate of 98.36%.

Comparison of LSTM and SARIMA palm oil production forecasting results

Determination of the best parameters from forecasting results both on training data and test data cannot be done directly, but hypothesis testing is carried out first. The test used in this study was to use the t test. The purpose of this test is to detect real differences in the average RMSE and MAPE values. The results of hypothesis testing conducted showed that the results of training data forecasting between LSTM and SARIMA methods had significant differences, p-value for the average RMSE and MAPE <0.05.

CONCLUSION

The conclusion of this study is that from data processing and analysis in the previous chapter, it can be concluded that forecasting the amount of palm oil production in PT X can be modeled with LTSM and SARIMA method using Time Series Cross Validation (TSCV) data. The results of the analysis conducted on monthly palm head production data at PT X from 1997 – 2023 showed the best LSTM model in data scenario 1 with 259 test data and 65 test data with initialization of 32 neuron count and 50 epoch count. While the best SARIMA model is SARIMA$(2,1,1)(1,1,1)_{12}$ in data scenario 2 with test data 194 and test data 39. The composition of test data and training data as well as Time Series Cross Validation (TSCV) data has a significant influence on forecasting. Overall, the results of the data scenario trial show that forecasting performance can be simulated with Time Series Cross Validation (TSCV) data. The performance of the SARIMA$(2,1,1)(1,1,1)_{12}$ model is better than LSTM. This performance is measured based on the MAPE value followed by variety analysis. The SARIMA model gives a MAPE value of 1.63% which is smaller than LSTM with a value of 14.06%. It can be concluded that the LSTM model is suitable to be used as a model to forecast PT X's monthly palm oil production.

From the results of the research that has been done, there are several suggestions that can be done for further research, namely adding the palm oil production dataset to daily so as to get more accurate forecasting results. In addition to palm oil production variables, other variables can also be used to see their effect on forecasting accuracy, such as rainfall, soil content. Although the models in this study have shown fairly high accuracy results, other models are needed that are better able to capture random patterns in the data. For future research, in order to adjust the method used with existing datasets. The more historical data the LSTM method uses, the more accurate the prediction results. Conversely, the more data sets used, the less accurate the SARIMA method tends to be.

REFERENCES

Adhiva, J., Putri, S. A., & Setyorini, S. G. (2020). Prediksi Hasil Produksi Kelapa
Sawit Menggunakan Model Regresi pada PT. Perkebunan Nusantara V. Jurnal Semin. Nas. Teknol. Informasi, Komun. dan Ind, 155–162. https://scholar.google.com/citations?view_op=view_citation&hl=id&user=eRDX3NAAAAAJ&citation_for_view=eRDX3NAAAAAJ:Y0pCki6q_DkC.

Agustina, L. (2013). Dasar Nutrisi Tanaman. Jakarta: Rineka Cipta.

Baskoro, F.M. (2023). Indonesia-Malaysia Bergerak Bersama Jaga Pasar Minyak Kelapa Sawit di India. https://www.beritasatu.com/ekonomi/1069016/indonesiamalaysia-bergerak-bersama-jaga-pasar-minyak-kelapa-sawit-di-india.

Cryer, J., & Chan, K.-S. (2013). Time Series Analysis With Apllication in R USA: Springer.

Ditjenbun. (2021). Statistik Perkebunan Unggulan Nasional 2019-2021, Kelapa Sawit. Jakarta: Direktorat Jendral Perkebunan Kementerian Pertanian Republik Indonesia.

Deng, A. (2023). A Note on Time Series Cross Validation: Theoretical Properties and Empirical Performance. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4366573.

Elvani, S. P., Utary, A. R., & Yudaruddin, R. (2016). Peramalan Jumlah Produksi Tanaman Kelapa Sawit dengan Menggunakan Metode Arima. Jurnal Manajemen, 8(1), 95–112. https://journal.feb.unmul.ac.id/index.php/JURNALMANAJEMEN/article/view/1189%0Ahttps://journal.feb.unmul.ac.id/index.php/JURNALMANAJEMEN/article/download/1189/115

Fauziah, F., Ningsih, Y. I., & Setiarini, E. (2019). Analisis Peramalan (Forecasting) Penjualan Jasa Pada Warnet Bulian City di Muara Bulian. Eksis: Jurnal Ilmiah Ekonomi Dan Bisnis, 10(1), 61. https://doi.org/10.33087/eksis.v10i1.160

Fisabti, D. A. (2022). Forecasting Jumlah Produksi Kelapa Sawit Menggunakan Metode Fuzzy Time Series Average Based. Tugas Akhir. Fakultas Sains dan Teknologi, Universitas Islam Negeri Sultan Syarif Kasim Riau. https://repository.uin-suska.ac.id/57810/1/LAPORAN%20LENGKAP%20TANPA%20HASIL%20PENELITIAN.pdf.

García-Rodríguez, L. D. C., Prado-Olivarez, J., Guzmán-Cruz, R., Rodríguez-Licea, M. A., Barranco-Gutiérrez, A. I., Perez-Pinal, F. J., & Espinosa-Calderon, A. (2022). Mathematical Modeling to Estimate Photosynthesis: A State of the Art. Applied Sciences (Switzerland), 12(11). https://doi.org/10.3390/app12115537

GAPKI. (2018). Sawit Indonesia Menyongsong Awal Tahun yang Lebih Menjanjikan. Jakarta. https://gapki.id/news/14413/sawit-indonesia-menyongsong-awal-tahun-yang-lebih-menjanjikan.

Ginting, R. (2013). Sistem Produksi. Yogyakarta: Graha Ilmu.

Gujarati, D., & Porter, D. C. (2013). Econometrics. New York: Mc. Graw Hill Inc.

Hasibuan, S. L., & Novialdi, Y. (2022). Prediction of Bulk and Packaged Cooking Oil Prices Using the Long Short-Term Memory (LSTM) Algorithm. Jurnal Ilmu Komputer Dan Agri-Informatika 9(2):149-157, 9. https://jurnal.ipb.ac.id/index.php/jika

Heizer, J., & Render, B. (2013). Operation Management (Manajemen Operasi). Jakarta: Salemba Empat.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Kiswanto, J.H., Purwanta, B., & Wijayanto (2008). Bogor Teknologi Budidaya Kelapa Sawit. Balai Besar Pengkajian dan Pengembangan Teknologi Pertanian. Bogor: Balai Pengkajian Teknologi Pertanian Lampung.

Lu, Y. Shi, Y., Jia, G., & Yang, J. (2018). A new method for semantic consistency verification of aviation radiotelephony communication based on LSTM-RNN. Int. Conf. Digit. Signal Process DSP, pp. 422–426.

Lipton, Z. C., Kale, D. C., Elkan, C., & Wetzel, R. (2015). Learning to diagnose with LSTM recurrent neural networks, arXiv preprint arXiv:1511.03677.

Luthfiah, Agmalaro, H., & Asyhar, M. (2018). Prediksi Temporal untuk Kemunculan Titik Panas di Kabupaten Rokan Hilir Riau Menggunakan Long Short Term Memory RNN. https://repository.ipb.ac.id/handle/123456789/94441.

Lv, S-X. (2022). Effective machine learning model combination based on selective ensemble strategy for time series forecasting. Information Sciences 612, Pages 994-1023. https://www.sciencedirect.com/science/article/abs/pii/S0020025522010465.

Lipton, Z. C., Berkowitz, J., & Elkan, C. (2015). A Critical Review of Recurrent Neural Networks for Sequence Learning. June. http://arxiv.org/abs/1506.00019

Marpaung, D., Sumarno, S., & Gunawan, I. (2020). Prediksi Produktivitas Kelapa Sawit di PTPN IV dengan Algoritma Backpropagation. Kajian Ilmiah Informatika & Komputer, 1(2), 35–41.

Montgomery, D. C., Johnson, L. A., & Gardiner, J. S. (2013). Forecasting and Time Series Analysis. New York: McGraw-Hill.

Mukhlis, M., Kustiyo, A., & Suharso, A. (2021). Peramalan Produksi Pertanian Menggunakan Model Long Short-Term Memory. Bina Insani Ict Journal, 8(1), 22. https://doi.org/10.51211/biict.v8i1.1492

Pang, M. B., & Zhao, X. P. (2008). Traffic Flow Prediction of Chaos Time Series by Using Subtractive Clustering for Fuzzy Neural Network Modeling. Proceedings - Second International Symposium on Intelligent Information Technology Application, IEEE Computer Society, 1, 23–27. http://doi.org/10.1109/IITA.2008.50.

Pahan, I. (2013). Panduan Lengkap Kelapa Sawit: Manajemen Agribisnis dari Hulu Hingga Hilir. Jakarta: Penerbit Swadaya.

Puspitasari, D. I. (2017). Penerapan Data Mining Menggunakan Perbandingan Algoritma Greedy Dengan Algoritma Genetika Pada Prediksi Rentet Waktu Harga Crude Palm Oil. Elinvo (Electronics, Informatics, and Vocational Education), 2(1), 21–26. https://doi.org/10.21831/elinvo.v2i1.13033.

Rusmilawati, N., & & Prasetyaningrum, P.T. (2021). Penerapan Data Mining Dalam Prediksi Hasil Produksi Kelapa Sawit PT Borneo Ketapang Indah Menggunaka Metode Linier Regression. Journal Of System and Artificial Intelligence 1(2), 1–7. http://jisai.mercubuana-yogya.ac.id/index.php/jisai/article/view/33%0Ahttp://jisai.mercubuana.

Sen, S., Sugiarto, D., & Rochman, A. (2020). Komparasi Metode Multilayer Perceptron (MLP) dan Long Short Term Memory (LSTM) dalam Peramalan Harga Beras. XII(1), 35–41.

Syarovy, M., Nugroho, A. P., Sutiarso, L., Suwardi, Muna, M. S., Wiratmoko, A., Sukarman, & Primananda, S. (2023). Prediction of Oil Palm Production Using Recurrent Neural Network Long Short-Term Memory (RNN-LSTM) (Vol. 1). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-122-7_6

Sastrosayono, S. (2013). Budidaya Kelapa Sawit. Jakarta: Agromedia Pustaka.

Syarovy, M., Nugroho, A. P., Sutiarso, L., Suwardi, Muna, M. S., Wiratmoko, A., Sukarman, & Primananda, S. (2023). Utilization of Big Data in Oil Palm Plantation to Predict Production Using Artificial Neural Network Model. Proceedings of the International Conference on Sustainable Environment, Agriculture and Tourism (ICOSEAT 2022), 26(January). https://doi.org/10.2991/978-94-6463-086-2_67

Setyamidjaja, D. (2013). Kelapa Sawit : Teknik Budi Daya; Panen, dan Pengolahan. Jakarta: Kanisius.

Syahputra, E., -, S., & Dian, S. (2011). Weeds Assessment di Perkebunan Kelapa Sawit Lahan Gambut. Perkebunan Dan Lahan Tropika, 1(1), 37. https://doi.org/10.26418/plt.v1i1.120

Supangat, A. (2013). Statistika Dalam Kajian Deskriptif. Jakarta: Gramedia Pustaka Utama

Sekaran, U., & Bougie. (2013). Research Methods For Business: A Skill Building Approach. New Delhi: Sharda Ofsett Press.

Widarjono, A. (2015). Ekonometrika. Yogyakarta: Ekonisia FE UII.

Wahyudi. (2021). Peramalan produksi Tandan Buah Segar (TBS) kelapa sawit di PT. Bintang Selatan Agro menggunakan jaringan syaraf tiruan algoritma Backpropagation dan Conjugate Gradient Powell- Beale Restarts. Indonesian Journal of Data and Science, 2(3), 133–147. https://doi.org/10.56705/ijodas.v2i3.56

Wiranda, L., & Sadikin, M. (2019). Penerapan Long Short Term Memory Pada Data Time Series Untuk Memprediksi Penjualan Produk Pt. Metiska Farma. Jurnal Nasional Pendidikan Teknik Informatika (JANAPATI), 8(3), 184–196.

Zahara, S., Sugianto, & M. Bahril Ilmiddafiq. (2019). Prediksi Indeks Harga Konsumen Menggunakan Metode Long Short Term Memory (LSTM) Berbasis Cloud Computing. Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), 3(3), 357–363. https://doi.org/10.29207/resti.v3i3.1086.