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Shallot Price Forecasting Models: Comparison among Various Techniques

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Abstract
Shallot is one of several horticultural products exported from Thailand to various countries. Despite an increase in shallot prices over the years, farmers face challenges in price forecasting due to fluctuations and other relevant factors. While different forecasting techniques exist in the literature, there is no universal approach due to varying problems and datasets. This study focuses on predicting shallot prices in Northern Thailand from January 2014 to December 2020. Traditional and machine learning models, including ARIMA, Holt-Winters, LSTM, and ARIMA-LSTM hybrids, are proposed. The LSTM model considers temperature and rainfall as influencing factors. Evaluation metrics include RMSE, MAE, and MAPE. Results indicate that the ARIMA-LSTM hybrid model performs best, with RMSE, MAE, and MAPE values of 10.275 Baht, 8.512 Baht, and 13.618%, respectively. Implementing this hybrid model can provide shallot farmers with advanced price information for informed decision-making regarding cultivation expansion and production management.

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1. Introduction

Shallots are one of the important agricultural products in Thailand, mainly exported to Asia (e.g., Malaysia, Indonesia, Singapore), the Middle East, and Europe (e.g., Netherlands, Germany, England, etc.) (Palangkaset, 2019). Shallot cultivation is mainly based in the northern, northeastern, and western regions of Thailand. It was reported that in 2020, the shallot price was higher than it was in the previous years, thus generating higher income for Thai farmers (Office of Agricultural Economics, 2020). As a result, there are possibilities that Thai farmers may expand their shallot cultivation for the next production cycle in response to the higher prices and market demand.

Although the shallot price in Thailand tends to increase, it still has high volatility as shown in Fig. 1 possibly because of the economic conditions, cultivation and harvesting areas, the number of shallot farmer households, import and export volumes, the weather conditions, and several other factors (Varun et al., 2010). Consequently, forecasting the shallot price often becomes a complex and challenging task for farmers and also policymakers. Although several forecasting techniques, ranging from naive to complex, have been proposed by researchers, there is no best technique due to the different nature and context of the time-series data. Additionally, the price is often affected by multiple factors and, therefore, maintaining a good balance between selecting the right predictors and establishing the model with simple architecture and interpretation becomes challenging (Bhandari et al., 2022).

This research, therefore, aims to develop the time series model for predicting the shallot price under the set of important factors, which focuses on the ARIMA-LSTM hybrid model, by performing a comparison of the hybrid model and other standalone models including ARIMA, Holt-Winters, and LSTM models. This research contributes to the literature by demonstrating that the hybrid model can cope with the shortcomings of the standalone models and thus provides better forecasting accuracy. In addition, effective price forecasting helps farmers in seizing revenue-generating opportunities and making better decisions throughout the value chain, spanning from planting to harvesting. By doing so, it will eventually contribute to poverty alleviation and enhance worldwide food security.

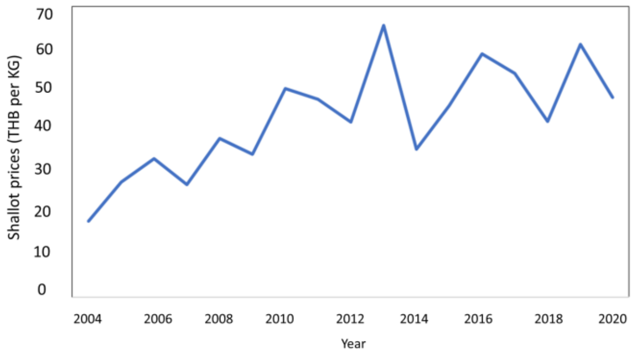

Fig. 1. Monthly shallot price from 2004 – 2020

2. Theoretical background and literature review

This research focuses on four forecasting techniques. First, the Auto-Regressive Integrated Moving Average (ARIMA) model is recognized as the well-known stochastic forecasting method which utilizes historical data and handles only the stationary time series data by default. According to Laosiritaworn (2011), the ARIMA model is generally denoted as ARIMA (p, d, q) (P, D, Q) where p is the number of auto-regressive terms, d is the differencing degree of time series data and previous value, q represents the number of parameters in the moving average model, P denotes the number of parameters in the autoregressive seasonal model, D signifies the degree of seasonal differencing, Q indicates the number of parameters in moving average seasonal model, and s represents the period of seasonality.

Second, the Holt-Winters smoothing model is a classical technique used for short-term forecasting with seasonal and trend patterns (Winters, 1960). It can be classified as an additive model and multiplicative model based on the seasonal component of the series with three smoothing equations.

Third, the Long Short-Term Memory Network model (LSTM) was introduced by Hochreiter and Schmidhuber (1997). It has been one of the most widely used variations of deep learning methods and recurrent neural networks. The purpose of LSTM is to effectively retain information over extended periods, enabling the identification of long-term patterns within time series trends. The fundamental components of LSTM are the cell stage and the gate structure, which includes the forget gate, input gate, and output gate. The cell is responsible for storing values at specific intervals, while the three gates regulate the data flow in and out of the cell based on the weight values.

Last, the ARIMA-LSTM is a novel hybrid model considering the advantages of linearity and nonlinearity. Specifically, the ARIMA model is utilized to analyze the linear aspect of the time series, while the LSTM model handles the non-linear component. This hybrid model is advantageous, particularly in cases where individual models are unable to capture all the patterns present in the time series data. The ARIMA-LSTM model can be constructed as shown in Fig. 2 where '*', '+', and '/2' mean being multiplied, added, and divided by two, respectively.

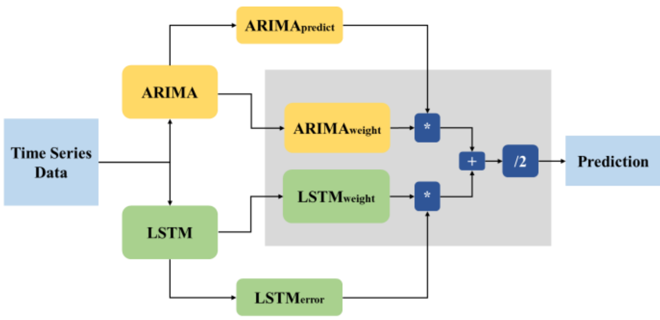

Fig. 2. The ARIMA-LSTM model

Literature often uses several indicators to evaluate the performance of the forecasting model. Common indicators include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The smaller the values of these indicators, the better the performance of the forecasting model. Nevertheless, it should be noted that there is no one-size-fits-all indicator (Ning et al. 2022). Each indicator consists of both benefits and drawbacks and requires a different interpretation. Therefore, several studies often employ multiple performance metrics for comparison among different forecasting models.

Given a variety of forecasting models, previous research focusing on the price of agricultural products often employs multiple techniques and then selects the best model that offers the maximum prediction accuracy. For instance, Sabu and Kumar (2020) predicted the areca nut prices in Kerala, India. In their research, it was discovered that the LSTM model outperformed the ARIMA model, the seasonal variation model of ARIMA (SARIMA), and Holt-Winter's Seasonal model, due to the lowest value of RMES. Jaiswal et al. (2021) developed deep long short-term memory (DLSTM) for predicting the prices of maize and palm oil. They presented that the DLSTM model gave superiority over the ARIMA model and conventional time-delay neural network model given that the RMSE, MAPE, and MAD were the lowest. Banerjee et al. (2022) reported that the LSTM model outperformed other models such as linear regression, K-Nearest Neighbor (KNN) algorithm, regression tree, Random Forest (RFJ) algorithm, Support Vector Regressor (SVR), ARIMA, and Markov switching model for predicting the long-term price of horticultural products.

Some studies investigate the performance of the hybrid model as compared to the stand-alone models. For example, Purohit et al. (2022) developed the ARIMA-LSTM hybrid model in addition to the other four models for the prediction of crop prices. Their significant findings indicated that there was no best method for every crop price due to the different characteristics of the crop price time-series data. Nevertheless, they observed that the ARIMA-LSTM hybrid model outperformed the individual models in forecasting crop prices, suggesting it as a superior choice.

3. Methods

3.1. Data preparation

There are two input data for developing the forecasting model. First, the dependent variable is the monthly shallot prices from January 2014 to December 2020 (84 months) in three provinces in Thailand: Chiang Mai, Lamphun, and Payao. Second, for machine learning models such as LSTM, rainfall and temperature are selected as important predictors of the shallot price. As suggested by prior research, the forecast of crop prices relies primarily on factors such as rainfall and temperature (Varun et al., 2010, Mohanty et al., 2023). This is also in line with Schlenker and Roberts (2009) that the production of agricultural products is influenced by weather conditions, consequently impacting prices.

Therefore, the monthly average temperature and the monthly total amount of rainfall were collected from the open-source database of the Fiscal Policy Office under the Ministry of Finance of Thailand. The data from 2014 to 2019 were assigned as the training dataset aiming to teach the model to recognize the pattern of the time series data. On the contrary, the data of 2020 were assigned as the testing dataset for evaluating the accuracy of the models.

Based on the time series decomposition in Fig. 3, the shallot price exhibited an increasing trend over seven years. The seasonal pattern of the shallot price also existed every year where the price was the lowest during March and April and was the highest during November and December due to the low temperature which was suitable for cultivating quality shallots. Fig. 4 shows that the monthly average temperature and monthly total rainfall in Chiang Mai (CM), Phayao (PY), and Lamphun (LP) also exhibited similar trends and patterns to the monthly shallot prices, thus confirming that temperature and rainfall could be the influencing predictors. In a nutshell, ARIMA, Holt-Winters smoothing, LSTM, and the ARIMA-LSTM hybrid models are appropriate for capturing both trend and seasonality of the shallot price.

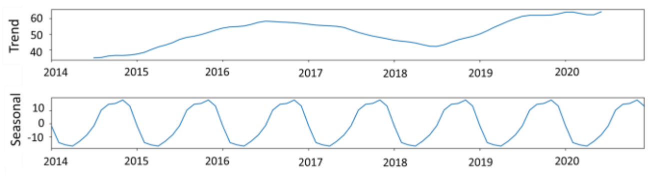

Fig. 3. Time series decomposition of shallot prices

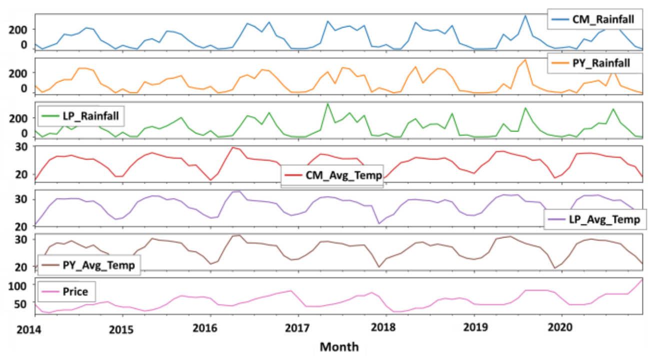

Fig. 4. Monthly average temperature and monthly total rainfall

Based on a correlation heatmap of all pairs between factors (e.g., temperature and rainfall) and provinces (Chiang Mai, Phayao, and Lamphun) presented in Appendix A (Fig. 1), the correlation coefficients between temperature and rainfall, both within and between provinces, are positively moderate (0.49 – 0.60), indicating that temperature and rainfall are independent. Focusing on each factor, the correlation coefficients from every pair of provinces are positively high (0.82 – 0.93), thus indicating that the temperature and rainfall of the three provinces are not different. The results from the One-Way ANOVA ($\alpha = 0.05$) confirm this assumption with the *p*-value of the temperature and rainfall equal to 0.086 and 0.615, respectively. Although the data from any province could be used for the LSTM model, this study selected the data from Chiang Mai given the lowest correlation coefficient of 0.49 to mitigate the collinearity issues.

3.2. The development of the ARIMA model

It is evident in Fig. 5 that the shallot price fluctuated over the years, indicating that the time-series data was not stationary. The data was then transformed by the first-order differencing ($d = 1$) as shown in Fig.6.

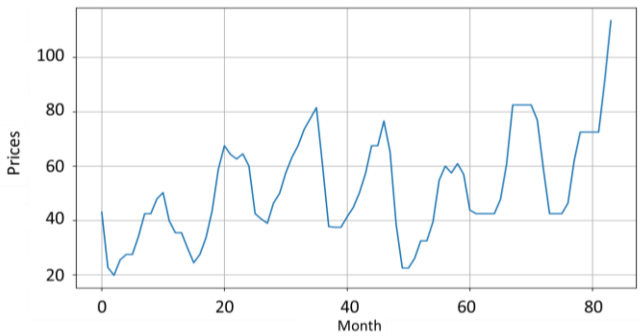

Fig. 5. Non-transformed time-series data of shallot price

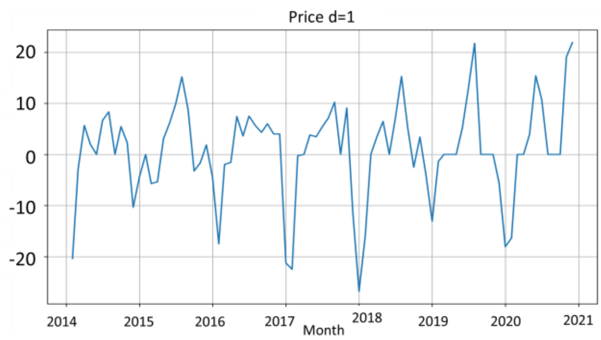

Fig. 6. Transformed time-series data of shallot price

According to the Augmented Dickey-Fuller (ADF) test results, the absolute ADF statistic value of 3.0996 is greater than the critical value of 2.9026 at the significance level of 0.05 (*p*-value = 0.0266). Therefore, the transformed time series was stationary.

Following that, the values of hyperparameters *p* and *q* were established by examining Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots displayed in Fig. 7 and Fig. 8, respectively. The blue bands represent confidence bands of significance, indicating that values within these bands are considered as 0. Both ACF and PACF plots exhibit a gradual decreasing pattern. Finally, the ARIMA (0,1,0) (3,1,1) model was developed.

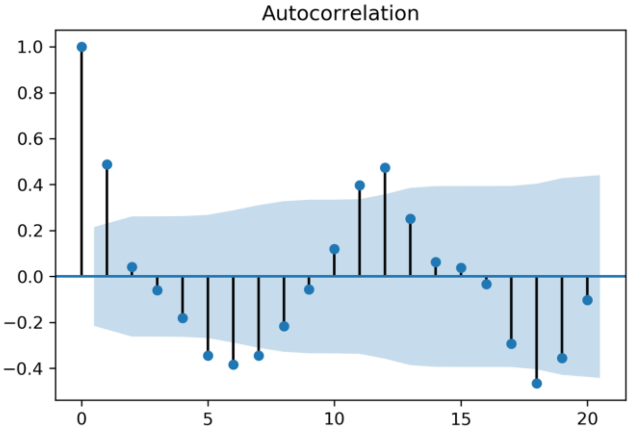

Fig. 7. ACF plot

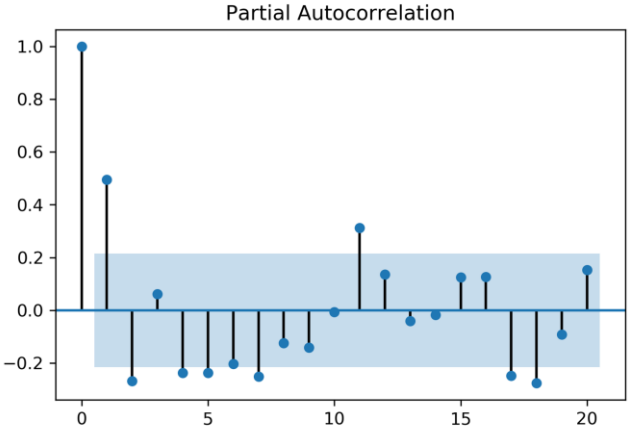

Fig. 8. PACF plot

3.3. The development of the Holt-Winters Smoothing model

In developing the Holt-Winters Smoothing model, the time series (Y_t) was divided into its constituent components of trend (T_t) and seasonality (S_t). The decomposition model is commonly classified as either additive or multiplicative, represented by equations (1) and (2) respectively.

$$\hat{Y}_t(p) = \hat{T}_t(t) + p\hat{\beta}_1(t) + \hat{S}_i(t) \quad (1)$$

$$\hat{Y}_t(p) = \left(\hat{T}_t(t) + p\hat{\beta}_1(t)\right)\hat{S}_i(t) \quad (2)$$

Where $\hat{T}_t(t)$ is the trend estimate, $p\hat{\beta}_1(t)$ is the level estimate, and $\hat{S}_i(t)$ is the seasonality estimate.

The trend component was determined by applying a simple linear regression model with the least squares estimates. To calculate the seasonal factor for each period, the time series was detrended. In this case, the multiplicative model of the decomposition method was chosen because the amplitude of the seasonal fluctuations varies based on the level of the series, as shown in Fig. 2. The parameter for seasonal periods was set to 12, as the seasonality occurred yearly.

3.4. The development of the LSTM model

The LSTM model consists of the input layer, hidden layer, and output layer. To construct the model, first, shallot price data were normalized into the range of 0 – 1 during training. Next, the input layer was reshaped to three-dimensional with the number of samples equal to 72 (60 for training and 12 for testing), the number of timesteps equal to 1, and the number of features equal to 1 due to only one variable (shallot price). To specify the LSTM hidden layer, the number of neurons in each hidden layer ranged from 100 to 400. The last layer was an LSTM dense output layer with a size of 12 referring to a prediction for monthly shallot price in 2020.

The next step is to fit the LSTM model into the training dataset. The number of epochs ranged from 100 to 400 indicating how quickly the model learned the training dataset. There were five different models with 200, 250, 300, 350, and 400 neurons. Every model was trained for 100, 200, 300, and 400 epochs, resulting in 20 different combinations. The results report that the best possible combination was 300 neurons and 200 epochs giving the minimum values of MAE, RMSE, and MAPE.

3.5. The development of the ARIMA-LSTM model

The hybrid model combines the use of two methods: the linear statistical approach of ARIMA and the deep-learning approach of LSTM. ARIMA was employed as an independent model to separate the linear and nonlinear elements present in the time series data. LSTM, on the other hand, was utilized to forecast the residuals generated by the nonlinear processes, which were extracted through ARIMA predictions. In simpler terms, the ARIMA model focuses on the trend component, while the LSTM model is applied to the seasonal and residual components.

3.6. Model accuracy evaluation

The prediction accuracy of each forecasting model was assessed based on three indicators: RMSE, MAE, and MAPE. It should be noted that the R-squared was not chosen since it was not appropriate for non-linear data. The formulas of RMSE, MAE, and MAPE were presented in equations (3), (4), and (5) respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_t - \hat{Y}_t\right)^2} \quad (3)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_t - \hat{Y}_t\right| \quad (4)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \quad (5)$$

Where Y_t was the original time series and $\hat{Y}_t$ represented the predicted time series computed from the model. The small values of these three indicators indicated a small variation between actual data and forecasted data.

4. Results and discussion

The prediction of shallot price from the ARIMA model is illustrated in Fig. 9. It can be seen that for the training dataset, the prediction (red dot) tends to follow the actual data (in blue), especially during 2017 and 2019. However, the prediction based on the testing dataset (in green) is still not accurate.

The results in Fig. 10 report that based on the training dataset, the predictions from both models (red dot and black dot) seem to follow the actual data (in blue). However, according to the testing dataset, the predictions (in red and green) do not properly overlap with the actual data (in orange). As shown in Table 1, the additive model performs better than the multiplicative model, given the lower MAE and MAPE. However, its RMSE is higher than that of the multiplicative model. This could be because the model works well in training but offers little predictive value in the testing.

Table 1. MAE, RMSE, and MAPE of the Holt-Winters Smoothing models

Model	MAE	RMSE	MAPE
Additive	9.039	14.910	10.891
Multiplicative	9.042	13.431	12.380

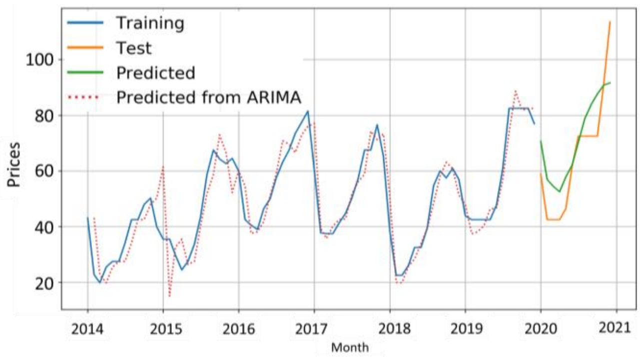

Fig. 9. Shallot price prediction from the ARIMA model

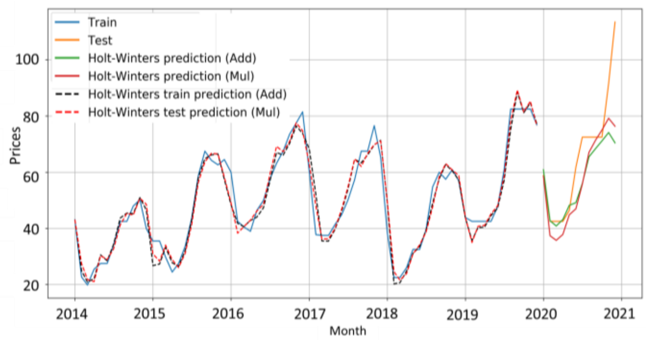

Fig. 10. Shallot price prediction from the Holt-Winters Smoothing model

From Fig. 11, it can be observed that the prediction in the training dataset does not completely follow the actual data. However, the performance of the LSTM model is better in the testing dataset. The prediction in the testing set is also more accurate compared to the ARIMA and Holt-Winters models, given that temperature and rainfall are included in the model.

Finally, the prediction results from all three components are accumulated for the final outcome, as shown in Fig. 12. Focusing on the testing dataset, the Holt-Winters model (in red) outperforms other models in predicting the shallot prices in the first quarter of 2020. However, for the rest of the year, the ARIMA model (in green), LSTM model (in orange), and ARIMA-LSTM hybrid model (in purple) provide more accurate forecasts.

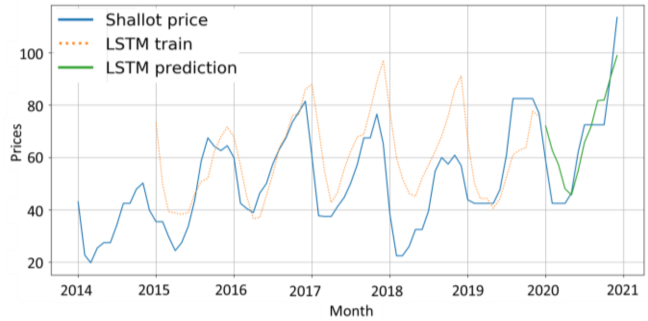

Fig. 11. Shallot price prediction from the LSTM model

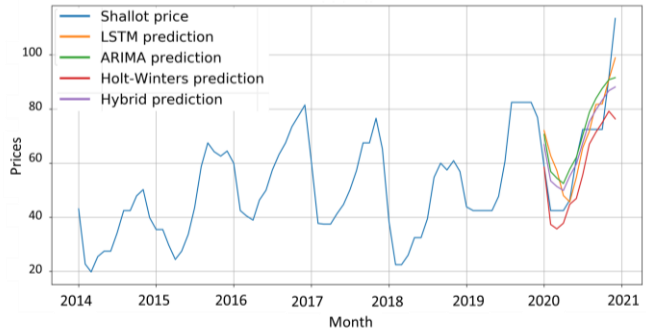

Fig. 12. Shallot price prediction from the ARIMA-LSTM model

The summary of the forecasts from all models is presented in Table 2.

Table 2. Forecasts of shallot prices in 2020

Month	Actual	ARIMA	Holt-Winters	LSTM	Hybrid
Jan.	58.86	70.63	60.91	72.07	66.88
Feb.	42.50	56.93	42.72	62.80	53.47
Mar.	42.50	54.50	40.86	57.33	51.40
Apr.	42.50	52.52	43.16	48.05	49.92
May	46.39	57.80	48.21	45.71	55.24
June	61.79	62.15	49.16	54.77	59.69
July	72.50	70.37	55.97	65.75	67.52
Aug.	72.50	78.79	65.48	71.80	75.29
Sep.	72.50	83.88	68.42	81.71	79.71
Oct.	72.50	87.65	71.16	81.94	83.31
Nov.	91.58	90.86	74.14	90.93	86.83
Dec.	113.5	91.63	70.46	98.93	88.18

Table 3 presents the RMSE, MAE, and MAPE of each forecasting model. It reports that the ARIMA-LSTM hybrid model outperforms other stand-alone models with the minimum values of RMSE (10.275 THB) and MAE (8.512 THB). Although the MAPE of the hybrid model, with a value of 13.618%, is higher than that of the Holt-Winters model (10.891%), the accuracy of the forecast is considered sufficiently good based on Lewis's MAPE criteria (Lewis, 1982), as presented in Table 4.

Table 3. RMSE, MAE, and MAPE of all forecasting models

Model	RMSE (THB)	MAE (THB)	MAPE (%)
ARIMA	11.56	9.795	16.601
Holt-Winters	14.91	9.039	10.891
LSTM	10.487	8.576	15.044
ARIMA-LSTM	10.275	8.512	13.618

Table 4. Lewis's MAPE criteria for model evaluation

MAPE	Forecasting power
< 10%	Highly accurate forecasting
10% - 20%	Good forecasting
20% - 50%	Reasonable forecasting
> 50%	Weak and inaccurate forecasting

The ARIMA model is simple and widely used since it offers effective predictions for univariate time series data and provides a good solution for short-term forecasting (Poornima and Pushpalath, 2019; Thiruvengadam et al., 2020). However, it predicts shallot prices based solely on historical prices and suffers from the limitation of assuming a pre-assumed linear relationship, which is not suitable for agricultural price series (Banerjee et al., 2022). On the other hand, although the Holt-Winters model can handle trends and seasonal variations, it is designed for univariate input data and is not suitable for price series with a large number of hidden or unknown variables (Thiruvengadam et al., 2020).

Among the machine learning methods, the LSTM model can capture nonlinear patterns and long-term dependencies and consider the influence of multiple factors simultaneously (Poornima and Pushpalath, 2019). However, it is resource-intensive and can be sensitive to outliers and local minima (Fan et al., 2021). The results of this study demonstrate that the ARIMA-LSTM hybrid models can leverage the strengths of the standalone models by recognizing both the linear patterns and the nonlinear relationships in the time series, thereby improving the forecasting accuracy and outperforming other models.

5. Summary and conclusion

Forecasting the prices of agricultural products is often challenging due to the need for careful selection of predictors and the absence of a universally superior forecasting technique. Achieving precise predictions is also difficult due to the diverse nature of time series data, which can be linear or nonlinear. This study builds upon the work of Phuruan and Kasemset (2022) by comparing different forecasting techniques, including ARIMA, Holt-Winters, LSTM, and ARIMA-LSTM models, for predicting shallot prices in Northern Thailand from January 2014 to December 2020. The results demonstrate that the ARIMA-LSTM hybrid model offers a better fit and higher prediction accuracy compared to individual models.

This research provides *two* key contributions. First, it compares multiple forecasting models and establishes the suitability of the ARIMA-LSTM hybrid model, which can assist farmers in improving shallot price predictions before making decisions regarding cultivation and harvest. Second, this study suggests that the ARIMA-LSTM hybrid model can be applied to other price prediction problems exhibiting a similar pattern. Researchers can first perform time series decomposition to identify the presence of trends and seasonal patterns, effectively separating the data into linear and nonlinear components. Furthermore, the results indicate that not all input variables need to be included in the model. As demonstrated in this research, incorporating temperature and rainfall improves forecasting accuracy without introducing unnecessary complexity to the model architecture. The MAPE value of 13.618 for the hybrid model indicates an acceptable level of prediction accuracy.

This study has a few limitations. It focuses on only two predictors (temperature and rainfall) due to data availability, while other factors such as date, yield, trade, wind speed, humidity, cloud coverage, and pesticides may also influence shallot prices (Varun et al., 2010). Incorporating these additional factors could enhance the accuracy and applicability of the findings. Additionally, researchers are encouraged to validate the selected predictors by forecasting the input variables since the model's accuracy heavily depends on them. Furthermore, while this study highlights the novel forecasting technique, the results are specific to shallot prices in three provinces of Northern Thailand from 2014 to 2020. Hence, the forecasting results should be carefully used when extrapolating to other regions which are geographically and temporally different.

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Reference

Banerjee, T., Sinha, S., Choudhury, P., 2022. Long term and short term forecasting of horticultural produce based on the LSTM network model, Applied Intelligence, 34(6), 9117-9147, DOI: 10.1007/s10489-021-02845-x.

Bhandari, H.N., Rimal, B., Pokhrel, N.R., Rimal, R., Dahal, K.R., Khatri, R.K., 2022. Predicting stock market index using LSTM, Machine Learning with Applications, 9, DOI: 10.1016/j.mlwa.2022.100320.

Schlenker, Wolfram, Michael J. Roberts. 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change, the National Academy of sciences, 106(37), 15594-15598, DOI: 10.1073/pnas.0906865106.

Fan, D., Sun, H., Yao, J., Zhang, K., Yan, X., Sun, Z., 2021. Well production forecasting based on ARIMA-LSTM model considering manual operations, Energy, 220(C), DOI: 10.1016/j.energy.2020.119708.

Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory, Neural computation, 9(8), 1735-1780, DOI: 10.1162/neco.1997.9.8.1735.

Jaiswal, R., Jha, G.K., Kumar, R.R., Choudhary, K., 2022. Deep long short-term memory based model for agricultural price forecasting, Neural Computing and Applications, 34(8), 9117-9147, DOI: 10.1007/s00521-021-06621-3.

Laosiritaworn, W.S., 2011. Supply chain forecasting model using computational intelligence techniques, Chiang Mai University Journal of Natural Sciences, 10(1), 19-28. Available: https://www.thaiscience.info/ journals/Article/CMUJ/10887604.pdf [Accessed: 19 July 2022].
Lewis, C.D., 1982. Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting, Boston: Butterworth Scientific, London, UK.
Mohanty, M.K., Thakurta, P.K.G., Kar, S., 2023. Agricultural commodity price prediction model: a machine learning framework, Neural Computing and Applications, 35, 15109–15128, DOI: 10.1007/s00521-023-08528-7.
Ning, Y., Kazemi, H., Tahmasebi, P., 2022. A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet, Computers & Geosciences, 164, DOI: 10.1016/j.cageo.2022.105126.
Office of Agricultural Economics, 2020. Agricultural Price Index June 2020, (in Thai). Available: http://www.oae.go.th/ [Accessed: 19 July 2022].
Palangkaset, 2019. Step-By-Step for Shallot Cultivation and Harvest, (in Thai). Available: https://www.palangkaset.com/ [Accessed: 30 August 2022].
Phuruan, K., Kasemset C., 2022. Shallot Price Forecasting Model Using Hybrid ARIMA-LSTM Model, Data Science and Engineering (DSE) Record, 3(1).
Poornima, S., Pushpalatha, M., 2019. Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network, Soft Computing, 23(18), 8399-8412, DOI: 10.1007/s00500-019-04120-1.
Purohit, S.K., Panigrahi, S., Sethy, P.K., Behera, S.K., 2021. Time series forecasting of price of agricultural products using hybrid methods, Applied Artificial Intelligence, 35(15), 1388-1406, DOI: 10.1080/ 08839514.2021.1981659.
Sabu, K.M., Kumar, T.M., 2020. Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala, Procedia Computer Science, 171, 699-708, DOI: 10.1016/j.procs.2020.04.076.
Thiruvengadam, S., Tan, J. S., Miller, K., 2020. Time Series, Hidden Variables and Spatio-Temporal Ordinality Networks, Advances in Applied Clifford Algebras, 30(3), 1-98, DOI: 10.1007/s00006-020-01061-z.
Varun, R., Neema, N., Sahana, H. P., Sathvik, A., Muddasir, M, 2019. Agriculture commodity price forecasting using Ml techniques, International Journal of Innovative Technology and Exploring Engineering, 9(2S), 729,-732, DOI: 10.35940/ijitee.B1226.1292S19.
Winters, P.R., 1960. Forecasting sales by exponentially weighted moving averages, Management science, 6(9), 324-342, DOI: 10.1287/mnsc. 6.3.324.

Appendix

Appendix A

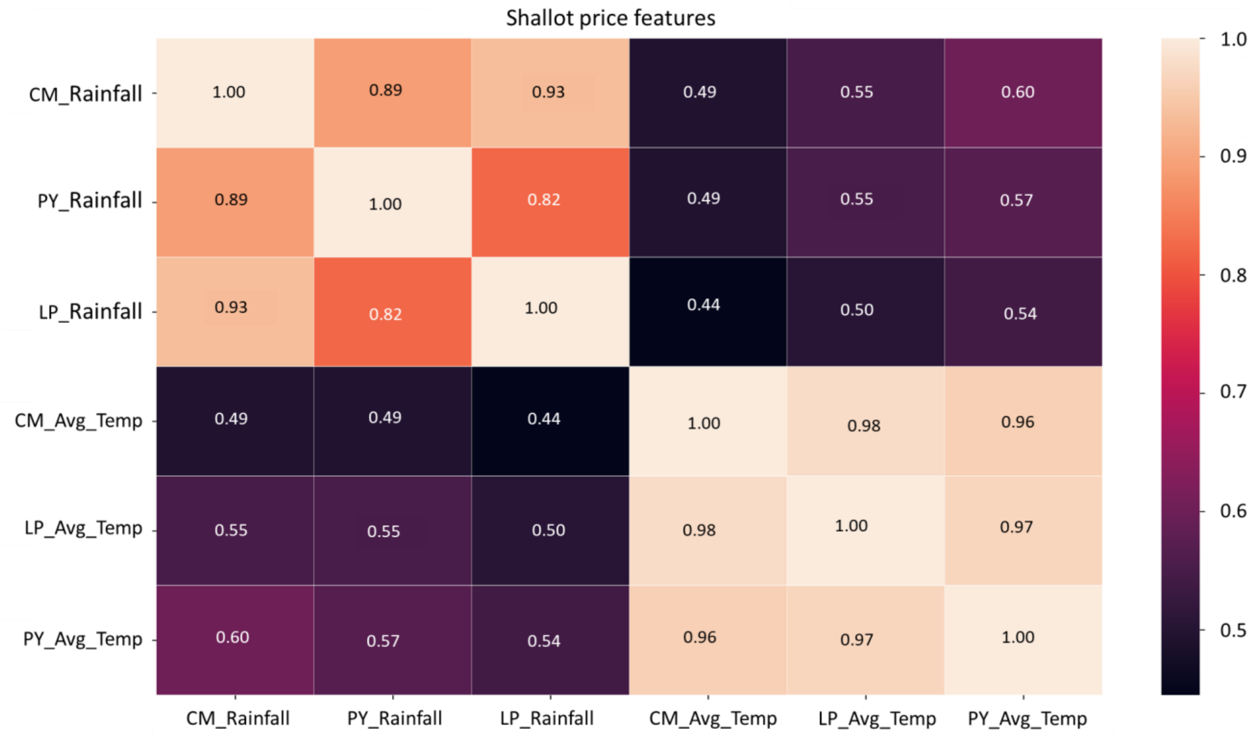

Fig. 1. Correlation heatmap

葱价格预测模型:各种技术的比较

關鍵詞
预测
阿里玛
长短期记忆网络
霍尔特-温特斯
ARIMA-LSTM
价值链

摘要
青葱是泰国出口到各国的几种园艺产品之一尽管近年来大葱价格不断上涨，但由于波动和其他相关因素，农民在价格预测方面面临挑战。 尽管文献中存在不同的预测技术，但由于问题和数据集不同，没有通用的方法。 本研究重点预测 2014 年 1 月至 2020 年 12 月泰国北部的葱价格。提出了传统模型和机器学习模型，包括 ARIMA、Holt-Winters、LSTM 和 ARIMA-LSTM 混合模型。 LSTM 模型将温度和降雨量作为影响因素。 评估指标包括 RMSE、MAE 和 MAPE。 结果表明，ARIMA-LSTM 混合模型表现最佳，RMSE、MAE 和 MAPE 值分别为 10.275 Baht、8.512 Baht 和 13.618%。 实施这种混合模式可以为葱农提供先进的价格信息，以便在种植扩大和生产管理方面做出明智的决策。