The Creation of Prediction Model for the Volumes of Thailand's Orchid Exports by Applying Machine Learning Methodologies

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Abstract

This study proposes a machine learning-based model for forecasting Thai orchid exports, aiming to aid decision-making processes, and ensuring high-quality products to meet global demand. The research employed the regression model with three estimation methods (1) K-Nearest Neighbors, (2) Random Forest, and (3) Deep Learning. Data from six websites spanning January 2011 to July 2023 included export volumes, prices, exchange rates, labor wages, and various economic indicators. The analysis involved data understanding, preparation, and modeling, with evaluation metrics such as Mean Squared Error (MES), Root Mean Squared Error (RMES), and Absolute Error (AE). Evaluation results reveal that the Random Forest technique exhibited the least error among the three methods, emphasizing that it was suitable for constructing a predictive model for orchid exports.

Keywords: 1) forecasting model 2) machine learning techniques 3) Thai orchid exports 4) random forest 5) deep learning

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Introduction

The global orchid market, valued at US$ 5,152.1 million in 2020, was poised for substantial growth and was projected to reach US$ 7,051.3 million by 2027. This expansion was driven by a robust Compound Annual Growth Rate (CAGR) of 4.6% during the period from 2021 to 2027. Orchids have gained significant traction in the global market, attributed in part to their extended shelf life, a spectrum of vibrant colors, and other desirable characteristics sought after by consumers. This surge in popularity is anticipated to propel the orchid market forward, with increased utilization in cosmetics, herbal medicines, culinary applications, and more (AllTheResearch, 2021).

The global reach of the orchid market extends to over 60 countries, with key players such as the United States, Vietnam, Japan, China, and the Netherlands driving international trade. Remarkably, these countries collectively account for 74.70 percent of total orchid exports, emphasizing their pivotal role in the global orchid market landscape. The United States commanded the largest market share, with a valuation of US$ 1,617.3 million in 2020. The escalating demand for orchids in America is particularly notable, driven by a rising preference for herbal beauty products among U.S. consumers, especially in skincare and hair care categories. Additionally, the premium beauty and personal care segment in the region has demonstrated noteworthy year-over-year growth (AllTheResearch, 2021; Yuan, et al., 2021, pp. 1-28).

Orchids, a significant export for Thailand, include varieties like Dendrobium, Mokkara, and Oncidium, with peak seasons from June to October. In 2022, Thailand produced 31,950 tons of orchids (Ketsa and Warrington, 2023, pp. 1829-1888). With improving COVID-19 conditions, 2023 anticipations suggest a positive outlook for Thailand's orchid exports to key destinations like the United States, Vietnam, Japan, China, Italy, and emerging markets such as France, Kuwait, and Qatar. Competitors like the Netherlands and Taiwan are also prominent in this sector. Conservation efforts are crucial as orchids face threats like habitat loss and climate change (Xue, et al., 2023, pp. 1-13). Understanding the evolution and distribution of orchids, especially Dendrobium species, provides insights into their adaptation to different photosynthetic pathways influenced by climate factors (Nargar and Chen, 2023, pp. 1-3). Orchid conservation priorities are essential, highlighting species in urgent need of protection (Dauhut, et al., 2023, pp. 325-347).

The decline in Thai orchid exports due to drought affecting production and quality, coupled with rising shipping costs, has impacted foreign demand (Kindlmann, Kull, and McCormick, 2023, pp. 1-3). To address diverse consumer preferences for quality and new orchid varieties, Thai entrepreneurs are striving to uphold production standards and innovate new breeds (Jongwanich, 2020, pp. 2674-2722). Thailand's goal to become a developed country by 2037 necessitates enhancing technological capabilities for higher-value products, emphasizing the importance of research and development (R&D) investments and university-industry linkages (Rattanakhamfu, 2023, pp. 283-284).

Various machine learning and deep learning methods are utilized in agricultural productivity to improve yield predictions and disease detection. The K-Nearest Neighbors (KNN) algorithm is effective in datasets with a small number of instances, such as the Iris dataset, but its performance may vary with dataset complexity (Suksomboon and Ritthipakdee, 2022, pp. 43-46). The Random Forest (RF) algorithm is robust and versatile, demonstrating superior predictive power in agricultural contexts and achieving high accuracy in predicting agricultural output and analyzing crop-climate variability (Panigrahi, Kathala and Sujatha, 2023, pp. 2684-2693). RF has been combined with deep learning models, like ResNet50, for plant disease classification, outperforming traditional machine learning models (Goel and Nagpal, 2023, pp. 509-517). Deep Learning (DL), including Convolutional Neural Networks (CNNs) and hybrid models, is successful in estimating crop yield and disease detection, with remarkable accuracy in classifying apple varieties and detecting plant diseases (Bal and Kayaalp, 2023, pp. 7808-7821). However, deep learning models do not consistently outperform RF in yield prediction tasks, suggesting that the choice of method depends on the specific application and data characteristics (Tripathy, et al., 2022, pp. 79-83).

These precedents not only demonstrate the potential of machine learning in agriculture and export prediction but also stress the importance of selecting appropriate methods to match specific data characteristics and research objectives. In response to the challenges and opportunities within the global orchid market, this study aims to leverage machine learning to offer a predictive model that aids Thai orchid exporters in decision-making, efficiency enhancement, and quality assurance to meet global demands by integrating insights from relevant research and applying them to the unique context of Thai orchid exports, this initiative seeks to contribute to the strategic development of Thailand's orchid industry and its position in the international market.

Research Objectives

In this study, the primary objectives are twofold: first, to develop a predictive model aimed at estimating the volume of orchid exports from Thailand to the United States; and second, to comprehensively evaluate and compare the effectiveness of the model in forecasting these export volumes. This dual-pronged approach is designed to not only create a robust and reliable forecasting tool but also to rigorously assess its performance and applicability, specifically in the context of Thai orchid exports to the United States.

Methods

The research methods employed for constructing and comparing the performance of the model in forecasting orchid export volumes involve utilizing data estimation techniques, specifically a Regression Model. According to Sukprasert (2022, p. 187), this research executed the following steps in the Data Analysis Process, encompassing six key stages namely, (1) business understanding, (2) data understanding, (3) data preparation, (4) modeling, (5) evolution and (6) deployment.

Initial data collection involved gathering information from six distinct websites, followed by the preparation of the dataset using the RapidMiner Studio program to ensure a suitable and high-quality dataset ready for analysis. Subsequently, machine learning techniques were applied to create a forecasting model, employing three estimation methods: (1) K-Nearest Neighbors (K-Nearest Neighbors), (2) Random Forest, and (3) Cognitive Learning techniques, specifically Deep Learning. The efficiency of data estimation was assessed using performance evaluation metrics, namely (1) mean squared error (MSE), (2) root mean squared error (RMSE), (3) absolute error (AE), and (4) square error (SE), with detailed insights provided for each.

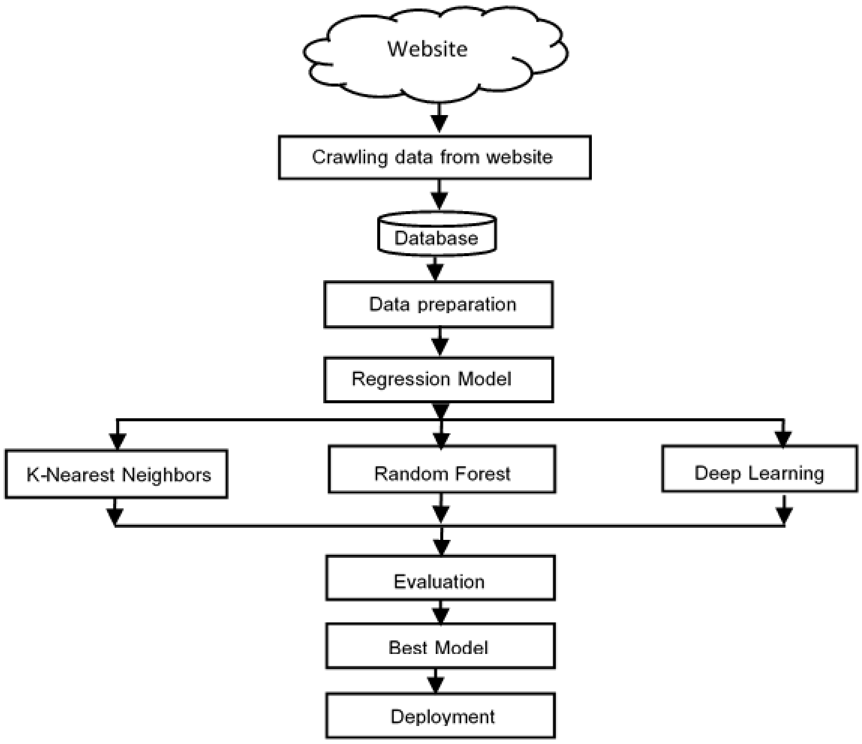

Figure 1 Operation steps

1. Business Understanding

Global climate change poses challenges to orchid cultivation for export due to irregular rainfall and rising temperatures, increasing disease and pest pressures, impacting production quality (Tiwari, et al., 2023, pp. 273-298). Traditional orchid varieties, labor shortages, rising costs, limited technological advancements, and the absence of centralized sorting facilities further affect quality and distribution (Dardi Suryanto and Mukhlis, 2022, pp. 3801-3807). To enhance Thai orchid exports, analyzing demand trends, pricing strategies, market entry barriers, and the competitive landscape is crucial (Saidah, Syamsiah, and Hardhiawan, 2022, pp. 87-95). Optimizing supply chain operations, understanding regulatory dynamics, and setting success benchmarks like market share growth and revenue increases are essential (Balilashaki, et. al., 2023, pp. 261-283). Machine learning, predictive modeling for demand, analyzing export volume and pricing factors, market segmentation, and evaluating competitor strategies are vital for securing Thailand's position in the global orchid market.

2. Data Understanding

The researcher has gathered information pertinent to the export of orchids in Thailand, intending to utilize it in the analysis employing machine learning techniques. The data collection spans the past 151 months, covering the period from January 2011 to July 2023, and is sourced from six websites: (1) www.oae.go.th, (2) www.bot.or.th, (3) https://th.investing.com, (4) https://fred.stlouisfed.org, (5) https://www.goldtraders.or.th/, and (6) www.aws-observation.tmd.go.th. Subsequently, the collected data has been selected and organized into an Excel file format. The sample data is illustrated in Table 1-6.

Table 1 information collected from the website. www.oae.go.th (Office of Agricultural Economics, 2022)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	Month	Polynominal	Months in which orchids are exported
3	Season	Ploynominal	season
4	Quantity	Integer	Volume of orchid exports
5	FOB	Integer	Orchid flower export price

Table 2 information collected from the website. www.bot.or.th (Bank of Thailand, 2022a; Bank of Thailand, 2022b)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	Exchange rate (EXTHB/USD)	Real	Foreign exchange rates: Thai baht to the US dollar
3	Diesel prices in Thailand (POT)	Real	Price of diesel fuel in Thailand
4	Average labor wages in Thailand (Bath)	Real	Average labor wage in Thailand
5	Bank of Thailand policy interest rate (INT)	Real	Policy interest rate of the Bank of Thailand

Table 3 details information collected from the website. https://th.investing.com/ (Investing, 2022)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	US inflation (US)	Real	United States inflation rate
3	Unemployment Rate (UMP)	Real	Unemployment rate of the United States

No.	Name	Data Type	Description
4	Gross Domestic Product (GDP/ US)	Real	Gross Domestic Product Value of the United States
5	Consumer Price Index (CPI/US)	Real	United States Consumer Price Index
6	Purchasing Manager Index (PMI)	Real	Manufacturing Purchasing Managers Index

Table 4 details information collected from the website. https://fred.stlouisfed.org/ (Federal Reserve Economic Data, 2022)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	Crude oil price USD/Barrel)	Real	crude oil price

Table 5 details information collected from the website. https://www.goldtraders.or.th/ (Gold Traders Association, 2022)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	Gold Price (XAU/USD)	Real	gold price

Table 6 details information collected from the website. www.aws-observation.tmd.go.th (Thai Meteorological Department Automatic Weather System, 2022)

No.	Name	Data Type	Description
1	Date	Date	Month of data recording each year
2	Temperature	Real	Average temperature per month

3 Data preparation

Data Preparation involves the meticulous arrangement of data to ensure its quality and reliability for research purposes. Using the RapidMiner Studio version 10, the researcher conducted the following steps:

3.1. Data Collection and Integration

The researchers imported data for analysis, gathered from six websites. Subsequently, all the data was integrated into a unified dataset to facilitate further processing, and this consolidated dataset was saved in Excel file format.

3.2. Data Transformation and Seasonal Categorization

Data Transformation involved using the information in the "Date" attribute to selectively extract months during which orchids were exported. The extracted months were then renamed as "Month." Subsequently, the "Month" column was utilized to categorize the seasons according to the Meteorological Department (Saengboon, Sukprasert, and Jantarajaturapath, 2022, pp. 2022-2035), as illustrated in Table 7.

Table 7 Season schedule

No.	Month	Season
1	January	winter
2	February	summer
3	March	summer
4	April	summer
5	May	summer
6	June	rainy season
7	July	rainy season
8	August	rainy season
9	September	rainy season
10	October	winter
11	November	winter
12	December	winter

3.3. Attribute Function Assignment.

In this step, functions were assigned to attributes by designating the date of recording the quantity of orchid flower exports as the identifier (ID). The quantity of orchid flower exports was specified as the variable to be predicted (Label), while the remaining variables were designated as factors influencing the quantity of flower exports of Thai orchids to the United States, as depicted in Table 8. The exchange rate, diesel price, average labor wages, interest rate, inflation, unemployment rate, gross domestic product, consumer price index, manufacturing purchasing manager index, crude oil price, gold price, orchid flower export price, and volume of orchid flower exports indicators were applied in this research based on the study of Jongwanich (2020, pp. 2674-2722) and Yuan, et al. (2021, pp. 1-28). Season and average temperature per month indicators were adapted in this study constructed from the study of Xue, et al. (2023, pp. 1-13), Ketsa and Warrington (2023, pp. 1829-1888).

Table 8 Data used for analysis.

No.	Name	Data Type	Description
1	Date	Date (ID)	Month of data recording each year
2	Month	Polynominal	Months in which orchids are exported
3	Season	Ploynominal	season
4	FOB	Integer	Orchid flower export price
5	Exchange rate (EXTHB/USD)	Real	Foreign exchange rates: Thai baht to the US dollar
6	Diesel price in Thailand (POT)	Real	Price of diesel fuel in Thailand

No.	Name	Data Type	Description
7	Average labor wages in Thailand (Bath)	Real	Average labor wage in Thailand
8	Bank of Thailand policy interest rate (INT)	Real	Policy interest rate of the Bank of Thailand
9	US inflation (US)	Real	United States inflation rate
10	Unemployment Rate (UMP)	Real	Unemployment rate of the United States
11	Gross Domestic Product (GDP/US)	Real	Gross Domestic Product Value of the United States
12	Consumer Price Index (CPI/US)	Real	United States Consumer Price Index
13	Purchasing Manager Index (PMI)	Real	Manufacturing Purchasing Manager Index
14	Crude oil price USD/Barrel)	Real	crude oil price
15	Gold Price (XAU/USD)	Real	gold price
16	Temperature	Real	Average temperature per month
17	Quantity	Integer (Label)	Volume of orchid exports

4. Modeling

In this phase, the data was analyzed through algorithmic processes using machine learning techniques. Specifically, three estimation techniques were employed: (1) K-Nearest Neighbors, (2) Random Forest, and (3) Deep Learning. The forecast models were generated using the RapidMiner Studio version 10.

4.1. K-Nearest Neighbors Technique.

The K-Nearest Neighbors technique stands out as a widely employed method for data classification, adaptable to various applications. Unlike methods that involve pre-creating models for data classification, K-Nearest Neighbors relies on a process wherein new data requiring classification is compared with similar existing data. The classification of new data is accomplished through cross-validation of k values, where the distance between the sample data of interest and other data is computed. Notably, when data are widely separated, it indicates minimal similarity. The Euclidean Distance is calculated using formula (1), as outlined below.

$$D_{Euclidian} = \sqrt{\sum_{k=1}^{n} (x_{i,k} - x_{j,k})^2} \qquad (1)$$

where

n is the number of features of the data used for comparison.

xi,k and *xj,k* represent the values of the kth feature for the ith and jth data points, respectively.

4.2. Random Forest Technique.

Derived from the Decision Tree technique, the Random Forest technique enhances work efficiency by increasing the number of trees. This augmentation leads to improved accuracy in the model. The Random Forest model is widely recognized and utilized in the field of Machine Learning

4.3. Deep Learning Techniques.

Deep learning techniques, also known as Deep Learning, constitute a set of instructions designed for machine learning. These instructions enable machines to efficiently process extensive datasets while endeavoring to comprehend and represent information. The foundation of deep learning lies in the artificial neural network technique, characterized by a structure comprising numerous nodes and layers. This architecture facilitates parallel processing, enabling the simultaneous handling of substantial amounts of data. As a result, machine learning using deep learning techniques can yield enhanced decision-making and prediction outcomes (Sukprasert, 2022, p.84).

5. Evaluation

To assess the effectiveness of the model, the researcher partitioned the data into two segments: (1) Model creation (Training Set) utilized for building the model, and (2) Testing Set employed for testing through the cross method. The researcher performed validation using the 10-fold cross-validation approach, dividing the data into 10 parts. The researcher executed a total of 30 regression performance experiments to ascertain the average performance of the model. The researchers employed the evaluation metrics to derive a suitable forecasting model for predicting the volume of ongoing Thai orchid exports to the United States. These metrics included:

5.1. Mean Squared Error (MSE)

MSE calculates the forecast error as the average of the squared differences between the forecasts and the observed values. This method gauges accuracy, and a smaller value indicates a more precise model. The formula for MSE is expressed as follows using formula (2).

$$MSE=\frac{1}{n}\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2 \qquad (2)$$

where

n is the amount of data used.

Y_t is the actual value at any time t.

$\hat{Y}_t$ is the value obtained from the forecast at time t.

5.2. The square root of the mean squared error (RMSE)

The RMSE is a commonly employed method for error measurement, exhibiting properties similar to the mean square error. However, it incorporates an additional step that subtracts the mean squared error value from the square root (Sukprasert, 2022, p. 207; Cohen and Aiche, 2023, p. 114079). The formula for the RMSE is expressed as follows using formula (3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t-\hat{Y}_t)^2} \qquad (3)$$

where

n is the amount of data used.

Y_t is the actual value at any time t.

$\hat{Y}_t$ is the value obtained from the forecast at time t.

5.3. Root Relative Squared Error (RRSE)

RRSE is defined as the square root of the combined squared errors of a predictive model, divided by the squared errors of a basic model, and then normalized. The formula for RRSE is as follows (4):

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2}} \qquad (4)$$

where

n is the amount of data used.

Y_t is the actual value at any time t.

$\hat{Y}_t$ is the value obtained from the forecast at time t.

5.4 The absolute error (AE)

The AE involves taking the error value and finding its absolute value. AE is as follows, presented in formula (5).

$$AE = |Y_t - \hat{Y}_t| \quad (5)$$

where

n is the amount of data used.

Y_t is the actual value at any time t.

$\hat{Y}_t$ is the value obtained from the forecast at time t.

5.5. Square error (SE)

SE is taking the error value to be squared with formula (6) as follows.

$$SE = (|Y_t - \hat{Y}_t|)^2 \quad (6)$$

where

n is the amount of data used.

Y_t is the actual value at any time t.

$\hat{Y}_t$ is the value obtained from the forecast at time t.

6. Deployment

Upon concluding the five-step analysis, the outcome is a technique well-suited for constructing a forecasting model to anticipate the volume of orchid exports from Thailand. The utilization of this model can aid in strategizing the development of standards and enhancing the quality of orchids intended for export, aligning them with global market demands. This approach promotes the integration of technology and innovation within the orchid industry, aiming to elevate the overall quality of orchid production. Furthermore, it serves to support and boost the international recognition and demand for Thai orchids.

Research Findings

The results of the model employed K-Nearest Neighbors, Random Forest, and Deep Learning to forecast Thailand's orchid export volumes. The study used a split-sample method and 10-fold cross-validation to do 30 rounds of thorough performance evaluation, focusing on metrics such as AE, SE, MSE, RMSE, and RRSE, which can be seen in Table 9.

Table 9 compares the test values of the efficiency of data estimation of the model for forecasting the volume of orchid exports in Thailand.

Regression Model	Regression Model Performance				
	MSE	RMSE	RRSE	AE	SE
DL	257,764,673,105.09	507,705.30	0.96	353,573.04	315,936,008,715.62
KNN	304,592,759,503.56	551,899.23	1.06	388,548.38	364,512,589,699.15
RF*	210,051,046,125.08	458,313.26	0.85	308,249.06	266,374,102,353.49

* is an apt methodology for constructing a predictive model for the volume of orchid exports.

From Table 9, the research results found that Random Forest technique gives the least amount of error. The results of the performance evaluation for the Regression Model using three techniques—Deep Learning, K-Nearest Neighbors, and Random Forest—are presented in the table. The MSE measures the average of the squared differences between predicted and actual values, with lower values indicating better accuracy. The RMSE represents the square root of the MSE, offering insight into the model's predictive precision. The RRSE normalizes the RMSE, providing a relative measure of accuracy. The AE reflects the average absolute differences between predicted and actual values. Lastly, the SE is the sum of squared differences between predicted and actual values.

According to the results, Table 9's statistical analysis unequivocally demonstrates that the Random Forest model is the superior predictive tool among the evaluated methods for forecasting the volume of orchid exports from Thailand. Specifically, the Random Forest model showcased the lowest MSE at 210,051,046,125.08 and the lowest RMSE at 458,313.26. Furthermore, the Random Forest model recorded an RRSE of 0.85 and an AE of 308,249.06, demonstrating its exceptional predictive accuracy and efficiency. These figures underline the Random Forest technique's robustness and reliability as a forecasting model, making it a highly valuable asset for stakeholders in the orchid export industry seeking to navigate and thrive in the global market.

Summary of Research Results

By comparing the efficiency and accuracy of three forecasting techniques—K-Nearest Neighbors, Random Forest, and Deep Learning—in predicting the volume of orchid exports in Thailand, this study assessed their performance. The results indicated that the Random Forest technique exhibited the least amount of error, aligning with prior research by Torsasukul and Kuttipong (2022, pp. 1-17), who found similar efficacy in predicting water volume in dams. This consistency was further supported by the work of Aliabadi, et al. (2022, pp. 482-493), who utilized the Random Forest algorithm to study musculoskeletal issues among mining truck users, reporting low root mean squared error.

This research offered valuable insights for forecasting orchid exports in Thailand, aiding in planning and decision-making for production volume in alignment with global market demands. It contributes to enhancing productivity and elevating production quality, providing valuable information for further research on orchid export quantity forecasting in Thailand. The results can be instrumental in risk management based on future predictions or for conducting further efficiency tests in the market. Moreover, the research findings can be leveraged for advancing models in forecasting the volume of orchid exports in Thailand, incorporating additional factors like shipping costs and export fees to enhance accuracy using machine learning techniques.

Suggestions

The current study's predictive accuracy, while robust, may be further refined by expanding the dataset beyond its current scope. The inclusion of a broader array of samples would not only mitigate the limitations imposed by the dataset's current scale but also amplify the model's predictive efficiency. Future research endeavors should prioritize the enlargement of the dataset to bolster the comprehensiveness and reliability of the forecasting model.

This study also focused on the number of export products to only the US. The future study should include the export data to other countries such as Vietnam, Japan or China because those countries also have an essential importing orchid products in the world market.

The predictive model's scope, primarily centered around a select set of variables in this study, presents an opportunity for enrichment by incorporating a wider spectrum of predictive factors. Future investigations should consider integrating variables such as gold prices, precipitation levels, and other pertinent factors that could significantly influence the dynamics of orchid exports from Thailand. For example, future study might include other indicators that reflect climate change such as rainfall, and also the indicators that reflect variations in import-export regulations from new ministry or new leaders from the political transitions. The inclusion of these additional variables is anticipated to provide a more nuanced understanding of the market forces at play and enhance the model's predictive accuracy in alignment with the complexities of the global orchid market.

These recommendations aim to foster a more granular and encompassing approach to forecasting in agricultural export domains, ultimately contributing to the strategic advancement of predictive modeling methodologies within the academic and practical realms of agricultural economics and trade analysis.

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