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Forecasting Iran's Saffron Export by Comparison of Machine Learning Algorithms

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Abstract

Imports and exports play an integral role in the economic growth of all countries. Therefore, selecting the right products can enhance a country's competitiveness in global trade. Saffron stands out as one of Iran's most vital and unique non-oil products for export. The objective of this study was to predict saffron exports using three data mining algorithms and determine the most suitable algorithm for forecasting. The sample period for the forecasting models encompasses saffron export data from Iran for the years 2012 to 2019, gathered from the Iran Saffron Association. Following the data preparation steps, saffron export was forecasted using three data mining algorithms: artificial neural network, deep learning, and gradient boost tree. The validity of the models plays a crucial role in selecting the best forecasting model. The predictive validity of the three designed models was evaluated using the absolute error (artificial neural network = 0.036, deep learning network = 0.031, and gradient boost tree = 0.047), R-squared (artificial neural network = 0.045, deep learning network = 0.044, and gradient boost tree = 0.073), and correlation coefficients (artificial neural network = 0.95, deep learning network = 0.98, and gradient boost tree = 0.97). Based on the findings, all models demonstrate high accuracy, with very low prediction errors that are closely matched. However, the deep learning network exhibits a slightly lower, albeit statistically insignificant, error. These results can be valuable for enhancing the precision of saffron export planning.

Keywords:
Deep learning; gradient boost tree; neural network; prediction; saffron exports

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INTRODUCTION

Economies consist of various sectors, typically including industry, services, and agriculture. Agriculture stands as one of the most vital sectors, serving as the backbone of many nations' economies. Despite its potential to be the driving force behind Iran's economy in the context of a resistance economy and to mitigate the impact of sanctions, it has not received sufficient attention. Remarkably, agricultural products, despite the diverse climate, land, and equipment available, require less technology compared to other industries (Karbasi & Akbarzade, 2008). Regrettably, the contribution of agricultural trade to Iran's GDP remains as low as approximately 10 percent. Recognizing the significance of exports and imports in this sector, governments pursue diverse policies to enhance its performance. A closer examination of Iran's foreign trade in agricultural products reveals that a significant portion of exports in this sector consists of medicinal herbs (Zarei and Jafari, 2015). Saffron, among these medicinal herbs, boasts distinct benefits. It is a strategic crop due to its lower water requirements compared to other crops, the presence of both domestic and foreign markets, and its high adaptability (Mohamadzadeh et al., 2016). Iran holds the position of the world's leading producer and exporter of saffron, with 65 percent of global saffron production originating from Razavi Khorasan and South Khorasan provinces. These two provinces alone account for over 92 percent of Iranian saffron production (Riahi et al., 2017).

Forecasting demand for agricultural commodities is a critical factor in promoting agricultural development and ensuring economic stability. The accuracy of these forecasts plays a pivotal role in guiding production decisions and investments (Wang et al., 2022). Notably, precise forecasts serve as valuable resources for investors seeking substantial returns and for hedgers aiming to formulate well-founded hedging strategies (Luo et al., 2022). Furthermore, such forecasts provide a valuable instrument for governments to fine-tune their agricultural policies in response to changing circumstances (Wang et al., 2022). Nevertheless, the agricultural commodities market is subject to a myriad of intricacies, including influences from the global economy, financial speculation, climate change, fluctuations in oil prices, and unforeseen global crises, such as the COVID-19 pandemic. These factors introduce complexities and nonlinear dynamics into forecasting decisions (Nazlioglu and Soytas, 2012). Consequently, accurately predicting agricultural commodity trends become a formidable challenge (Wang et al., 2022; Li et al., 2022). Therefore, having an appropriate tool for forecasting agricultural output becomes of paramount importance for effective policy-making.

Previous studies have put forth various potential forecasting models. However, an optimal forecasting model tailored to a specific problem has yet to be proposed (Kourentzes et al., 2019). As a result, a combination of multiple models has emerged as one of the most effective approaches for forecasting, typically yielding more reliable and accurate results. One key concern with hybrid methods involves the ensemble strategy's diversity; that is, the degree of dissimilarity among individual forecasting models (Mendes-Moreira et al., 2012). For example, homogeneous models are generated using the same induction algorithm, while heterogeneous models are created through different learning algorithms. Homogeneous models generally share similar architectures and levels of computational complexity, whereas heterogeneous models tend to exhibit greater diversity. Semi-heterogeneous models comprise both homogeneous and heterogeneous individual models (Wang et al., 2018).

A variety of hybrid methods have been proposed to address forecasting challenges. The primary objective behind the development of diverse forecasting methods is to enhance accuracy and reliability. In the literature, numerous forecasting algorithms have emerged, with artificial intelligence (AI) models, particularly data mining algorithms, being widely acknowledged and recommended over classical models. In this study, we introduce a framework for predicting future saffron demand. Specifically, we employ a hybrid AI algorithm, consisting of artificial neural networks (ANN), deep learning, and gradient boosting, to uncover hidden patterns in this agricultural product, enabling us to make nonlinear future demand predictions. Of course, alternative models can also be utilized based on individual preferences or specific requirements.

The remainder of the paper is structured as follows: Section 2 briefly reviews existing studies on forecasting agricultural products. Section 3 outlines the methodology and research framework. Section 4 presents the empirical results obtained from the proposed algorithms. Finally, in Section 5, we provide conclusions and offer recommendations for further research.

Literature review

The literature offers a range of both linear and non-linear methods employed for forecasting the export and import of non-oil products. The development of diverse forecasting methods and algorithms is driven by the overarching goal of enhancing the accuracy and reliability of these forecasts. Devi et al. (2021) utilized both the autoregressive integrated moving average (ARIMA) model and artificial neural network (ANN) methodology to estimate the forecasting behavior of wheat in Haryana, India. Their analysis revealed consistently positive growth rates in all subperiods concerning wheat area, production, and yield. Notably, Haryana ranked second in wheat yield sustainability, following Punjab. Tashakkori and Torkashvand (2020) explored the performance of ANN, multiple linear regression (MLR), and adaptive neuro-fuzzy inference system (ANFIS) in estimating saffron yield in select lands of Golestan province, Iran. Their findings demonstrated that ANN exhibited higher accuracy compared to MLR and ANFIS. Li et al. (2020) introduced a text-based forecasting framework designed to effectively identify and quantify factors influencing agricultural futures based on a vast corpus of online news headlines. This framework underwent empirical testing in forecasting soybean futures prices in the Chinese market. Results indicated that the identified influential factors and sentiment-based variables were effective, with the proposed framework significantly outperforming the benchmark model in medium-term and long-term forecasting. Kouzegaran et al. (2020) predicted future saffron yields using the yield-extreme indices model. Their research highlighted an increasing trend in warm climate extreme indices and a decreasing trend in precipitation indices as pivotal factors contributing to reduced saffron yields. Price prediction plays a pivotal role in enabling the agricultural supply chain to make informed decisions for minimizing and managing the risks associated with price fluctuations. Sabu and Kumar (2020) forecasted the monthly prices of areca nut in Kerala, employing SARIMA, Holt-Winter's seasonal method, and the LSTM neural network. Among these models, the LSTM neural network was identified as the most effective for price prediction.

Wang et al. (2022) introduced an Artificial Bee Colony (ABC) algorithm to forecast soybean and corn futures prices. They applied the ABC approach to three forecast combinations: heterogeneous, semi-heterogeneous, and homogeneous combinations. Experimental results demonstrated that the semi-heterogeneous forecast combination outperformed the other strategies. Kyriazi et al. (2019) introduced an innovative forecasting methodology known as the Adaptive Learning Forecasting method. They employed this method to forecast agricultural prices for various agricultural products and real GDP growth for corresponding countries. Their results supported the effectiveness of this new approach and the predictability of agricultural prices. Zhang (2019) proposed a yield prediction model based on the BP neural network (BPNN) algorithm, optimizing it with a set of algorithms for the prediction of production and export scales of aquaculture products. Results revealed that the model achieved a lower Root Mean Square Error (RMSE) and higher learning efficiency compared to traditional BPNN. Ramezani et al. (2018) conducted a study to assess the efficiency of saffron fields in Gonabad County using Data Envelopment Analysis (DEA). They provided solutions for improving cultivation factors. Barimnejad and Bekshelu (2017) predicted the weekly price of tomatoes from 2009 to 2010 using linear and nonlinear models. Results indicated that among the regression models, Artificial Neural Networks (ANN) and ARIMA ANN performed better in prediction. Salari et al. (2017) applied data mining techniques to predict annual saffron yield and identify suitable saffron cultivation areas in Khorasan Razavi province based on climatic parameters. Their findings showed that an increase in the average temperature during cold months and a decrease in the average temperature during warmer months led to increased crop yield. Among various methods, Support Vector Machine (SVM) and Radial Basis Function (RBF) demonstrated superior performance. Shafieyan et al. (2017) investigated strategies for the sustainable development of rice, a significant agricultural crop in Guilan Province, using a SWOT analysis. They proposed strategies to promote the sustainable development of this product.

Nasabian and Gashghaei (2017) predicted global wheat prices using ARIMA models based on data from 2009 to 2015. Nazemi (2016) conducted an investigation into the factors influencing the export of pistachios and saffron, proposing solutions to enhance exports. The findings highlighted a significant and direct relationship between saffron exports and the agricultural sector. Omidi and Omidi (2016) forecasted saffron exports using both Artificial Neural Networks (ANN) and the gray method, with ANN delivering more accurate results. Nekuei et al. (2015) predicted saffron performance utilizing ANN and meteorological data. Their results indicated that independent variables such as maximum temperature, evapotranspiration, rainfall, and humidity yielded better performance and greater accuracy. Fazlollahi and Fattahi (2014) predicted rice prices employing ARIMA, Autoregressive Moving Average (ARMA), and Moving Average (MA) models, with ARIMA exhibiting the best performance among them.

Amirzade Moradabadi (2014) employed autoregressive (AR), moving average (MA), autoregressive integrated moving average (ARIMA), and autoregressive conditional heteroscedasticity (ARCH) algorithms to predict wheat prices using data spanning from 1974 to 2011. The ARIMA model demonstrated superior performance among them. Akbari et al. (2013) predicted date exports using econometric methods such as ARIMA, ARCH, and artificial intelligence algorithms. Their findings revealed that the Artificial Neural Network (ANN) algorithm provided more accurate predictions. Kuchakzade et al. (2013) forecasted date exports using ANN, Radial Basis Function (RBF), Multilayer Perceptron (MLP), and ARIMA models. Their results indicated that the RBF method outperformed the others. Moghadasi et al. (2011) predicted Iran's non-oil exports from 1999 to 2009 using Seasonal Autoregressive Integrated Moving Average (SARIMA) and ANN models. They reported that ANN yielded better results with lower evaluation error. Abbasi et al. (2012) predicted the monthly prices of corn and soybeans, two crucial oilseeds, based on data from 1991 to 2008. They found that ARMA and exponential smoothing models delivered the best results. Sanainejad et al. (2007) investigated saffron performance in South Khorasan using statistical methods. Their results indicated that an increase in temperature during the first months of the year led to a reduction in saffron yield.

Shaygan et al. (2007) introduced a model using ARIMA and Artificial Neural Network (ANN) methods based on data from 1981 to

2001 to predict rice and corn production. Their research confirmed the superiority of neural networks in this context. Farajzade and Shahvali (2018) presented a model for predicting the prices of rice, saffron, and cotton based on data spanning from 1971 to 2005. They employed ARIMA, Autoregressive Conditional Heteroscedasticity (ARCH), ANN, and exponential smoothing methods. Results indicated that ARIMA was a suitable model for predicting rice and saffron prices, while ANN proved effective for predicting cotton prices. Today, artificial intelligence algorithms have made significant inroads into various industries, emerging as competitors to traditional statistical methods. This study aimed to forecast saffron exports, a vital and strategic crop in the agricultural sector, using three metaheuristic algorithms to identify the most suitable algorithm for demand forecasting. This proposed hybrid method is a novel contribution to the agricultural commodities forecasting literature.

METHODOLOGY

This study has an applied objective, employs descriptive data collection, and follows a causal or post-occurrence research method. The research dataset comprises Iran's saffron export data from 2012 to 2019, sourced from the Khorasan Saffron Exporters Union website. Figure 1 illustrates the framework of the proposed hybrid forecasting method. The research process began with data extraction from the Iranian Saffron Association dataset. Subsequently, the collected data underwent screening to eliminate noise and normalization for uniformity in analytical algorithm processing. In the third stage, three artificial intelligence algorithms—Artificial Neural Network (ANN), Deep Learning, and Gradient Boost Tree—were applied to analyze the empirical data. Finally, the proposed algorithms' validity was assessed using various validity indexes, and their performance scores were ranked accordingly.

Data mining is a process that involves discovering patterns within large datasets, employing methods that intersect machine learning, statistics, and database systems. This process comprises seven distinct steps: data cleaning, data transformation, data integration, feature selection, data mining, pattern evaluation, and knowledge representation. It's worth noting that each of these steps may be iterated multiple times during the data mining process. The initial four steps are often referred to as "pre-processing." Data screening, or data cleaning, is a crucial step in this process. It involves the identification and rectification (or removal) of corrupt or inaccurate records within a dataset, table, or

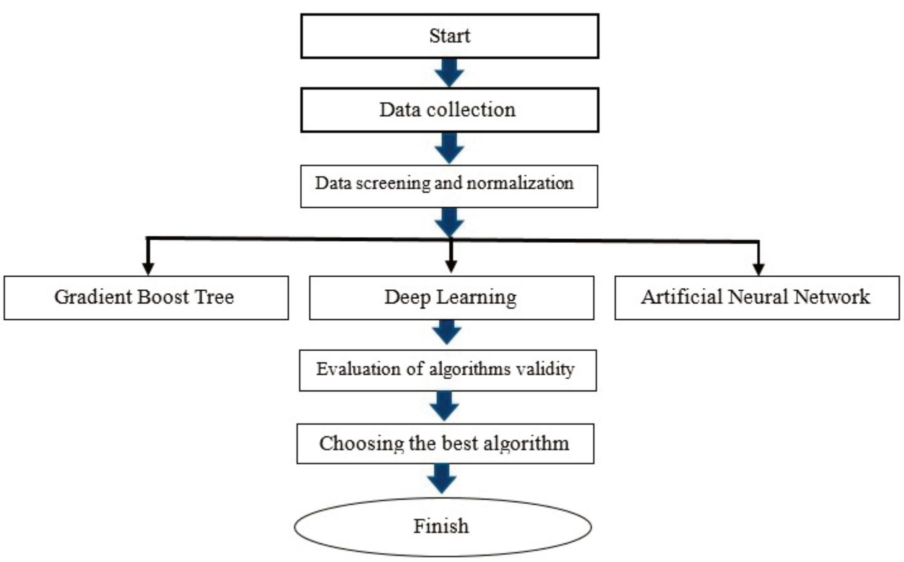

Figure 1. The Research Framework

Table 1

Saffron Export Data (Iransaffronunion.com)

Year	Month	Weight (kg)	Year	month	Weight (kg)	Year	Month	Weight (kg)	Year	Month	Weight (kg)
2012	1	—-	2014	1	14864	2016	1	164243	2018	1	28307
2012	2	—-	2014	2	8777	2016	2	13992	2018	2	20747
2012	3	—-	2014	3	—-	2016	3	13597	2018	3	24074
2012	4	8571	2014	4	6697	2016	4	10343	2018	4	12194
2012	5	9896	2014	5	12725	2016	5	13708	2018	5	25669
2012	6	3678	2014	6	—-	2016	6	10125	2018	6	13698
2012	7	8884	2014	7	8916	2016	7	9373	2018	7	14356
2012	8	7972	2014	8	7031	2016	8	7252	2018	8	17230
2012	9	9363	2014	9	10850	2016	9	5363	2018	9	18435
2012	10	7837	2014	10	9751	2016	10	4049	2018	10	18503
2012	11	15140	2014	11	15338	2016	11	18297	2018	11	32517
2012	12	16563	2014	12	18951	2016	12	30167	2018	12	27547
2013	1	9365	2015	1	14127	2017	1	25913	2019	1	22928
2013	2	12853	2015	2	13933	2017	2	19329	2019	2	20867
2013	3	11908	2015	3	15694	2017	3	18137	2019	3	26461
2013	4	6274	2015	4	9483	2017	4	11373	2019	4	9474
2013	5	11888	2015	5	16041	2017	5	17004	2019	5	-
2013	6	7197	2015	6	8763	2017	6	15301	2019	6	-
2013	7	6411	2015	7	6045	2017	7	10188	2019	7	-
2013	8	5066	2015	8	7741	2017	8	9611	2019	8	-
2013	9	7896	2015	9	4467	2017	9	8660	2019	9	-
2013	10	6958	2015	10	342	2017	10	13102	2019	10	-
2013	11	10798	2015	11	23917	2017	11	29963	2019	11	-
2013	12	17984	2015	12	41595	2017	12	30407	2019	12	-

database. This step aims to detect incomplete, incorrect, inaccurate, or irrelevant data segments and subsequently replace, modify, or delete these problematic or coarse data entries. Table 1 presents the statistics of saffron export data for the period from 2012 to 2019, offering a snapshot of the dataset's characteristics.

RESULTS AND DISCUSSION

As outlined in the research framework, data collection is followed by a crucial step involving data cleaning and normalization. In the context of meta-heuristic algorithms, it is essential to normalize all data to ensure that input parameters to the network fall within the range of zero to one. This normalization process serves to reduce error rates while simultaneously increasing computational speed. The choice of the normalization norm, whether it's the L1, L2, or infinite norm, depends on the nature of the relationships between the variables and is typically determined by the software used. For reference, Table 2 provides an example of data that has been normalized using the infinite norm, showcasing the transformation of data into a standardized range.

Initially, we start with the assumption that network weights are randomly selected. In each training stage, adjustments to the weights are made based on the discrepancies between the network's output and the optimal output, with the ultimate goal of minimizing the error value. The overall error of the network is calculated as the sum of errors across each external layer neuron. The test data serves as a means to assess the accuracy of the network. Various methods have been proposed for error examination. As evident

Table 2
Normalized Saffron Export Data

Year	Month	Weight (kg)	Year	Month	Weight (kg)	Year	Month	Weight (kg)	Year	Month	Weight (kg)
2012	1	-	2014	1	0.36	2016	1	0.39	2018	1	0.68
2012	2	-	2014	2	0.21	2016	2	0.34	2018	2	0.50
2012	3	-	2014	3	-	2016	3	0.33	2018	3	0.58
2012	4	0.21	2014	4	0.16	2016	4	0.25	2018	4	0.29
2012	5	0.24	2014	5	0.31	2016	5	0.33	2018	5	0.62
2012	6	0.09	2014	6	-	2016	6	0.24	2018	6	0.33
2012	7	0.21	2014	7	0.21	2016	7	0.23	2018	7	0.35
2012	8	0.19	2014	8	0.17	2016	8	0.17	2018	8	0.41
2012	9	0.23	2014	9	0.26	2016	9	0.13	2018	9	0.44
2012	10	0.19	2014	10	0.23	2016	10	0.10	2018	10	0.44
2012	11	0.36	2014	11	0.37	2016	11	0.44	2018	11	0.78
2012	12	0.40	2014	12	0.46	2016	12	0.73	2018	12	0.66
2013	1	0.23	2015	1	0.34	2017	1	0.62	2019	1	0.55
2013	2	0.31	2015	2	0.33	2017	2	0.46	2019	2	0.50
2013	3	0.29	2015	3	0.38	2017	3	0.44	2019	3	0.64
2013	4	0.15	2015	4	0.23	2017	4	0.27	2019	4	0.23
2013	5	0.29	2015	5	0.39	2017	5	0.41	2019	5	-
2013	6	0.17	2015	6	0.21	2017	6	0.37	2019	6	-
2013	7	0.15	2015	7	0.15	2017	7	0.24	2019	7	-
2013	8	0.12	2015	8	0.19	2017	8	0.23	2019	8	-
2013	9	0.19	2015	9	0.11	2017	9	0.21	2019	9	-
2013	10	0.17	2015	10	0.01	2017	10	0.31	2019	10	-
2013	11	0.26	2015	11	0.57	2017	11	0.72	2019	11	-
2013	12	0.43	2015	12	1.00	2017	12	0.73	2019	12	-

in the software outputs (Figures 5 to 7), the actual and predicted results for the samples considered in all three methods closely align, indicating that the models are well-suited for training. Finally, the extent of prediction error in each method is determined using error evaluation criteria. In this study, we employed the root mean square error (RMSE), coefficient of determination (R^2), and the sum of absolute error (AE) for this purpose. The results of these evaluations are presented in Table 5.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_t - F_t)^2} \quad (1)$$

$$R^2 = 1 - \frac{Unexplained\ Variation}{Total\ Variation} \quad (2)$$

$$AE = \sum_{i=1}^{n}|A_t - F_t| \quad (3)$$

Figure 1 depicts the process of predictive work using ANN in the software.

The characteristics of ANN used in forecasting saffron export are presented in Table 3.

In machine learning algorithms, the predicted output is compared to the actual value to calculate the prediction error. Subsequently, the model's parameters are adjusted to minimize this prediction error. In neural networks, parameters are distributed across multiple layers, necessitating the use of a backpropagation algorithm to ensure proper updates across all layers. In the backpropagation algorithm, errors in deeper layers are transmitted backward to shallower layers, facilitating the adjustment of parameters in every layer of the model (Figure 2) (Garcia et al., 2018).

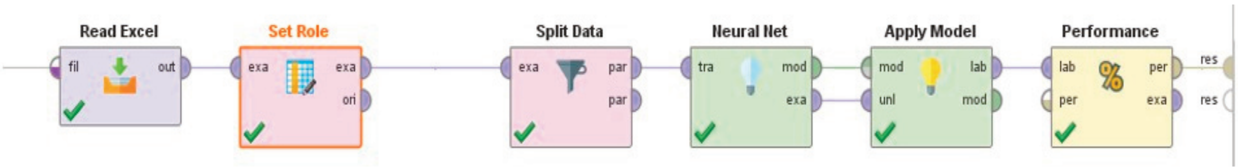

Figure 2. The Predictive Work Process by Artificial Neural Network

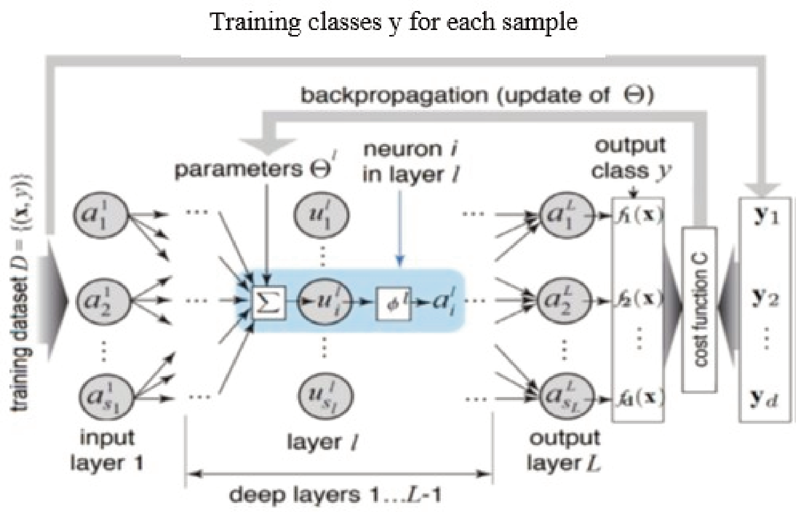

Figure 3. Deep Neural Network (Garcia et al. 2018)

Table 3

ANN Characteristics

Training	Learning rate	Momentum	Error epsilon
0.8	0.1	0.5	10^{-5}

The target function through a loss function and subsequently updating parameters through backward propagation is clear. Here's a slight refinement for readability: After the output is calculated, it undergoes a comparison with the target function using a loss function, allowing for the calculation of the error rate. Subsequently, the backward propagation process begins, during which all parameters are adjusted based on their impact on the overall network training error. This process repeats iteratively until the desired level of training is achieved.

Figure 3 illustrates the process of predictive work using deep learning in the software, providing a visual representation of these steps.

The characteristics of deep learning in the saffron export forecast are presented in Table 4.

Gradient boosting is a machine-learning technique used for both regression and classification tasks. It constructs a prediction model in the form of an ensemble comprising weak prediction models, often in the form of decision trees. The model-building process is carried out incrementally, similar to other boosting methods. What sets gradient boosting apart is its capacity to optimize any differentiable loss function (Breiman, 1997). Figure 4 provides a visual representation of the saffron prediction process using the Gradient Boosting method, offering insight into how it operates in this context.

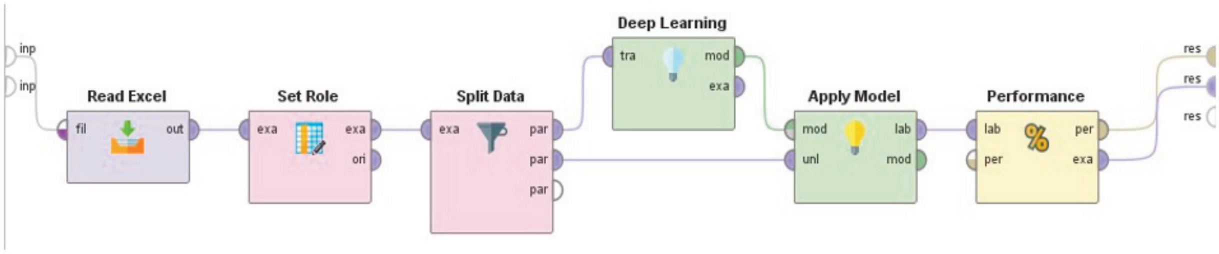

Figure 4. The Saffron Predictive Process by Deep Learning

Table 4

Deep Learning Characteristics

Distribution function	Loss function	Epochs	Activation
Gaussian	Absolute	50	rectifier

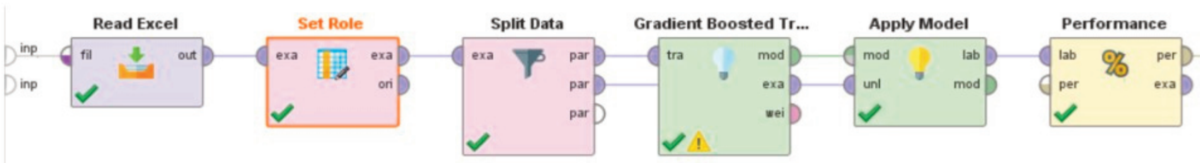

Figure 5. The Saffron Predictive Process by Boost Gradient

Table 5

Boost Gradient Characteristics

Number of trees	Maximum depth	Min rows	Learning rate	Number of bins	Sample rate
50	10	1	0.1	30	1

The characteristics of the boost gradient in the saffron export forecast are presented in Table 5.

Tables 3-5 provide the specifications, while Figures 6-8 present the outputs. In these figures, the horizontal axis represents the independent variable, which corresponds to the years, while the vertical axis represents the dependent variable, showcasing the actual and predicted annual data.

CONCLUSION

The production planning process encompasses several crucial stages, with forecasting being a fundamental step. In this phase, companies must anticipate their future production needs. While forecasting may seem hypothetical, companies can employ forecasting tools to achieve maximum accuracy. In the context of Iran's economy, which faces challenges due to limited oil resources and export market fluctuations, a shift towards non-oil exports, especially agricultural products like saffron, can significantly contribute to economic development. Accurate forecasting of saffron production plays a pivotal role in production planning, providing a competitive advantage for Iranian saffron exporters.

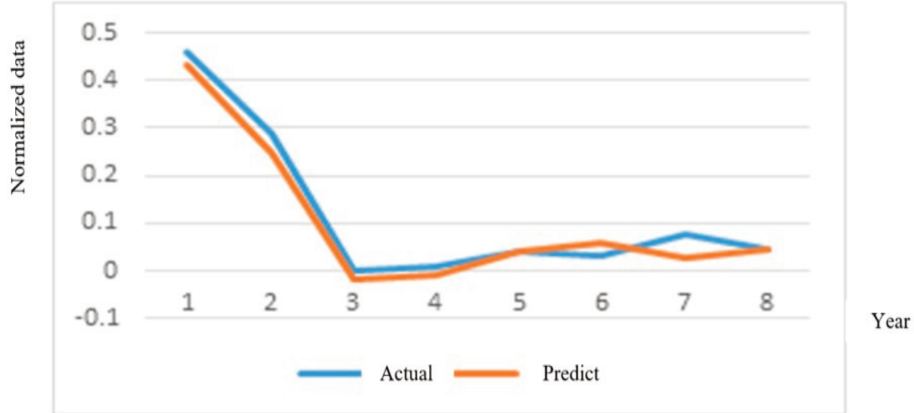

Figure 6. A Sample of Actual and Predicted Results by Artificial Neural Network

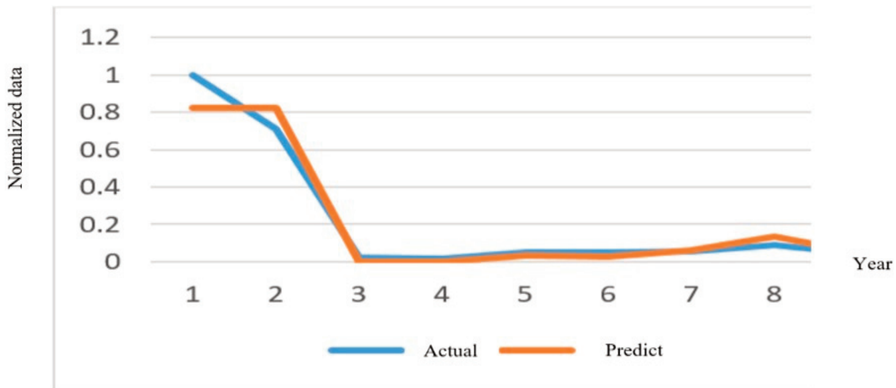

Figure 7. Sample Results of Actual and Predicted Values by Deep Learning Network

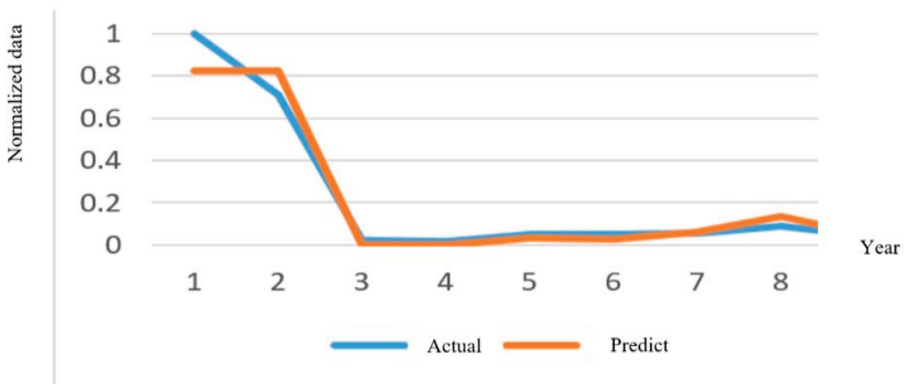

Figure 8: Sample Results of Actual and Predicted Values by Boost Tree Gradient Network

Deviating from the forecast can result in various costs, including storage expenses, auction losses, and missed opportunities. Hence, it is imperative to design a forecasting model with minimal deviation. In this study, a hybrid forecasting method was proposed to enhance the accuracy of saffron export forecasts in Iran. While previous agricultural forecast-

Table 6
Evaluation of Forecast Results

AE	R^2	RMSE	Type of network
0.036	0.95	0.045	Artificial neural network
0.031	0.98	0.044	Network Deep learning
0.047	0.97	0.073	Gradient boost tree

ing studies, especially those related to saffron, have proposed various algorithms, an optimal model has not yet been established. Consequently, the combination of multiple models has emerged as one of the most effective approaches to forecasting, often yielding more reliable and accurate results. To achieve this, the study designed and implemented three data mining prediction models: artificial neural network, deep learning, and gradient boost tree. Finally, to select the best forecasting model, the validity of these models was evaluated using three criteria: RMSE, R2, and AE, as summarized in Table 6. The findings indicate that all models exhibited good accuracy, with the deep learning network showing insignificantly lower error and consequently being chosen as the optimal model.

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CONFLICT OF INTEREST

The authors have not declared any conflict of interest.

AUTHORS' CONTRIBUTIONS

Mansour Soufi, As the researcher and responsible author of the manuscript, conceived the research idea, designed the study, collected and analyzed the data, and wrote the majority of the manuscript. Alireza Amirteimoori assisted with data collection, conducted statistical analyses, and contributed to the writing and revision of the manuscript. Mehdi Fadaei and Mahdi Homayounfar provided expertise and guidance throughout the research process, assisted with data interpretation, and critically reviewed the manuscript. All authors have read and approved the final version of the manuscript.

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