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Price forecasting using machine learning: A solution driving sustainable Vietnamese coffee supply chains

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ABSTRACT

Coffee is a vital commodity in Vietnam, providing economic and social significance. Additionally, Vietnamese coffee significantly contributes to global coffee production and is a crucial component of the worldwide coffee supply chain. Price forecasting provides essential information to supply chain members, enabling them to manage their supply chains better, minimize waste, and promote sustainable development. Thus, improving price forecasting accuracy will be beneficial in stabilizing and boosting coffee production by enabling supply chain actors to make informed production decisions, promoting sustainable coffee supply chains, and enhancing Vietnamese coffee competitiveness. However, coffee prices have shifted considerably since the COVID-19 pandemic, making forecasting challenging. As a result, adopting advanced forecasting techniques is critical to enhancing forecasting accuracy. Machine learning (ML), a subset of artificial intelligence (AI), has proven effective and widely used in various fields, particularly forecasting. This study employed a quantitative approach to evaluate the effectiveness of ML models, specifically the Long Short-Term Memory (LSTM) model, in forecasting coffee prices. This study utilized a comprehensive dataset comprising daily global coffee prices for over 50 years. The LSTM model delivered a remarkable forecast accuracy of 98.31%. The experiment results showed that LSTM outperformed Autoregressive Integrated Moving Average (ARIMA) models, one of the most frequently employed classical forecasting methodologies. Moreover, this study demonstrated the effectiveness of ML techniques in forecasting coffee prices, including LSTM, artificial neural networks (ANN), Gradient Boosting, and Random Forest. All ML models achieved excellent forecast accuracy, with values above 98%. LSTM produced the best performance among ML models. Furthermore, this study offers practical solutions to promote the application of ML methods, enhance forecasting accuracy, and improve coffee production efficiency, ultimately developing sustainable supply chains. These solutions involve major stakeholders, including the government, supply chain agents, technology suppliers, and researchers. Collaboration among these stakeholders is critical to successfully installing and optimizing ML forecasting systems.

Key words: coffee, forecasting, machine learning, sustainability

INTRODUCTION

Vietnam, the world's second-largest coffee exporter, is a key player in the global coffee supply chain [1]. Vietnam accounts for a considerable portion of global coffee output. Many supply chain stakeholders, including importers, roasters, and instant coffee manufacturers, rely on Vietnamese farming. The European Union (EU) remains Vietnam's top coffee export destination for the 2023/2024 crop year, accounting for 38% of the volume and 37% of the total value [2].

Additionally, coffee is a vital commodity in Vietnam's economic system. Exports of coffee in the 2023/2024 crop year contributed to over 5.4 billion USD of the country's export turnover [2]. Coffee generates numerous jobs and income, particularly in rural areas. Coffee is primarily cultivated in Vietnam's central highlands. Additionally, coffee has become a popular beverage in Vietnam. Vietnam boasts a diverse range of coffee cafés. Vietnamese people often drink coffee in the mornings and evenings. As a result, stabilizing and boosting coffee production is crucial to ensuring sufficient coffee quantity, country, and farmer earnings, promoting the coffee industry's sustainable growth, and enhancing Vietnamese coffee competitiveness.

Moreover, coffee prices have fluctuated dramatically in recent years, significantly impacting production activities. Figure 1 depicts coffee production and prices for the 2022/2023 and 2023/2024 harvest years. In 2023/2024, total coffee production rose by 200,000 60-kg bags to 27.5 million 60-kg bags. Additionally, coffee prices increased during the same period. Besides, exports account for roughly 90% of total coffee production. Thus, global coffee prices will influence local coffee prices, affecting farmers' profits and corporate revenue.

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Coffee, Green/ 1000 60kg bags	2022/2023	2023/2024
Arabica Production	900	880
Robusta Production	26300	26620
Total production	27300	27500
Total import	499	720
Total bean export	25400	23000
Domestic consumption	3200	3200

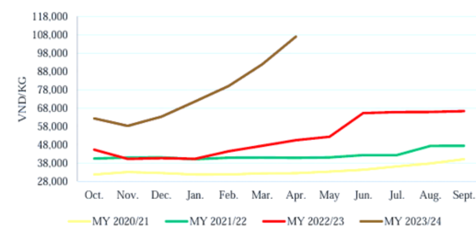

Figure 1: Coffee production (a) and local prices of Robusta coffee (b) in Vietnam . Source: [3]

Furthermore, previous research revealed that price will significantly impact production. They emphasized that crop product prices are directly related to supply and demand [4]. Thus, price forecasting is crucial in helping supply chain stakeholders, including farmers, businesses, exporters, and investors, make informed decisions about production, purchasing, and selling. For example, farmers can determine the best time to sell their products to maximize profits [5] and take timely actions to improve crop production [6]. Additionally, it benefits external stakeholders, including policymakers, the agribusiness industry, and investors [5,7]. Higher export prices benefited Vietnam's coffee producers and the industry, leading to a rise in local coffee prices [3].

Coffee prices have fluctuated over the years (Figure 2). This is due to an imbalance between supply and demand. On the demand side, consumption is expanding in emerging nations, such as China [8]. Climate change, crop diseases, logistical disruptions, and hoarding and hedging costs can all restrict coffee production, driving prices even higher [9]. Besides, coffee prices are soaring, far above professional estimates, causing numerous problems, including coffee counterfeiting and market speculation. In addition, farmers keep their coffee to wait for higher prices [10]. This can result in significant losses if the price drops unexpectedly. As a result, forecasting prices is crucial in helping stakeholders make informed decisions.

Numerous models have been employed to enhance forecasting accuracy. They can be categorized into two main types: classical and ML techniques. This study examines widely utilized methods of forecasting agricultural prices that have proven useful, such as ARIMA, LSTM, and ANN. ARIMA is a well-known classical model, whereas LSTM is a powerful ML model. Both have been successful in several cases. Recent research has shown the superiority of LSTM over other forecasting methods [11]. Moreover, this paper compares machine learning approaches to statistical models, utilizing ARIMA as a representative example. The findings demonstrate ML techniques' superior performance and practicality in predicting agricultural prices.

This research will enable accurate forecasting of coffee, address concerns about escalating prices, and assist supply chain actors in making informed production decisions. Moreover, this study provided practical solutions for adopting ML methods, enhancing forecasting accuracy, improving coffee production and supply chain performance, promoting the sustainable growth of the coffee industry, and strengthening Vietnamese coffee competitiveness.

RELATED WORKS

Sustainable supply chains

The supply chain encompasses all phases, from raw material sourcing to final product delivery to customers [12]. The coffee supply chain comprises multiple players, including growers, merchants, corporations, exporters, importers, roasters, distributors, and retailers [11]. Supply chain management (SCM) refers to the systemic, planned collaboration of standard business operations and techniques within a specific organization and among businesses throughout the supply chain. It aims to enhance the long-term performance of individual firms and the overall supply chain by increasing customer value and satisfaction, ultimately resulting in a competitive advantage [13]. However, SCM could cause negative implications such as greenhouse gas emissions, electronic waste creation, the usage of conflict minerals, and involvement in human trafficking. Thus, it is vital to manage the supply chain sustainably. Developing sustainable supply chains helps reduce negative environmental consequences and provides long-term economic, social, and reputational benefits to firms.

Sustainable supply chain management covers all supply chain activities and integrates environmental, economic, and social performance objectives [15]. Building

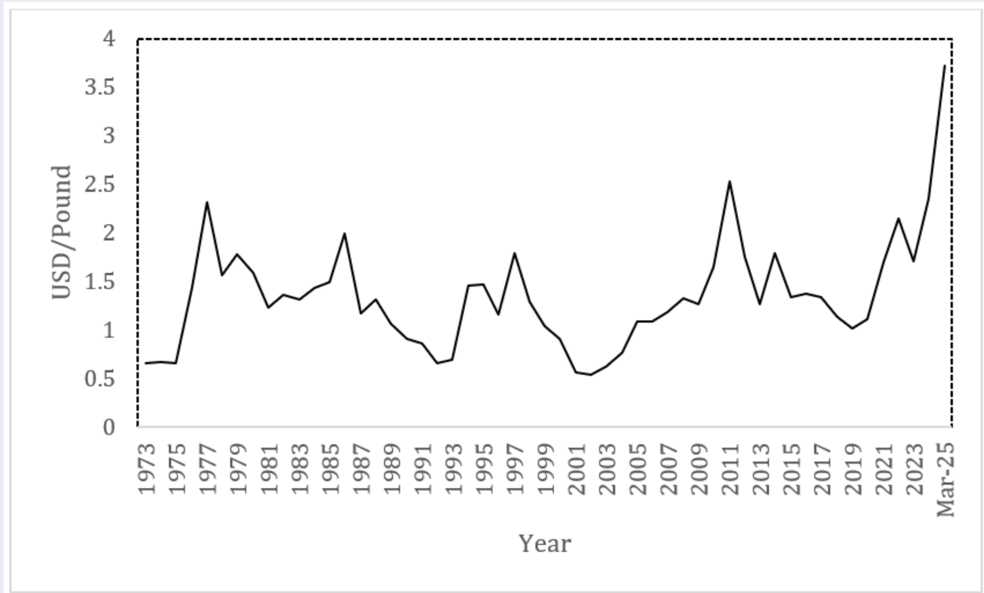

Figure 2: Averagedaily coffee price from 8/1973 to 12/3/2025. Source: https://www.macrotrends.net

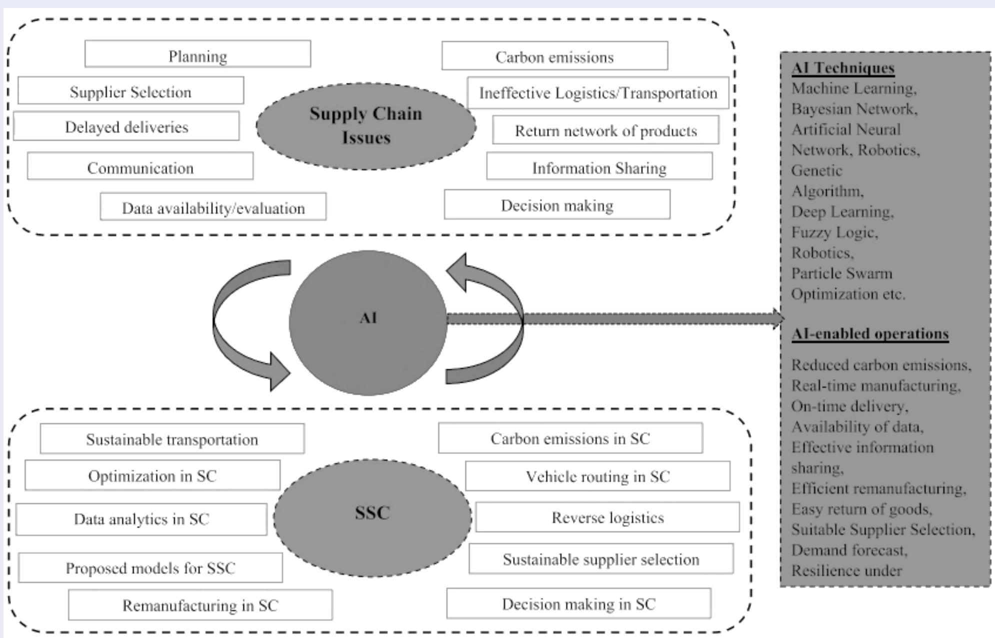

Figure 3: AI and Sustainable Supply Chain (SSC). Source: [14]

sustainable supply chains is crucial to achieving the Sustainable Development Goals, which are universal objectives established by the United Nations and its member states to protect the planet by 2030. Numerous studies have demonstrated that digital technologies enhance supply chain efficiency and sustainability. AI has a substantial impact on supply chain efficiency and resilience [16]. Figure 3 shows the role of AI in SSC. AI can help address supply chain issues and support SSC, including sustainable transportation, effective remanufacturing, demand forecasting, and reverse logistics [14].

Forecasting is one of the key business functions of supply chain management [13]. Accurate forecasts are critical so that the main stakeholders can accurately predict coffee demand and better plan future production capacities, such as crop planning and green coffee bean supply [11]. AI-based models can predict noisy and chaotic economic and financial series and commodity prices [17]. For example, LSTM boosted the forecasting accuracy of Arecanut prices [6]. Thus, adopting AI not only improves forecasting accuracy but also fosters SSC.

Price forecasting

Price forecasting has received attention from various researchers. They employ different methods to predict commodity prices. There are two main forecasting techniques: statistical techniques and ML [18,19]. The statistical methods perform well with time series linear features [20]. Meanwhile, ML models can capture nonlinear patterns and larger datasets [17,21]. For example, [4] ARIMA is suitable for small-scale periodic data and requires less training time. In contrast, the LSTM model performs well with complex data and nonlinear trends [11].

Prior research has shown that predicting coffee prices is a challenging task. Coffee data exhibits linear and nonlinear patterns [22]. Additionally, prices for agricultural commodities shift much more than those of other industries' products [23]. Coffee prices were the most volatile among all crops in 2021 [24]. Thus, selecting the appropriate forecasting techniques for coffee prices is critical for maximizing accuracy.

Previous research has employed the Autoregressive Integrated Moving Average (ARIMA) model and its extensions to forecast prices [25,26]. For example, [27] ARIMA was used to forecast Indian Robusta coffee prices. Similarly, [26] the estimated prices of Arabica and Robusta coffee in Brazil are as follows: Moreover, [5] discovered that ARIMA outperformed various techniques in forecasting monthly tomato prices, including exponential smoothing with error, trend, and seasonality (ETS), support vector machine for regression (SVM), LSTM, and multilayer perceptron (MLP). Thus, this study will select ARIMA models.

ARIMA has been shown to function effectively with linear trends, but has limited experience with large datasets. Most previous studies used ARIMA for monthly crop records. For example, authors [28] employed ARIMA models to forecast monthly wheat prices in the United States. Similarly, authors [29] employed the ARIMA model to predict monthly coffee prices in Indonesia. Thus, this work contributes to the current literature review by demonstrating the performance of ARIMA models with daily coffee pricing.

Moreover, this study aims to utilize ML models to forecast coffee prices, which have fluctuated substantially. Authors [30] reviewed AI forecasting techniques in the past decade and discovered that LSTM is one of the most prevalent due to its high efficacy. LSTM has several benefits over other ML forecasting models. Firstly, it succeeds at working with sophisticated data and nonlinear patterns [11]. Secondly, it is a neural network developed to learn long-term dependencies [31]. LSTM used a memory cell concept to build the neural network structure [32]. Thirdly, several papers have presented empirical evidence suggesting that the LSTM network outperforms other machine learning and traditional methods. Recently, demonstrated that LSTM outperformed ARIMA models and ANN in capturing future and coffee demand patterns [11]. As a result, this study will use LSTM. Additionally, this study utilizes the ARIMA model as a benchmark to evaluate and demonstrate the performance of LSTM networks.

Used models

ARIMA

ARIMA is composed of three components: autoregression (AR), integration (I), and moving average (MA) [6,33]. AR projected values based on a prior lagged value. Integrated is used to convert a time series into a stationary one. MA predicts values e based on lagged error data. Thus, ARIMA denotes ARIMA(p,d,q). ARIMA can be calculated as Equation 1 [11]:

$$y_t = c + \sum_{i=1}^{p} \varnothing_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad \text{(A2)}$$

Where $\varnothing_i \neq 0$; $\theta_i \neq 0$; and $\sigma_\varepsilon^2 > 0$; y_t: the stationary variable or real price at date t; c: constant; $\varnothing$: autocorrelation coefficients at lags 1,2,..,p; ε_t : Gaussian white noise series with mean zero and variance σ_ε^2; θ : the weights assigned to the stochastic term's current and prior values in the time series and θ_0 =1; p: lagged observations; q: the size of moving average window; (d): difference.

LSTM

LSTM has input gate $x(t_i)$, forget-gate $f(t_i)$, internal state (cell memory) $c(t_i)$, and an output gate $o(t_i)$ [11,33]. Figure 4 illustrates the LSTM structure.

LSTM performs as follows: The forget gate $f(t_i)$ process $x(t_i)$ and output value at the time point $t_{i-1}(h(t_{i-1}))$ to compute the data should be kept in $c(t_{i-1})$ by utilizing a sigmoid activation function. The output results of the input gate $a(t_i)$ uses $x(t_i)$ and $h(t_{i-1})$ to determine the value of $c(t_i)$. Meanwhile, the output gate $o(t_i)$ controls an LSTM cell's output by considering $c(t_i)$ and using both sigmoid and tanh layers.

METHODOLOGY

This study conducts a quantitative study to investigate the efficacy of ML models, represented by LSTM, in forecasting coffee prices. The research method comprises five primary stages: defining research questions, reviewing relevant works, price predictions, finding analysis, and suggestions.

Stage 1. Research questions

• How accurate is the machine learning model in predicting prices?

• What solutions should be provided to promote machine learning techniques in price forecasting?

Stage 2. Related works

This stage will examine related research to investigate prevalent forecasting approaches and the roles of AI and ML in sustainable supply chains and price forecasting.

Stage 3. Price forecasting

This study forecasts coffee prices in four steps: data collection, preprocessing, hyperparameter tuning, and model evaluation.

Data gathering

This paper gathers daily global coffee prices. As shown in Figure 1, coffee is primarily exported. Coffee data is publicly available at https://www.macrotrends.net/2535/coffee-prices-historical-chart-data. This website was developed by MACROTRENDS LLC, headquartered in Seattle, Washington, USA. This open data source offers daily statistics from August 20, 1973, to March 12, 2025.

Data preprocessing

This step will clean and normalize the data acquired from the previous stage. This stage removes missing and noisy values to guarantee smooth time series data. The data were divided into training and test sets, with 80% used for training and the remaining 20% for testing.

Tune Hyperparameters

This study uses ARIMA and LSTM to forecast coffee prices. This study will determine the lowest AIC (Akaike Information Criterion) to identify the ideal ARIMA (p, d, q) model. This study employs a random search method to determine the optimal parameter combination for the LSTM model. The parameters include the number of neurons, the Adam optimization algorithm, the Mean Squared Error (MSE) loss function, the number of epochs, the batch size, and the dense output layer. All models have been developed and implemented on Google Colab, a cloud-based platform for robust and accessible computing.

Model evaluation

This study will calculate performance errors using different measures, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and forecasting accuracy. They are calculated in Equations (1)-(5), respectively.

$$RMSE = \sqrt{\frac{\sum_t^n (Y_t - \widehat{Y}_t)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_t^n \left|Y_t - \widehat{Y}_t\right|}{n} \quad (2)$$

$$MAPE = \frac{1}{n}\sum_t^n \frac{\left|Y_t - \widehat{Y}_t\right|}{|Y_t|} \times 100 \quad (3)$$

$$Accuracy = 1 - MAPE \quad (4)$$

Where Y_t The actual demand at time t; $\widehat{Y}_t$ is the forecast demand at time t; $\overline{Y}_t$ is the average of actual demand; n is the forecasting period, $Y_t - \widehat{Y}_t$ which measures the forecast error.

Stage 4. Result analysis

This stage will review the results of ML models. This study also compared its findings to ARIMA, a statistical model.

Stage 5. Recommendations

This study will recommend practical solutions to overcome the identified forecasting challenges and encourage the usage of machine learning forecasting approaches.

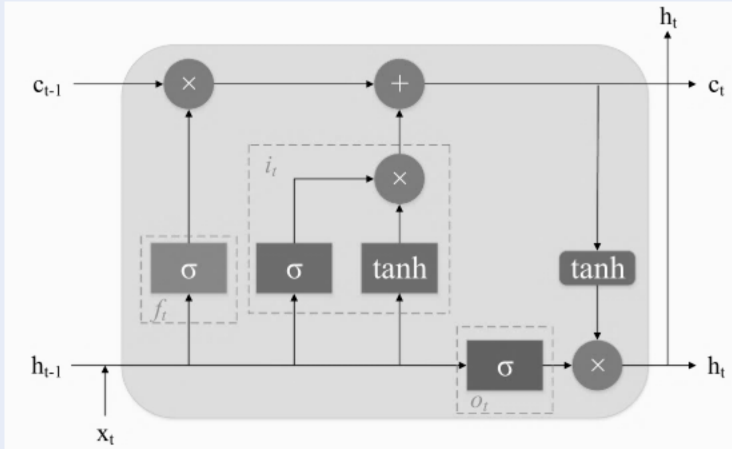

Figure 4: LSTM cell. Source: [34]

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Price   No. Observations:                10364
Model:                 ARIMA(5, 1, 3)   Log Likelihood               21003.676
Date:                Mon, 16 Jun 2025   AIC                         -41989.352
Time:                        23:52:36   BIC                         -41924.138
Sample:                             0   HQIC                        -41967.316
                              - 10364
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.1190      0.366      0.325      0.745      -0.598       0.836
ar.L2         -0.0536      0.246     -0.218      0.827      -0.535       0.428
ar.L3         -0.2541      0.231     -1.100      0.271      -0.707       0.199
ar.L4          0.0132      0.032      0.416      0.678      -0.049       0.075
ar.L5         -0.0409      0.016     -2.609      0.009      -0.072      -0.010
ma.L1         -0.0877      0.366     -0.240      0.811      -0.805       0.629
ma.L2          0.0306      0.236      0.130      0.897      -0.431       0.493
ma.L3          0.3129      0.218      1.436      0.151      -0.114       0.740
sigma2         0.0010    5.1e-06    199.318      0.000       0.001       0.001
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):            109510.77
Prob(Q):                              0.93   Prob(JB):                         0.00
Heteroskedasticity (H):               0.80   Skew:                             0.22
Prob(H) (two-sided):                  0.00   Kurtosis:                        18.92
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Figure 5: ARIMA performance. (Source: Own research results)

RESULTS AND DISCUSSION

Parameters of ARIMA and LSTM

Figure 5 presents the results of ARIMA models. This study found that ARIMA (5,1,3) has the lowest AIC of –41989.352 and BIC of -41924.138.

Additionally, this study employs an LSTM model with 50 neurons, the Adam optimizer, and the mean squared error as the loss function. It is trained for 20 epochs with a batch size 32 and has a single dense output layer. Figure 6 illustrates forecasting values produced by ARIMA and LSTM. LSTM generates predictive patterns that closely resemble real data trends. In contrast, ARIMA could not predict the upward trend in the data. This finding illustrates that LSTM can estimate reliable coffee prices.

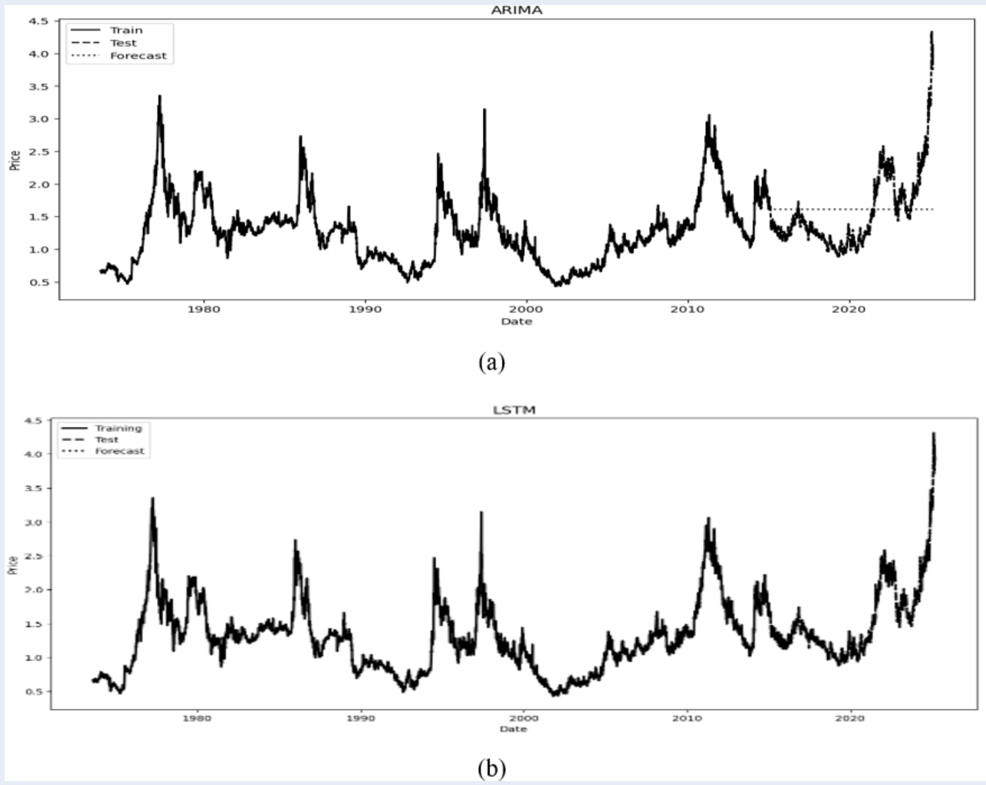

Figure 6: ARIMA andLSTM prediction values (a)- (b). Source: Own research results

Comparison of forecasting performance of ARIMA and LSTM

Table 1 shows the forecasting measures for each model. ARIMA has an RMSE of 0.567, MAPE of 29.82%, and MAE of 0.447. In comparison, LSTM has an RMSE of 0.04, MAPE of 1.69%, and an MAE of 0.0276. Thus, LSTM models outperform ARIMA models in terms of metrics. This finding is consistent with previous studies [5,11,33].

Table 1: Performance indicators of ARIMA and LSTM

	ARIMA	LSTM	ANN	Gradien Boosting	Random Forest
RMSE	0.567	0.040	0.0443	0.0888	0.088
MAPE	29.82%	1.69%	1.79%	1.78%	1.87%
MAE	0.447	0.0276	0.0292	0.0333	0.0346
Accuracy	70.18%	98.31%	98.21%	98.22%	98.13%

Source: Own research results

Moreover, this study examines the performance of various ML models, including Artificial Neural Networks (ANN), Gradient Boosting, and Random Forest. The findings show that all ML models had great forecasting accuracy, reaching 98%. These results suggest that ML methods outperform classical models. Furthermore, the study demonstrates that the LSTM model outperforms other ML models in predicting coffee prices.

Table 2 displays some forecasting results obtained using ARIMA and LSTM.LSTM produces values that are similar to actual values. LSTM-generated forecasting values are typically smaller than exact values. In comparison, ARIMA produces the same values and differs from the real ones. Thus, the gap between LSTM and real values is less than that of ARIMA models. Therefore, supply chain stakeholders can base their decisions on the predicted values provided by LSTM.

Based on the results, this study reveals that ML can outperform classical methods for predicting coffee prices. This finding supports the past researchers [11,33,35]. However, these findings contradict those of a previous author [5], who demonstrated that ARIMA outperformed LSTM in forecasting tomatoes. Crop prices vary per product, and coffee has been one of the commodities with the highest soaring prices in

Table 2: Some examples of ARIMA and LSTM prediction values

Date	Real data	ARIMA	LSTM
25/02/2025	3.749	1.609	3.706
26/02/2025	3.769	1.609	3.684
27/02/2025	3.783	1.609	3.703
28/02/2025	3.894	1.609	3.716
03/03/2025	3.894	1.609	3.821
04/03/2025	4.053	1.609	3.970
05/03/2025	4.133	1.609	4.044
06/03/2025	3.931	1.609	3.855
07/03/2025	3.925	1.609	3.850

Source: Own research results

recent years. As a result, researchers should experiment with various predicting methodologies to determine which are the most reliable. ML forecasting algorithms are among the top options for estimating agricultural prices.

RECOMMENDATIONS

Price forecasting is crucial for supporting supply chain participants in better managing their operations, lowering costs, and improving customer satisfaction. Accurate forecasting of prices enables them to establish an effective planning procedure. Organizations can proactively modify their purchasing strategies to mitigate risks and increase earnings. They can buy raw materials in advance to avoid losses if prices rise. Additionally, they can select suitable suppliers. Also, they can predict their earnings based on predicted prices.

Given the importance of price forecasting in the agricultural sector, this study provides various practical recommendations to enhance and promote the use of advanced forecasting algorithms, specifically LSTM models. The recommendations engage key stakeholders, including the government, coffee supply chain agents, technology companies, and scientists (Figure 7). Each stakeholder plays a crucial role and must collaborate to ensure the successful deployment and optimization of forecasting systems.

This study discusses recommendations for four major stakeholders, as described below. Firstly, the Vietnamese government is crucial in promoting technology adoption in the agricultural sector. Developing and applying ML forecasting models aligns with Vietnamese policies, including Decision No.127/QD-TTg, which implements the "National Strategy on Research, Development, and Application of Artificial Intelligence to 2030". Coffee is typically farmed in remote areas with minimal infrastructure. As a result, the government should prioritize investment in information technology systems in those regions. Besides, governments should offer financial incentives to encourage businesses to deploy ML forecasting models, such as tax exemptions and low-interest rates.

Secondly, this study focuses on farmers and coffee enterprises as key agents in the supply chain. Companies should implement ML-based forecasting tools to help them make more informed and strategic decisions. Companies can use these advanced techniques to enhance their purchasing methods, procuring coffee beans at lower prices while assuring fair remuneration for farmers. This strategy would improve purchase efficiency, especially during peak pricing periods. Additionally, companies can inform and educate farmers on how to utilize forecasting tools.

Thirdly, technological businesses are significant in investigating and developing improved forecasting systems. They may provide the latest market information to help coffee supply chain stakeholders and researchers with their research and decision-making. Additionally, they can develop numerous AI systems and applications that offer consumers free access to coffee price predictions and other factors influencing prices. Furthermore, these corporations can help develop AI APIs that are easy to integrate with supply chain management systems, enabling coffee businesses to utilize them directly within their systems.

Finally, scholars should collaborate with business and technology groups to improve forecasting methods. Academics should focus on developing and evaluating various ML-based forecasting methods. Additionally, researchers can investigate the factors that influence corporate behavior and intentions to improve the adoption of these technologies.

CONCLUSIONS

Price forecasting provides supply chain members with valuable information to help them manage their supply chains more effectively, avoid waste, and support sustainable development. Price forecasting is crucial for all products and services, particularly those in the agricultural sector. This study utilizes an advanced forecasting system to predict the yield of one of the well-known crops, coffee. Coffee is an essential agricultural product in Vietnam, with economic and social implications. It significantly contributes to global coffee production. Thus, improving price forecasting accuracy can help supply chain members make more

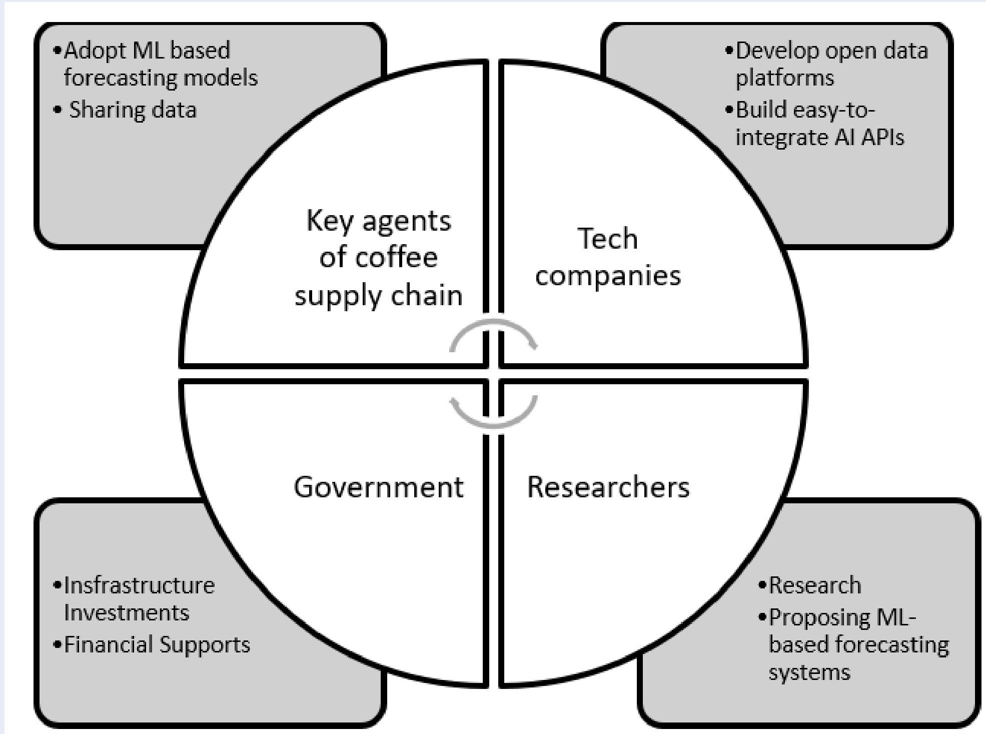

Figure 7: Practicalsolutions to promote the use of ML-powered forecasting models. Source: Own research results

informed production decisions, foster sustainable coffee chains, and enhance Vietnamese coffee competitiveness.

This study has gathered data on coffee for over 50 years, including the most recent peak period. Many stakeholders, including governments, farmers, coffee firms, traders, and exporters, have expressed concern throughout this period. This study addressed the current problem, enabling supply chain participants to make data-driven decisions. This study forecasted coffee prices using various models, including ARIMA, LSTM, ANN, Gradient Boosting, and Random Forest. LSTM is an intelligent ML model that has recently been deployed. This study demonstrated the effectiveness of ML techniques in forecasting coffee prices. They outperform ARIMA across all measures. Compared to other ML models, LSTM gives better outcomes. Moreover, this study recommends practical solutions to various parties to stimulate the use of ML approaches, improve forecasting accuracy, optimize coffee production and supply chain performance, promote the long-term growth of the coffee industry, and enhance Vietnamese coffee competitiveness. The recommendations engage major stakeholders, including the government, coffee supply chain agents, technological companies, and scientists.

Although this study provides empirical support for using ML forecasting approaches, some future work is recommended. Future research should incorporate supply chain variables, such as quantity and quality parameters, and demand-side dynamics, to improve the robustness and application of forecasting models. Additionally, future researchers can forecast coffee prices by incorporating more factors that influence prices, such as GDP, coffee production, and currency rates. Furthermore, future papers may propose novel, advanced ML-powered forecasting systems. These systems should be straightforward to use, encouraging farmers to adopt them. Furthermore, future studies should examine the impact of enhanced price forecasting on sustainability, specifically in terms of environmental, social, and economic measures.

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ABBREVIATIONS

AI: Artificial Intelligence

ARIMA: Autoregressive Integrated and Moving Average

ANN: Artificial Neural Network
ML: Machine learning
LSTM: Long Short-Term Memory
BiLSTM: Bidirectional Long Short-Term Memory
SCM: Supply chain management
SSC: Sustainable supply chain

COMPETING INTERESTS

The authors declare that they have no conflicts of interest.

AUTHORS' CONTRIBUTIONS

The author confirms being the sole contributor of this work, including the ideas, data collection, data analysis, and solutions, and has approved it for publication.

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Dự báo giá bằng máy học: giải pháp thúc đẩy chuỗi cung ứng cà phê bền vững tại Việt Nam

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TÓM TẮT

Cà phê là một nông sản chủ lực của Việt Nam, đóng góp đáng kể vào kinh tế và xã hội. Ngoài ra, cà phê Việt Nam đóng góp lớn vào sản lượng cà phê toàn cầu và là một phần quan trọng của chuỗi cung ứng cà phê toàn cầu. Dự báo giá cung cấp thông tin cần thiết cho các thành viên trong chuỗi cung ứng, cho phép họ quản lý tốt hơn chuỗi cung ứng của mình, giảm thiểu lãng phí và thúc đẩy phát triển bền vững. Do đó, việc cải thiện độ chính xác của dự báo giá góp phần ổn định và thúc đẩy sản xuất cà phê bằng cách hỗ trợ các tác nhân trong chuỗi cung ứng đưa ra quyết định sản xuất hiệu quả, thúc đẩy quản lý chuỗi cung ứng cà phê bền vững và tăng cường khả năng cạnh tranh của cà phê Việt Nam. Tuy nhiên, giá cà phê đã thay đổi đáng kể kể từ đại dịch COVID-19, khiến việc dự báo chính xác trở nên khó khăn. Do đó, việc áp dụng các kỹ thuật dự báo tiên tiến là rất quan trọng để nâng cao độ chính xác của dự báo. Học máy (ML), một tập hợp con của trí tuệ nhân tạo (AI), đã chứng minh tính hiệu quả và được sử dụng rộng rãi trong nhiều lĩnh vực, đặc biệt là dự báo. Nghiên cứu này sử dụng phương pháp định lượng để đánh giá hiệu quả của các mô hình học máy, cụ thể là Bộ nhớ dài ngắn hạn (LSTM), trong việc dự báo giá cà phê. Nghiên cứu này sử dụng giá cà phê toàn cầu hàng ngày trong hơn 50 năm. Mô hình LSTM có độ chính xác dự báo đạt 98,31%. Kết quả thử nghiệm cho thấy LSTM vượt trội hơn ARIMA, một trong những phương pháp dự báo thống kê được sử dụng thường xuyên nhất. Hơn nữa, nghiên cứu này chứng minh tính hiệu quả của mô hình ML trong việc dự báo giá cà phê, cụ thể là LSTM, ANN, Gradient Boosting và Random Forest. Tất cả các mô hình ML đều đạt độ chính xác dự báo cao, với giá trị trên 98%. Trong đó, LSTM có kết quả tốt nhất trong các mô hình ML. Từ đó, nghiên cứu này đưa ra các giải pháp có tính thực tiễn nhằm thúc đẩy ứng dụng các phương pháp ML, cải thiện độ chính xác dự báo và hiệu quả sản xuất cà phê và góp phần phát triển chuỗi cung ứng bền vững. Các giải pháp này gắn liền với các chủ thể chính trong chuỗi cung ứng bao gồm chính phủ, các tác nhân chính trong chuỗi cung ứng, nhà cung cấp công nghệ và các nhà khoa học. Sự hợp tác giữa các chủ thể này đóng vai trò then chốt để triển khai và ứng dụng thành công các mô hình dự báo học máy.

Từ khoá: cà phê, dự báo, học máy, bền vững

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