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Research Article

A Review of Demand Forecasting Models for Indian Coffee Exports: Bridging Gaps and Opportunities

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ABSTRACT

Accurate demand forecasting is crucial for Indian coffee exports, given the sector's vulnerability to market volatility, shifting consumer preferences, and global trade dynamics. While traditional models like ARIMA are widely used, they struggle to address the nonlinear complexities and external factors such as climate variability and trade policies. This review critically synthesizes forecasting methodologies for Indian coffee exports, evaluating their strengths, limitations, and gaps. A systematic review of studies published between 2004 and 2024 was conducted, using databases like Scopus, Springer, and Elsevier, with a focus on relevance to coffee demand forecasting. Findings reveal that while traditional statistical models are effective for linear trends and seasonality, they fail to capture the dynamic nature of the market. Machine learning and hybrid models provide improved accuracy but face scalability and computational challenges. This review highlights gaps in integrating real-time data and domain-specific factors, offering insights for refining forecasting approaches and addressing emerging challenges in the field.

Keywords: Indian Coffee Exports, Demand Forecasting, Machine Learning Models, Long Short-Term Memory (LSTM) Networks, Hybrid Forecasting Models, U.S. Coffee Market.

1. Introduction

India is at a high rank as the world's best coffee producer, and is also famous for producing the Arabica and Robusta variety. In all, this variety is mainly cultivated in the southern states of Karnataka, Kerala, and Tamil Nadu, respectively. These cultivations engage millions of farmers [1]. The export of coffee has substantially contributed to the agricultural economy of India and made this industry a vital actor in national and international trades. However, the international coffee market is characterized by inherent volatility due to factors such as fluctuating consumer preferences, dynamic global trade policies, unstable prices, and complex supply chains [2]. Demand forecasting, in such a setting, becomes an important enabler of supply chain management, price stabilization, and indeed, policy decision making. However, there is a lack of adequate representation of sophisticated nonlinear characteristics of the coffee market in many existing forecasting methodologies, including climate change, fluctuations in the exchange rate and shift in the global economy [3]. This divergence serves to emphasize the importance of smarter, more subtle, and context-sensitive forms of forecasting.

Agricultural demand forecasting literature is highly diversified and consists of a variety of methodologies, from more common statistical models to advanced machine learning techniques. Traditionally, such methods include ARIMA and SARIMA for capturing linear trends and seasonal patterns and have been intensively applied for short-term forecasting. These models, however, depend on linearity assumptions that render them incapable of tackling the dynamic multifaceted nature of the coffee export market. Machine learning models, including LSTM networks, CNNs, and hybrid frameworks, have demonstrated outstanding potential in the treatment of complex nonlinear relationships as well as combining various sources of data [4]. Advanced approaches include real-time data, external variables, and market dynamics that could contribute to more accurate and robust forecasting. However, these models are linked to a computational burden, scaling problems, and requirements for higher quality data sets, so their practical applications are constrained. Other research approaches that involve statistical methods as well as the utilization of machine learning also seem to show great potential. However, the practical application of applying these concepts in the Indian coffee export investigation have not been explored at all, and as such form another significant research gap.

This review aims to fill these gaps by synthesizing the strengths and limitations of current methodologies in forecasting and evaluating their relevance for the unique challenges of the Indian coffee export market. By critically examining traditional, advanced methods with actionability, it attempts to provide insights towards developing more robust and adaptable forecasts in this context. In contrast to most prior review papers that focused either on statistical models or on standalone machine learning techniques, the work underlined the promise of hybrid frameworks as it enables a reconciliation between traditional models' interpretability and machine learning power of prediction. It also indicates how external aspects of climate change, trade policies, and global market conditions should be input into a projection system in order to have practical applicability to real decision environments. Therefore, this review outlines the present gaps and how computation and scalability would help build directions for further work, policy building, and implementation in industries, in regard to agricultural demand projection. The main objective are as follows:

- To analyze and synthesize existing forecasting methods, including traditional statistical models, hybrid approaches, and advanced AI techniques, in the context of coffee export demand prediction.
- To identify and address the limitations of current forecasting approaches, particularly in handling nonlinear dynamics, seasonality, and market variability, to propose a comprehensive framework for Indian coffee export forecasting.

Research Gap

The emergence of India as a major coffee exporter globally makes the precise forecasting of export demand to the USA extremely crucial. Yet, current models cannot possibly represent the diverse impacts of dynamic factors like changes in market trends, evolving consumer preferences, price fluctuations, and trade policy shifts. The classical methods like ARIMA and exponential smoothing [5] fail to accommodate nonlinear patterns and seasonal changes. In addition, in other industries, advanced hybrid and AI-driven methods have promise, but their application toward Indian coffee exports is merely minimal. This gap requires innovative, integrative forecasting that combines diverse methodologies to deliver a precise prediction, which supports better supply chain management and market responsiveness.

Research Questions

1. What are the strengths and limitations of existing forecasting methods, including traditional statistical models, hybrid approaches, and advanced AI techniques, for coffee export demand prediction?
2. How can current forecasting approaches be enhanced to better address nonlinear dynamics, seasonality, and market variability in Indian coffee exports?
3. What framework can effectively integrate diverse forecasting methods to improve the accuracy and operational efficiency of demand prediction in the Indian coffee export sector?

RQ1. What are the strengths and limitations of existing forecasting methods, including traditional statistical models, hybrid approaches, and advanced AI techniques, for coffee export demand prediction?

Traditional statistical models such as ARIMA and exponential smoothing are very popular in forecasting coffee export demand since they are simple, easy to interpret, and good for short-term linear trends and seasonality. But the models often fail to capture complex nonlinear dynamics and need large, stationary datasets to produce accurate predictions. Hybrids can be made by combining the strengths of ARIMA models with machine learning models, such as SVM or neural networks, to improve precision and adaptability. For instance, advanced AI methods, such as LSTM, CNN-BLSTM, and XGBoost-GRU, are excellent in nonlinear pattern modeling, long dependencies, and unstructured data prediction for superior predictive power. Despite these advantages, their limitations include high computational requirements, parameter optimization difficulties, and challenges in interpretability, which may not favor their practical application in dynamic markets such as Indian coffee exports.

RQ2. How can current forecasting approaches be enhanced to better address nonlinear dynamics, seasonality, and market variability in Indian coffee exports?

These can be integrated with the domain-specific data and advanced hybrid models to forecast the nonlinear dynamics, seasonality, and market variabilities in Indian coffee exports. Features like climate data, market trends, and exchange rates in the model will help improve accuracy by reflecting external factors influencing coffee exports. This technique is known as transfer learning, it is useful in adapting AI models trained on global coffee datasets to Indian-specific contexts. Another type of model that combines the advantages of deep learning and statistical techniques is hybrid models; for instance, using an LSTM network in conjunction with ARIMA for seasonality correction or applying XGBoost in feature selection. Optimization algorithms such as genetic programming will also enhance the performance of the model while dealing with computation challenges.

RQ3. What framework can effectively integrate diverse forecasting methods to improve the accuracy and operational efficiency of demand prediction in the Indian coffee export sector?

A framework that is effective for the improvement of demand forecasting of coffee exports from India should involve a multi-level approach that incorporates traditional statistical methods, hybrid models, and advanced AI techniques. This will begin with statistical models like ARIMA to capture initial trend and seasonality, then use hybrid models that include deep learning in order to capture nonlinear patterns. More on the feature engineering layer based on domain-specific factors-such as environmental conditions or global market indices-would make the data more applicable for current relevance. Then, employing advanced AI models like CNN-LSTM or XGBoost-GRU during fine-tuning and predicting in the long run ensures robust performance, scalability, and adaptability, further providing policymakers and exporters with some decision-making insights into optimizing and even cushioning market risks in terms of supply chain management.

2. Review Methodology

This study utilized a systematic literature review methodology to examine scholarly and industry-based research related to forecasting models for Indian coffee exports to the USA. The SLR process was carried out by identifying, screening, and evaluating studies to ensure alignment with the research objectives. Reputable databases, including Scopus, Springer, Elsevier, and Google Scholar, served as primary sources for data collection. Eligibility criteria prioritized recent studies focusing on advancements in forecasting methodologies and their applicability to agricultural trade, while exclusion criteria filtered out irrelevant or outdated research. Through a rigorous synthesis of the retrieved data, the review established a foundation for assessing and comparing different forecasting models, facilitating the identification of innovative approaches relevant to the Indian coffee trade.

2.1 Selection Criteria

The selection criteria for studies and models are meticulously defined to ensure relevance and reliability. First, the studies included must align with the objective of improving the forecasting accuracy of coffee exports, particularly in the context of Indian trade with the USA. The selected timeframe is set to include recent advancements, primarily focusing on publications from the last decade (2004-2024). Priority is given to works addressing forecasting methods in agriculture, international trade. Further, studies are assessed based on their relevance to Indian exports, considering factors such as production characteristics, market demands, and socio- economic influences. The models reviewed are diverse, encompassing statistical approaches like ARIMA and SARIMA, machine learning techniques such as neural networks, and hybrid models to explore their comparative effectiveness. Only peer-reviewed articles, industry reports, and case studies with robust methodological descriptions are included.

2.2 Data Sources

The data sources comprise a comprehensive collection of academic and industry-related materials. Databases such as Scopus, Springer, Elsevier are utilized to retrieve scholarly articles and reviews. Additionally, specialized agricultural and trade databases, including FAOSTAT and the Indian Coffee Board reports, are leveraged to access real-time data and trends. Industry publications, such as reports from the International Coffee Organization

(ICO) and trade policy briefs from WTO, provide contextual insights into the dynamics of coffee trade. Journals focusing on agricultural economics, sustainability, and data science are consulted to identify relevant forecasting methodologies. Moreover, conference proceedings and white papers addressing innovations in forecasting and trade modeling are incorporated to capture cutting-edge developments.

2.3 Inclusion and Exclusion Criteria

To ensure the selection of high-quality and pertinent studies for the current research project on forecasting models for Indian coffee exports to the USA, specific inclusion and exclusion criteria were established. Standard peer-reviewed journal articles and conference proceedings from reputable sources such as IEEE Xplore, Springer, Elsevier, and Scopus were prioritized. Studies focusing on advanced forecasting techniques, data-driven modeling approaches, and applications of machine learning and statistical models in agricultural trade forecasting were included. The publication window was limited to the period from 2004 to 2024 to capture the most recent advancements and trends in the field. Articles were included if they addressed key aspects like model accuracy, computational efficiency, adaptability, and relevance to coffee exports. Table I outlines the detailed criteria for including and excluding publications, guiding the selection process to ensure the relevance and quality of the chosen studies.

Table I Current review process inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Literature accessibility	Full-text	Papers without a full text are excluded
Language	English	Non-English papers have been excluded
Timeline	Between 2004 and 2024	Articles classified as grey papers (those published prior to 2004 or those lacking any bibliographic details like issue and volume numbers, publication dates, etc.)

2.4 Systematic Review Process

PRISMA Flow Diagram for Study Selection Process is given in fig.1. This framework outlines the systematic literature review process. A total of 230 records were identified, of which 200 were from database searches and 30 from other sources. After removing 30 duplicates, 200 records were screened at title and abstract level, which led to the exclusion of 110 irrelevant studies. Full-text assessment of 90 studies resulted in 44 being excluded for lacking relevant process or performance information. Eventually, 46 studies were taken into the qualitative synthesis, thereby ensuring a focused and high-quality review.

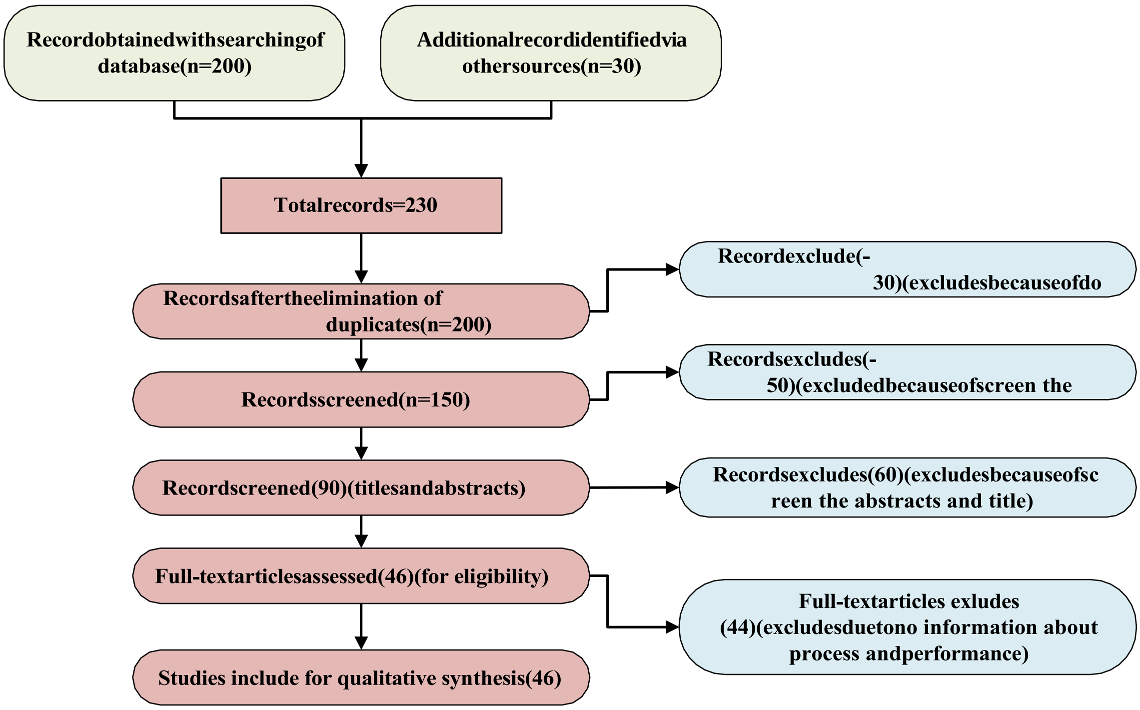

Fig.1 Framework of PRISMA

2.5 Search Result

The process of gathering research articles for this study involved a meticulous and systematic search to ensure comprehensiveness and alignment with the research objectives. Major academic databases, including Scopus, Springer, IEEE Xplore, and Google Scholar, were utilized to retrieve relevant studies. A combination of carefully curated keywords, such as forecasting models, Indian coffee exports, agricultural trade prediction, and data-driven methods, guided the search to capture diverse perspectives on the topic. Additionally, manual searches through prominent journals, conference proceedings, and trade reports were conducted to identify studies that might have been overlooked in database queries. This rigorous methodology ensured the inclusion of high-quality and relevant research, offering a broad and nuanced understanding of advancements in forecasting techniques applicable to Indian coffee exports to the USA.

3. Systematic Literature on Demand Forecasting Models

3.1 Machine Learning and AI Applications in Coffee Demand and Price Forecasting

Deina [6] introduced a novel approach for forecasting coffee price using ELM's combined with preprocessing to increase the model's ability to provide accurate results. They used methods which involved removing seasonal and trend components, and chose temporal lags using Partial Autocorrelation Function techniques. The study then compared ELM models against conventional mode such as ARIMA and MLP and found out that ELM were superior in making accurate price prediction for both Arabica and Robusta coffee prices. Kilimci [7] developed an intelligent demand forecasting model that incorporates the past data, time series analysis and SVR as well as the decision-making process. Their boosting ensemble approach enhanced the predictive accuracy even further in real retail context. In their study of BDA in the supply chain context, Seyedan and Mafakheri [8] classified approaches such as neural networks and clustering. Operational and analytical research gaps were identified like the limited use of BDA in closed-loop supply chains to provide scope in predicting analytics for the future. Awwad [9] examine how Big Data Analytics (BDA) holds potential in reshaping the contours of supply chain management especially in Industry 4.0 context. Data generated by machines, processes and services are huge data that cannot be handled by more conventional methods, only BDA allows for Big Data analysis. The paper also reveals the role of supply chains in the process of creating Big Data in which Manufacturing, logistics and retail data aid in the formulation of improved strategies. BDA helps in making proactive decision making, resulting into effective demand forecasting, inventory and logistics management. Despite challenges such as data integration and computational demand, BDA offers transformational benefits, including improved efficiency, resource optimization, and agility. Thus, the research stresses on the importance of data analytics in today's supply chain management. Jin [10] developed the application of price forecasts for agricultural exports utilizing enhanced Prophet models involving RNN and GRU. This combination has eradicated gradient vanishing issues, and offered improved logistics accuracy and risk reduction. Feizabadi [11] proposed a combination of ARIMAX models with neural network and they used both the explanatory and time series variable to formulate hybrid models for accurate forecasting. Mekala [12] proposed a CNN-BLSTM model where convolutional networks were used for feature extraction, combined with bidirectional LSTM for better temporal analysis and the model distinguished high accuracy in uncertain price scenario of coffee. Certainly, to overcome demand fluctuations in the coffee supply chains, Wang [13] developed a hybrid forecasting model using grey Bernoulli models with Fourier residuals. Finally, Nguyen [14] made a comparison between the ARIMAX and LSTM models and the authors employed LSTM since it determined superior operational performance in terms of turnover of inventories and transportation cost efficiently. Overall, these studies are evident of the possibility of AI and machine learning to improve coffee forecast accuracy and decision making.

In Milas, Otero, and Panagiotidis [15], both linear and nonlinear error correction models were employed to examine spot price behaviors for four sub types of coffee. These were Unwashed Arabica from Brazil, Colombian Mild Arabica from Colombia, Other Mild Arabica from other parts of Latin America and Robusta from Africa and Asia. In their analysis, they concentrated on the short- and long-run coefficient adjustments of the coffee spot prices as they employed ECMs to explain the likelihood of price changes across different varieties of coffee. In other works, linear models were widely discussed by Naveena, Subedar, [16] and Naveena [17] and are considered as exponential smoothing approaches, including Holt's model, Brown's linear trend model, Winter's seasonal exponential smoothing, and Holt-Winters method. They also used ARIMA, GARCH, ANNs, Markov Chains for price and export forecasting of Indian coffee. These models offered rich architectures for the market forecast and available seasonality's with the exponential smoothing methods showing significant performance for the time-series pattern. The study is useful to consider because of the specificity of coffee exports in India. In N. Ayyanathan and Kannammal [18] both the ANN & SVM models were used to forecast the green coffee prices in the Indian stock market was the machine learning methods that were applied to illustrate the effectiveness of the identified model for nonlinear and complexity datasets. Subsequently, Na Ayyanathan and Kannammal [19] proposed a cognitive decision support system for green coffee supply chain in India. This system integrates the ARIMA models and LS-SVR to respond to logistical and financial decisions; they showcased a detailed way for making the best of supply chain using predictive analytics. It was found that Yashavanth [20] and Fousekis, [21], applied various forms of ARIMA models in the context of coffee price forecasting; thereby showing the multifaceted applicability of this technique when dealing with univariate time series data. These also compared other linear techniques for the purpose of improving accuracy of ARIMA which was noted to be one of the most used methods because of its simplicity and its high performances. Following the ideas of Pradkhan [22], this study employed quantile regression models to gauge the Granger causality of trading activities that affect the commodity price in the United States. This approach determined causal co variables which enhance understanding of market forces and the causes of price changes particularly suitable for policy and investment decision making. Last, Puchalsky [23] used Wavelet Neural Networks (WNNs) to forecast commodity prices with special reference to soybean prices and demand for perishable products. Their work showed that construction of WNNs provided enhancement to time-frequency techniques and offered robust representation of time-frequency characteristics of price signal that are non-stationary and multi-scale in nature. In this work, building on WNNs, the authors introduced a novel strategy for enhancing the accuracy of forecasts in agricultural and perishable products' markets, such as coffee.

Table II Summary of Forecasting Methods for Coffee Price and Demand Prediction

Method	Reference	Objective	Advantage	Disadvantage
ELM with preprocessing	Deina [6]	Coffee price forecasting	High accuracy; effective handling of seasonal/trend components	May require careful preprocessing steps
SVR with boosting ensemble	Kilimci [7]	Coffee demand forecasting	Improved predictive accuracy	Computationally intensive

Neural networks & clustering for BDA	Seyedan and Mafakheri [8]	Supply chain analytics	Enhanced decision-making for closed-loop supply chains	Limited adoption in closed-loop supply chains
Enhanced Prophet models (RNN + GRU)	Jin [10]	Agricultural price forecasting	Solves gradient vanishing; improved accuracy	Complexity in model training
ARIMAX + Neural Networks hybrid	Feizabadi [11]	Price forecasting using time series and explanatory variables	Robust hybrid modeling approach	High computational demand
CNN-BLSTM	Mekala et al. [12]	Temporal analysis in coffee price forecasting	High accuracy in uncertain price scenarios	Complexity in combining CNN and BLSTM
Grey Bernoulli models with Fourier residuals	Wang et al. [13]	Demand forecasting in supply chain	Effective handling of demand fluctuations	Limited interpretability
LSTM vs ARIMAX	Nguyen et al. [14]	Comparison of forecasting models	Better performance in inventory turnover and transportation costs	Training LSTM can be time-intensive
Error Correction Models (ECMs)	Milas, Otero, and Panagiotidis [15]	Spot price behavior analysis for different coffee types	Explains short- and long-run price adjustments	Linear assumptions in models
Exponential smoothing methods	Naveena et al. [16], Naveena [17]	Coffee price and export forecasting	Handles seasonality effectively	Limited to linear time-series data
ANN & SVM	N. Ayyanathan and Kannammal [18]	Coffee price forecasting in Indian markets	Effective for nonlinear, complex datasets	Requires significant computational resources
ARIMA + LS-SVR	Na Ayyanathan and Kannammal [19]	Decision support for green coffee supply chain in India	Combines ARIMA's simplicity with SVR's accuracy	Model integration complexity
Quantile regression	Pradkhan [22]	Analyzing commodity price changes	Effective in identifying causal covariables	Focused on specific causal variables
Wavelet Neural Networks (WNNs)	Puchalsky et al. [23]	Forecasting agricultural and perishable product prices	Robust representation of non-stationary and multi-scale signals	Complex implementation; requires expertise

The analysis from Table II shows that hybrid and advanced models, such as CNN-BLSTM, ARIMAX + Neural Networks, and Wavelet Neural Networks, are the best when dealing with complex, nonlinear price and demand forecasting but come at the cost of high computational demands and complexity in implementation. Traditional models such as exponential smoothing and ARIMA provide simplicity and good trend handling but fail to capture non-linear or multi-scale patterns.

3.2 Advanced Methods for Forecasting and Optimization

Sohrabpour [24] proposed a novel Genetic Programming approach, combined with an evolutionary algorithm to build causal models to enhance the forecast of the export sales, consequently increasing the accuracy of the model. Achmadin [25] elected to use the Holt Winters Exponential method to quantify the amounts of coffee exported by Indonesia and for confirmation of their strategy they use parameter optimization. Bacci [26] introduced the FA-NBI multi-objective method for forecasting performance metrics utilising Principal Components Factor Analysis employed to find the best method with high MAPE, MPE, and SMAPE. Aamer [27] surveyed the application of machine learning methods in demand forecasting and concluded that the dominating methods in this field are artificial neural networks and support vector machines but they are still under-researched in the context of agriculture. Zohdi [28] further showed how extreme learning machines and artificial neural network was effective for intermittent demand forecasting owing to the predictive capabilities of the two algorithms. These studies highlight the improvement of existing methodologies in supply chain and the effectiveness of detailed forecasting approaches.

There has been a good recognition of exponential smoothing techniques especially for their ability to handle different pattern of short-term data. These are 'Double Exponential Smoothing' by Holt is best used for data that contains trend and 'Triple Exponential Smoothing' by Holt-Winters is best used for data that also contain seasonal variations. However, the application of these methods often raises a parameter selection problem, and this is solved, by means of the trial-and-error method. This process, however, takes a long time and may reduce the ways and windows through which such methods can be implemented in dynamic forecasting. Siringoringo [29] has attempted to combine the golden section optimization method for filtering parameters of exponential smoothing methods. Following the Actual export values of East Borneo Province, this study utilised Holt DES, additive Holt-Winter TES, Multiplicative Holt Winter TES models all of which were supported by Golden Section optimisation. All three methods have attained an MAPE of less than 10 % which implies highly accurate forecasts. Of all the models identified, the additive Holt-Winter TES, with golden section optimization of parameter settings, predict export values with the best accuracy. Returning, this work demonstrates that integrating conventional simulation models and sophisticated optimization procedures can enhance accuracy and algorithm time at the same time, thus having important implications to employ in economic and business forecasting.

Table III Overview of Forecasting Methods for Export Sales and Demand Prediction

Method	Reference	Objective	Advantage	Disadvantage
Genetic Programming + Evolutionary Algorithm	Sohrabpour et al. [24]	Enhance export sales forecasting	High accuracy in building causal models	Complex implementation
Holt-Winters Exponential Smoothing	Achmadin et al. [25]	Quantify Indonesian coffee export amounts	Handles trend and seasonal variations effectively	Parameter selection requires trial-and-error, time-consuming
FA-NBI Multi-objective Method	Bacci et al. [26]	Forecast performance metrics	Incorporates PCA to improve forecast accuracy	High computational demand
Machine Learning Methods (ANN, SVM)	Aamer et al. [27]	Survey of ML in demand forecasting	Highlights potential in agriculture	Limited research in agricultural contexts
Extreme Learning Machines (ELM) + ANN	Zohdi et al. [28]	Intermittent demand forecasting	Effective predictive capabilities for intermittent data	High sensitivity to parameter selection
Holt Double Exponential Smoothing (DES)	Andriani, Wahyuningsih, & Siringoringo [29]	Forecast export values	Handles data with trends effectively	Parameter optimization required
Holt-Winter Triple Exponential Smoothing (TES) - Additive	Andriani, Wahyuningsih, & Siringoringo [29]	Forecast export values	Best accuracy with golden section optimization (MAPE < 10%)	Time-intensive parameter optimization process

Holt-Winter Triple Exponential Smoothing (TES) - Multiplicative	Andriani, Wahyuningsih, & Siringoringo [29]	Forecast export values	Handles seasonality and trend for dynamic forecasting	Performance dependent on parameter tuning
Golden Section Optimization + TES	Andriani, Wahyuningsih, & Siringoringo [29]	Optimize parameter settings for TES methods	Enhances forecast accuracy and algorithm runtime	Requires additional computational resources for optimization

The insights from Table III indicate that such advanced methods as Genetic Programming and TES with Golden Section Optimization improve the accuracy of exported goods and demand prediction while demanding high computational power and require quite complex parameter tuning. In contrast, simpler models such as Holt-Winters Exponential Smoothing proved useful for trends and seasonality but require iterative optimization processes which limit scalability.

3.3 Time Series Analysis in Demand Forecasting

The most popular technique of demand analysis is employed in the examination of chronological sequences which involves the modeling and forecasting of the past demand data trends in the future. It encompasses such techniques as naïve method, moving average, trend curve analysis, exponential smoothing and ARIMA models, which are cherished for their cheaper, easier to employ and simple approaches. These techniques are typically used in fields such as advance estimating of sales or of the economy, analysing the budget, sharing prices of the common stock or studying inventories Gosasang, Chandraprakaikul, and Kiattisin, [5]. These models are more useful where trends or averages can be given, but not the forces that affect the variable to be predicted Illeperuma & Rupasinghe [30]. While in causal models, demand is affected by certain known variables, aims to establish the causality and likely impact between the variable to be forecasted and the other predictor variables, such as the price of the product, the cost of advertisement and the promotions to be made Armstrong, [31]. Compared to both the time series and the causal models explained above, both methodologies are highly convenient to build and apply, but they may fail to identify nonlinear relationships between the factors under consideration. Neural network modeling can be used as an effective solution to address such a limitation. Chen [32] highlighted on the benefits of this neural network in explaining such features with nonlinearity of the data flow. A comparative study on several moving average, ARIMA, feed-forward neural networks, nonlinear autoregressive networks with exogenous inputs presented by Mitrea [33]. This proved that ANN models as a rule had significantly better predictive power of the results to be compared, thereby illustrating the ability of the ANN models to overcome the shortcomings of more conventional approaches and yield more accurate forecasts.

The autoregressive moving average (ARMA) based methods of forecasting typically involve using history data to estimate these demand patterns including seasonal ones. Miller and Williams [34] have added to this by seeking to improve the accuracy of forecasting by including seasonal variations in the model. To enhance the estimation of cyclic movements, they applied a multiplicative mode to establish seasonality to model the components of demand. Combined with those seasonal factors, their methodology allowed to enhance ARMA and improve the account of such recurrent patterns of demand. But Hyndman [35] built on [34] by allowing a variety of relationships between trend and seasonality under the SARIMA system. ARIMA is modified by the addition of a seasonal component and seasonal differencing and seasonal autoregressive and seasonal moving average terms in order to capture both the trend and seasonality of time series data. Although SARIMA gives a more solid way of modeling and forecasting seasonal data it comes with strengths and weakness when used in seasonal adjustment order that is relatively high. The classical ARIMA model, in particular, can become rather cumbersome when attempting to deal with high value seasonal adjustment orders or when the diagnostics suggest that the time series is non-stationary after seasonal adjustment. LW128 Time series forecasting has been used extensively with various industries to tackle demanding demand prediction issues. ARIMA models were used by Ghosh [36] to forecast the demand for a food manufacturing company. The Box-Jenkins method was used in the development of multiple models including different ARIMA models using the Akaike criterion along with the maximum likelihood approach. ARIMA (1, 0, 1) model outcome was statistically tested for its adequacy in forecasting sustained in operational and strategic planning and execution.

Similarly, Miller and Williams [34] enhanced the use of forecasting accuracy trough using seasonal factors on ARIMA equation using multiplicative method while Hyndman [35] advanced on this work by investigating relationship between trend and seasonality within the frame work of seasonal ARIMA. However, classical ARIMA models have some drawbacks: problems with the stabilization of the higher-order seasonal adjustments, non-stationarities, and the need for big data samples, and in general, they do not cope well with highly variable demand patterns. In order to overcome these problems, there are other possibilities including the advanced approaches, which belongs to the machine learning clique, namely the SVMs. Sapankevych and Sankar [37] have presented a discussion on applying SVM in time series forecasting over domains including financial market and electricity load forecasting. While generalizing over linear and noisy data the SVMs are also superior to more traditional models like autoregressive or neural networks by means of their ability to find the global optimum while not overfitting the dataset. To improve the prediction accuracy, the application of the hybrid models, for instance SVMs combined with GA or wavelet transforms has been developed. But, as in several other local methods, complexity of choosing the parameters, and the computational cost of training are the main drawbacks that might hinder application in real-time systems. It is in the recent decades that integration of machine learning and statistical models appeared to be promising. In 2020, Zhai, Yao and Zhou [38] designed the XGB-GRU where XGBoost was used to extract the feature while GRU extracts temporal patterns. This mixed model yielded a higher accuracy than using either unduly XGBoost or GRU models on multivariate time series predictive modeling especially in industry i.e., heating furnace temperature. Explaining the results This model successfully provided a solution to the problem of creating explainability for a neural net based on an XGBoost model's variable importance output and provided a strong architectural framework to deal with the attributing factors which are usually embedded in industrial data sets. Altogether, these investigations describe the transition from conventional inferential analyses that generated simple forecasting models towards intricate forms of machine learning, which exhibit enhanced compatibility into a wide range of forecasting paradigms.

Table IV Comparison of Forecasting Methods for Demand and Time Series Analysis

Method	Reference	Objective	Advantage	Disadvantage
Naïve, Moving Average, Trend Curve Analysis	Gosasang et al. [5]	Simple demand forecasting	Cheap, simple, and easy to apply	Limited ability to capture causality or nonlinear relationships
Causal Models	Armstrong [31]	Establish causality between demand and predictor variables	Identifies causality effectively	Fails to handle nonlinear relationships
Neural Networks	Chen [32]	Overcome limitations of linear models	Handles nonlinearity in data effectively	Requires large datasets and computational power
ARMA with Seasonal Factors	Miller and Williams [34]	Improve seasonal demand forecasting	Enhanced accuracy by modeling seasonality	Limited for highly complex seasonal data
SARIMA (Seasonal ARIMA)	Hyndman et al. [35]	Model demand with trend and seasonality	Flexible modeling of seasonal and trend data	Cumbersome for high seasonal adjustment orders
Box-Jenkins ARIMA	Ghosh [36]	Demand forecasting for food manufacturing	Effective for operational and strategic planning	Struggles with highly variable or non-stationary data
Support Vector Machines (SVM)	Sapankevych and Sankar [37]	Time series forecasting for noisy and nonlinear data	Finds global optimum and avoids overfitting	Computationally expensive and challenging parameter tuning

SVM + Hybrid Models (e.g., GA, Wavelet)	Sapankevych and Sankar [37]	Improve prediction accuracy	High accuracy through hybridization	High complexity and computational cost
XGB-GRU (XGBoost + GRU)	Zhai, Yao, and Zhou [38]	Multivariate time series forecasting for industrial data	Combines feature extraction and temporal pattern analysis	Complexity in model design and interpretability

Table IV shows that traditional models like ARIMA and SARIMA may be good for trends as well as seasonality and poorly handle nonlinearity but advanced techniques like SVM or XGB-GRU may be very good to capture complex patterns, especially when high computational power along with expertise is used but add complexity and make these models less accessible for easy use in simple applications.

3.4 Hybrid Forecasting Techniques

In order to capture fluctuating demand of spring onion seeds, Zhu [39] develop a HW-SVM integrated forecasts model with good performance. The model is able to forecast demand by incorporating dynamic factors that may include historical sales, seed inventory available, crop market prices, and even the prevailing weather conditions thus minimizing errors in forecasting. For three seed varieties, numerical experiments showed improved accuracy of the proposed model in comparison with standard statistical methods. Seed inventory is acknowledged as a short-term factor and crop market price, historic crop sales volume as middle-term factors; and absolute minimum temperature as the long-term factor influencing the demand. Indeed, this valuable concept helps to determine tendencies within changing factors and seeds consumer demand, which is the key to expect low operational expenses and effective supply chain management. Since it has been used in PMV4S, it has implication in improving other crop seeds essential in developing agricultural forecasting techniques.

In Herrera-Jaramillo [40], the role of Machine Learning approaches to stabilize the price of coffee in Colombia is studied. They discuss the methods of forecasting and use a LSTM RNN algorithm, which was found to be more accurate among the models for predicting volatility. The model is enhanced by a linear self regression component incorporating a multilayer perceptron type of neural network included in the modeling to represent the chaotic behavior of the coffee prices. These results imply that current price is explained by the prices that were as current in the last four years. The logistics method having uncorrelated, homoscedastic residuals proves useful as a forecast for the coffee-growing community to prepare for price volatilities. Predicting prices of coffee pose some certain problem since the price movements are found to possess chaotic property and thus its future value is best handled by special concern. The same method has been utilized to model the coffee price in other research studies that have relied on other forms of more sophisticated and composite models in an attempt to capture the underlying nature of coffee price volatility. For instance, Henao and Dumar [41] has designed a hybrid technique which consist of autoregressive model with multi-layer perceptron (MLP) neural network used for foreign exchange rate prediction of Colombian coffee prices on New York Stock Exchange. In aspects of both linear and nonlinear, this model proved helpful through triangulation of statistical procedures with ANN in order to obtain higher levels of predictive accuracy in the price data. Berhane [42] in another study, predicted Ethiopian coffee prices using Kalman Filtering Algorithm. A recursive algorithm known as the Kalman filter to estimate the state of dynamic systems make it easier for the researchers to model the time-varying stuff like coffee prices. This approach was useful to develop a way to point out changes occurring in the coffee market patterns, which increases the ability to predict prices, particularly in a dynamic scenario. Furthermore, Rodríguez and Melgarejo [43] suggested a new forecasting model for the original multiscroll Chua system which is a type of a chaotic system in nonlinear dynamics. In their model, they equated Colombian coffee prices with the multiscroll Chua system that has a set of oscillations. In using this chaotic system, the researchers were able to capture the nonlinear oscillation of coffee prices within a given observation time as a powerful technique in forecasting prices. Many of these studies demonstrate the relevance of using advanced, hybrid, and chaotic systems in the modeling and forecasting of coffee prices, to illustrate a rich and versatile set of approaches for addressing the complex nature of the forecast environment.

Table V Comparative Analysis of Methods for Coffee Price Forecasting and Volatility Prediction

Method	**Reference**	**Objective**	**Advantage**	**Disadvantage**
HW-SVM Integrated Model	Zhu et al. [39]	Forecast demand for spring onion seeds	Incorporates dynamic factors (historical sales, weather, prices) for accuracy	Limited scalability beyond specific applications
LSTM RNN with Multilayer Perceptron	Herrera-Jaramillo et al. [40]	Stabilize and predict coffee price volatility	Captures chaotic price behavior; improved accuracy with 4-year price data	Computationally intensive for large datasets
AR Model with MLP Neural Network	Henao and Dumar [41]	Predict Colombian coffee prices in the NYSE	Combines linear and nonlinear modeling; higher predictive accuracy	Complexity in combining models and parameter tuning
Kalman Filtering Algorithm	Berhane et al. [42]	Predict Ethiopian coffee prices	Adapts to time-varying patterns; recursive and dynamic	Limited application for highly nonlinear systems
Multiscroll Chua System	Rodríguez and Melgarejo [43]	Model Colombian coffee prices using chaotic dynamics	Captures nonlinear oscillations in price trends	Requires expertise in nonlinear chaotic systems

The Table V shows that more sophisticated hybrid models such as LSTM and AR-MLP effectively capture the nonlinearity and dynamics of coffee price forecasting with high accuracy, however, requiring much computation and expertise. More simplified models such as Kalman filtering adapt to time-varying patterns but suffer in highly nonlinear systems.

3.5 Regional Coffee Industry Analysis and Case Studies

On Indian coffee export competitiveness Jagadeesh [44] highlights India's growing production but suggests its export performance lags behind leading exporters like Ethiopia, Honduras, and Colombia. Studies using RCA and RSCA indices show that India's competitiveness remains suboptimal. The gravity model analysis reveals that larger economies import more, but geographic distance impacts trade negatively. Research also points to a misalignment between India's export focus and untapped markets such as the UK, France, and the Netherlands. While key markets like Italy and Belgium are well-exploited, there is significant growth potential in underutilized regions. Enhancing production efficiency, improving product quality, and redirecting export strategies toward high-growth markets are crucial for strengthening India's position globally. Duran [45] employed ARIMA models to forecast export patterns of Peruvian coffee attributed to export quantity, physical infrastructure for exports, and competitive policy support. According to their studies, the goals of their business models focused on scale economies and operational efficiency. Gómez [46] identified the Colombian specialty coffee market, examined its consumer profile and supply chain for better strategic guidance to German investors. This study focused on sustainability and efficient management so as to unlock the specialty coffee market. Temesgen [47] examined the price risk analysis of Ethiopian coffee export using ARMA-EGARCH models and find out other important factors such as oil price and exchange rate that are crucial while dealing with Ethiopian coffee export market risk. Duran [45] explore export competitiveness of Peru's coffee industry through ARIMA model to evaluate exports of volume and price. The paper shows how ARIMA captures trend and seasonality and offers insights into the future position of the market. Through demand modeling in key import markets, the study provides considerations on the profitability as well as sustainability. This analysis helps the producers and policymakers in policy formulation to improve export and competitiveness. This marks a shift away from decision-making approaches that rely only on the experiential model and towards quantitative approaches as a way of extending the peru brand in the global market. It supports long-term sustainable and profitable business opportunity within coffee trade.

Table VI Comparative Analysis of Methods for Coffee Export Competitiveness and Forecasting

Method	**Reference**	**Objective**	**Advantage**	**Disadvantage**
RCA and RSCA Indices	Jagadeesh et al. [44]	Assess India's coffee export competitiveness	Provides quantitative insights into export performance and competitiveness gaps	Limited ability to address underlying causes of competitiveness issues
Gravity Model Analysis	Jagadeesh et al. [44]	Analyze factors influencing Indian coffee exports	Highlights the impact of market size and geographic distance on trade	Does not account for cultural or policy barriers affecting exports
ARIMA Model	Duran et al. [45]	Forecast Peruvian coffee export patterns	Captures trend and seasonality; provides actionable insights for policy formulation	Limited in addressing nonlinear or external factors influencing trade
ARMA-EGARCH Model	Temesgen [47]	Price risk analysis of Ethiopian coffee exports	Accounts for volatility and external factors like oil prices and exchange rates	Requires complex data and expertise for implementation
Consumer and Supply Chain Analysis	Gómez [46]	Strategic guidance for Colombian specialty coffee market targeting Germany	Focus on sustainability and efficiency; aligns strategies with market demand	Context-specific findings may limit generalizability to other markets
Demand Modeling via ARIMA	Duran et al. [45]	Evaluate Peruvian coffee exports' volume, price, and market profitability	Enables quantitative and data-driven decision-making; supports long-term sustainable growth	Relies heavily on historical data, which may not fully predict future scenarios

From table VI, it can be understood that quantitative models such as RCA, ARIMA, and ARMA-EGARCH give deep insights on competitiveness of coffee exports, trade pattern, and price risks, though such models require more data. The strategic guidance is given by the market-specific analysis, like consumer study and supply chain analysis but lacks generalizability.

3.6 Demand Forecasting in Business Operation

Demand forecasting methods have currently become part of the whole process of making operational decisions as well as strategic choices within any business. The research work by Silva, Figueiredo, and Braga [48] developed a demand forecasting model customized to a delicatessen firm referred to as PR belonging to the food sector. It was designed using combination multiple forecasts that form tool supporting production planning and inventory control management, and results are kept being tested. Similarly, Ingle [49] did a detailed literature review on the different types of forecasting techniques used in retail, supermarkets, and supply chains. They further went to detail the diversity of the approaches being applied, from the old traditional statistical models up to machine learning, deep learning, and hybrid approaches. The review highlighted to choose methods according to data types and time horizons as well as forecast, and it highly recommends an integrated approach. Here, models are implemented, monitored, and selected for optimal accuracies in particular datasets. Observations from these, Priyadarshi [50] highlighted demand forecasting model selection for the retail-stage demand of agricultural produce, which is vegetables in nature. The present study has considered traditional models like ARIMA, which have been compared with the performance of machine learning algorithms like LSTM, SVR, Random Forest Regression, and XGBoost. This research shows that the errors associated with the performance in forecasting, cost on inventories, and produce wastage is minimized by maximizing the revenue by the LSTM and SVR models. Although the results are case-specific, they present the potential of advanced algorithms in improving the accuracy of forecasts in dynamic retail environments. Together, the studies depict a growing reliance on customized, data-driven forecasting solutions to fulfill the diversified needs of the industry, thereby underlining the necessity of integrating traditional and advanced methods to make a proper demand prediction.

Table VII Comparative Analysis of Forecasting Methods for Retail and Agricultural Demand

Method	Reference	Objective	Advantage	Disadvantage
Combination of Multiple Forecasts	Silva, Figueiredo, and Braga [48]	Develop a demand forecasting model for a delicatessen firm (PR)	Supports production planning and inventory control; results continuously tested for refinement	Customization limits general applicability; requires continuous monitoring and adjustment
Literature Review on Forecasting	Ingle et al. [49]	Review and analyze various forecasting techniques for retail, supermarkets, and supply chains	Highlights diversity of approaches; provides guidance on method selection based on data types and time horizons	No direct implementation or testing; serves as a guideline rather than a practical tool
ARIMA	Priyadarshi et al. [50]	Forecast retail-stage demand for agricultural produce	Proven traditional method; suitable for capturing trends and seasonality	Less accurate in dynamic or non-linear environments
LSTM (Long Short-Term Memory)	Priyadarshi et al. [50]	Improve forecasting accuracy for agricultural produce in retail	Handles non-linear relationships; minimizes inventory costs and wastage while maximizing revenue	Requires large datasets and significant computational resources
SVR (Support Vector Regression)	Priyadarshi et al. [50]	Predict retail-stage demand for vegetables	Effective in capturing non-linear patterns; reduces errors in forecasting	Sensitive to parameter selection; can be computationally intensive
Random Forest Regression	Priyadarshi et al. [50]	Compare advanced machine learning algorithms with traditional models	Robust to overfitting; handles high-dimensional datasets well	May not perform as well as LSTM for time-series data
XGBoost	Priyadarshi et al. [50]	Optimize demand forecasting in dynamic retail environments	High accuracy; efficient in handling missing data and variable importance	Can be sensitive to overfitting with complex datasets

Table VII shows that machine learning techniques, like LSTM and XGBoost, which are highly accurate and suitable for dynamic demand forecasting and are less dependent on data and computational requirements, while the traditional techniques, such as ARIMA and SVR, are effective but less preferable in complex, non-linear environments.

4. Findings and Discussion

The review discusses the changes and use of demand forecasts of coffee exports through evolution in methodologies, including those aspects that are beneficial along with their limitations and prospect of improvement in Indian Coffee Exports. Exports of Indian coffee to the USA are a big share in total Indian coffee export. Thereby the demand for Indian coffee among US consumers is increasingly high these days. The USA is neither the largest Indian coffee importers nor in comparison to European countries, Italy, and Germany, but a very important one as India has a big demand there for specialty varieties of Arabica coffee. Major importers of Indian coffee in 2023 are given in table VIII. Italy leads at 19.59% of the total export value, followed by Germany at 15.14%. European countries occupy the major share of the list, thereby showing a major chunk of exports. Middle Eastern countries like Jordan, UAE, and Saudi Arabia also represent considerable markets, thereby showing a diversification of export destinations. At $747.2 million, total export value signified the global appeal of Indian coffee. Data were also provided regarding important markets, offering insights to be targeted through specific export enhancement strategies.

Table VIII Major Importers of Indian Coffee in 2023 (Export Value in Million US$) [44]

Importers	Export Value (million US$)	Percentage (%)
Italy	146.3	19.59
Germany	113.1	15.14
Belgium	57.8	7.74
Jordan	47.9	6.40
United Arab Emirates	42.5	5.69
Libya, State	35.9	4.81
Kuwait	30.5	4.08
Saudi Arabia	19.3	2.58
Greece	17.7	2.37
Australia	17.5	2.34
World	747.2	100

The table IX below compares in detail coffee production in Indian states for the years 2023-24 and 2022-23, split between Arabica and Robusta varieties. Karnataka stands out as the leading producer, accounting for more than 70% of the total, with robust dominance in both years. Kerala is the second largest producer, with most being Robusta coffee, followed by Tamil Nadu and Andhra Pradesh, with modest shares. The states of Orissa and North Eastern Region have little contribution to the total output. As a whole, India increased total coffee production from 3,52,000 MT in 2022-23 to 3,74,200 MT in 2023-24, with an increase in both Arabica and Robusta yields.

Table IX Coffee Production in India by State (2023-24 vs. 2022-23) [44]

States	2023-24 (in MT)	2022-23 (in MT)
	Arabica	Robusta
Karnataka	81,960 (72.53%)	184,925 (70.80%)
Kerala	2,075 (1.84%)	70,750 (27.09%)
Tamil Nadu	13,045 (11.54%)	5,390 (2.06%)
Andhra Pradesh	15,340 (13.58%)	40 (0.02%)
Orissa	500 (0.44%)	0 (0.00%)
North Eastern Region	80 (0.07%)	95 (0.04%)
Grand Total (India)	1,13,000 (100%)	2,61,200 (100%)

India's production of coffee hails primarily from Karnataka and accounts for over 70%, with increases in total output noted in the year 2023-24. Here, Arabica as well as Robusta varieties experienced vigorous growth. On the export side, Italy, Germany, and Belgium take precedence as key importers of Indian coffee. Meanwhile, diversification into markets such as the USA represents efforts to enhance its global coffee trade footprint. In this review, the role of traditional statistical models - ARIMA and exponential smoothening Naveena, Subedar, [16] and Naveena [17], used so far in demand for its simplicity and effective identification of short-term trends or seasonality, cannot be overemphasized. These models, limitations in handling issues of nonlinear dynamics, variability in markets, and influence from external factors that define the highly dynamic Indian export sector of coffee. A hybrid model that uses the strengths of statistical methods as well as machine learning models has shown promise in allowing the interpretability of the statistical method to blend seamlessly with the predictive power of machine learning. This has led to enhanced accuracy and adaptability through models like ARIMA-SVM, ARIMA-neural network combinations. The further horizons opened by such models are of the sort of LSTM networks, CNN-BLSTM, XGBoost-GRU that model long-term dependencies well and open up patterns hidden in vast data Mekala [12]. These also pose significant problems of computational intensity, reduced interpretability, and strict reliance on quality data. Frameworks that particularly suit this market for Indian coffee export need to be designed.

The most significant implication of this review is to integrate different methodologies into one comprehensive, multilevel framework to address the singular nature of the Indian coffee export sector. Such a framework can begin with basic models, such as ARIMA for foundational trend and seasonality analysis, simply because they are easy to interpret and provide quick insights. This layer can also be improved with hybrid models, such as ARIMA in combination with deep techniques, such as LSTMs, to improve detecting nonlinear patterns and temporal relationships. Feature engineering that brings external factors, such as climate conditions, exchange rates, and global market movements, can be used to enhance the accuracy of contextual predictions. With the CNN-LSTM or XGBoost-GRU model Zhai, Yao and Zhou [38], fine-tuning is possible, making accurate long-term predictions along with revealing complex interactions of variables. Optimization techniques may include genetic programming to fit the parameters of the model such that the computational complexity would be reduced while increasing accuracy in predictions. By filling the gaps of methodology and harnessing the power of advanced technology, this framework not only mitigates the current limitations but also provides a foundation for a robust, scalable, and adaptive forecasting system, which can transform demand forecasting for Indian coffee exports toward strategic decision- making, the reduction of risks, and sustainable support for this critical sector of the economy.

5. Conclusion and Future Work

This review is a comprehensive analysis of the methodologies used in demand forecasting for Indian coffee exports. Both the strengths and weaknesses of traditional statistical models and advanced machine learning approaches are considered. Traditional models like ARIMA and SARIMA are very commonly used due to their simplicity and effectiveness in capturing linear trends and seasonality. However, the above methods can't handle the complexities of a coffee market with nonlinear dynamics and climate variability; the integration of real-time data into the model is also hard to handle. Techniques in LSTM networks, CNNs, and even hybrid approaches are developed with promising potential in dealing with the above-mentioned challenges. Yet, these complex models are confronted with computational complexity, scalability issues, and dependence on high-quality data. This review identifies critical gaps in the existing body of research that includes the absence of comprehensive frameworks that integrate real-time data, external factors, and hybrid methodologies. It also emphasizes the point that the models for forecasting have to be developed keeping in mind the peculiar problems that Indian coffee exports face, such as the fluctuations in consumer preferences, trade policies globally, and the market. Environmental, economic, and market factors play a crucial role in domain-specific feature engineering that would improve the accuracy and relevance of the forecasting.

The results of this review indicate that hybrid models, such as ARIMA-LSTM and XGBoost-GRU, are highly promising if customized to the dynamic nature of the Indian coffee market. Through the synthesis of insights from previous studies, this review underscores the need for further exploration of hybrid frameworks that balance the interpretability of traditional methods with the predictive power of advanced AI techniques. Adaptive frameworks for forecasting shall be developed. These shall alleviate computational challenges in the models by using optimization by genetic algorithms, transfer learning techniques, etc. Incorporating external factors, such as climatic changes, worldwide pricing indices, and consumer trend indices shall help improve model accuracy and relevancy. Facilitating collaboration among researchers, policymakers, and industry stakeholders will ensure access to high-quality datasets, real-world model validation, and alignment with economic and regulatory goals. Through this, future research will help close those gaps to ensure improvement in global competitiveness for exports of Indian coffee, supporting the sustainability of the supply chain and the general cause of agricultural demand forecasting. In conclusion, the review serves as a roadmap towards advancing the research in the area and, for researchers and practitioners, actionable are hereby presented.

References

[1] A. B. Ahmadzai, B. K. Sidana, and A. Guleria, “Direction and export performance of coffee in India,” *International Journal of Bio-resource and Stress Management*, vol. 13, no. 9, pp. 995–1002, 2022, doi: http://dx.doi.org/10.23910/1.2022.2765a.

[2] K. Rhiney *et al.*, “Epidemics and the future of coffee production,” *Proceedings of the National Academy of Sciences*, vol. 118, no. 27, p. e2023212118, 2021, doi: https://doi.org/10.1073/pnas.2023212118.

[3] C. Soujanya, M. Venkataramana, and B. P. Babu, “Growth in Production and Export Performance of Indian Coffee in International Market.,” *Mysore Journal of Agricultural Sciences*, vol. 57, no. 2, 2023.

[4] Y. Chaovanapoonphol, J. Singvejsakul, and A. Wiboonpongse, “Analysis of Exogenous Factors to Thailand Coffee Price Volatility: Using Multiple Exogenous Bayesian GARCH-X Model,” *Agriculture*, vol. 13, no. 10, p. 1973, 2023, doi: https://doi.org/10.3390/agriculture13101973.

[5] V. Gosasang, W. Chandraprakaikul, and S. Kiattisin, “A comparison of traditional and neural networks forecasting techniques for container throughput at Bangkok port,” *The Asian Journal of Shipping and Logistics*, vol. 27, no. 3, pp. 463–482, 2011, doi: https://doi.org/10.1016/S2092-5212(11)80022-2.

[6] C. Deina *et al.*, “A methodology for coffee price forecasting based on extreme learning machines,” *Information Processing in Agriculture*, vol. 9, no. 4, pp. 556–565, 2022, doi: https://doi.org/10.1016/j.inpa.2021.07.003.

[7] Z. H. Kilimci *et al.*, “An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain,” *Complexity*, vol. 2019, no. 1, p. 9067367, 2019, doi: https://doi.org/10.1155/2019/9067367.

[8] M. Seyedan and F. Mafakheri, “Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities,” *Journal of Big Data*, vol. 7, no. 1, p. 53, 2020, doi: https://doi.org/10.1186/s40537-020-00329-2.

[9] M. Awwad, P. Kulkarni, R. Bapna, and A. Marathe, “Big data analytics in supply chain: a literature review,” in *Proceedings of the international conference on industrial engineering and operations management*, 2018, pp. 418–25. doi: http://dx.doi.org/10.3390/bdcc6010017.

[10] L. Jin, “Exploration of cross-border e-commerce and its logistics supply chain innovation and development path for agricultural exports based on deep learning,” *Applied Mathematics and Nonlinear Sciences*, vol. 9, no. 1, 2024, doi: https://doi.org/10.2478/amns.2023.2.00338.

[11] J. Feizabadi, “Machine learning demand forecasting and supply chain performance,” *International Journal of Logistics Research and Applications*, vol. 25, no. 2, pp. 119–142, 2022, doi: https://doi.org/10.1080/13675567.2020.1803246.

[12] K. Mekala, V. Laxmi, H. Jagruthi, S. A. Dhondiyal, A. P. Dabral, and others, “Coffee Price Prediction: An Application of CNN-BLSTM Neural Networks,” in *2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, IEEE, 2023, pp. 1–7. doi: https://doi.org/10.1109/ACCAI58221.2023.10199369.

[13] C.-N. Wang, M.-C. Yu, N.-N.-Y. Ho, and T.-N. Le, “An integrated forecasting model for the coffee bean supply chain,” *Applied Economics*, vol. 53, no. 28, pp. 3321–3333, 2021, doi: https://doi.org/10.1080/00036846.2021.1887447.

[14] T. T. H. Nguyen, A. Bekrar, T. M. Le, and M. Abed, “The Effect of Machine Learning Demand Forecasting on Supply Chain Performance-The Case Study of Coffee in Vietnam,” in *Modelling, Computation and Optimization in Information Systems and Management Sciences: Proceedings of the 4th International Conference on Modelling, Computation and Optimization in Information Systems and Management Sciences-MCO 2021 4*, Springer, 2022, pp. 247–258. doi: https://doi.org/10.1007/978-3-030-92666-3_21.

[15] C. Milas, J. Otero, and T. Panagiotidis, “Forecasting the spot prices of various coffee types using linear and non-linear error correction models,” *International Journal of Finance & Economics*, vol. 9, no. 3, pp. 277–288, 2004, doi: https://doi.org/10.1002/ijfe.245.

[16] K. Naveena, S. Subedar, and others, “Hybrid time series modelling for forecasting the price of washed coffee (Arabica Plantation Coffee) in India,” *International Journal of Agriculture Sciences, ISSN*, pp. 0975–3710, 2017.

[17] K. Naveena, “Statistical modelling for forecasting of price and export of Indian coffee,” PhD Thesis, Institute of Agricultural Sciences, Banaras Hindu University, 2016. [Online]. Available: http://krishikosh.egranth.ac.in/handle/1/79699

[18] N. Ayyanathan and A. Kannammal, "Share price time series forecasting for effective supply chain information exchange," *International Journal of Logistics Systems and Management*, vol. 18, no. 1, pp. 139–158, 2014, doi: https://doi.org/10.1504/IJLSM.2014.062125.

[19] N. Ayyanathan and A. Kannammal, "Combined forecasting and cognitive Decision Support System for Indian green coffee supply chain predictive analytics," in *2015 International Conference on Cognitive Computing and Information Processing (CCIP)*, IEEE, 2015, pp. 1–6. doi: https://doi.org/10.1109/CCIP.2015.7100735.

[20] B. Yashavanth, K. Singh, A. K. Paul, R. K. Paul, and others, "Forecasting prices of coffee seeds using vector autoregressive time series model," *Indian Journal of Agricultural Sciences*, vol. 87, no. 6, pp. 754–758, 2017, doi: https://doi.org/10.56093/ijas.v87i6.70960.

[21] P. Fousekis, "Price co-movement and the hedger's value-at-risk in the futures markets for coffee," *Agricultural Economics Review*, vol. 18, no. 1, pp. 35–47, 2017, doi: http://dx.doi.org/10.22004/ag.econ.330599.

[22] E. Pradkhan, "Financial activity in agricultural futures markets: evidence from quantile regressions," *Australian Journal of Agricultural and Resource Economics*, vol. 61, no. 4, pp. 610–625, 2017, doi: https://doi.org/10.1111/1467-8489.12222.

[23] W. Puchalsky, G. T. Ribeiro, C. P. da Veiga, R. Z. Freire, and L. dos Santos Coelho, "Agribusiness time series forecasting using Wavelet neural networks and metaheuristic optimization: An analysis of the soybean sack price and perishable products demand," *International Journal of Production Economics*, vol. 203, pp. 174–189, 2018, doi: https://doi.org/10.1016/j.ijpe.2018.06.010.

[24] V. Sohrabpour, P. Oghazi, R. Toorajipour, and A. Nazarpour, "Export sales forecasting using artificial intelligence," *Technological Forecasting and Social Change*, vol. 163, p. 120480, 2021, doi: https://doi.org/10.1016/j.techfore.2020.120480.

[25] W. N. Achmadin, D. A. Retnowardani, D. Mashitasari, and F. Fatimah, "Forecasting Coffee Exports to the United States Using the Holt-Winters Exponential Method," *EIGEN MATHEMATICS JOURNAL*, vol. 7, no. 1, pp. 44–49, 2024, doi: https://doi.org/10.29303/emj.v7i1.202.

[26] L. A. Bacci, L. G. Mello, T. Incerti, A. P. de Paiva, and P. P. Balestrassi, "Optimization of combined time series methods to forecast the demand for coffee in Brazil: A new approach using Normal Boundary Intersection coupled with mixture designs of experiments and rotated factor scores," *International Journal of Production Economics*, vol. 212, pp. 186–211, 2019, doi: https://doi.org/10.1016/j.ijpe.2019.03.001.

[27] A. Aamer, L. Eka Yani, and Im. Alan Priyatna, "Data analytics in the supply chain management: Review of machine learning applications in demand forecasting," *Operations and Supply Chain Management: An International Journal*, vol. 14, no. 1, pp. 1–13, 2020, doi: http://doi.org/10.31387/oscm0440281.

[28] M. Zohdi, M. Rafiee, V. Kayvanfar, and A. Salamiraad, "Demand forecasting based machine learning algorithms on customer information: an applied approach," *International Journal of Information Technology*, vol. 14, no. 4, pp. 1937–1947, 2022, doi: https://doi.org/10.1007/s41870-022-00875-3.

[29] N. Andriani, S. Wahyuningsih, and M. Siringoringo, "Application of Double Exponential Smoothing Holt and Triple Exponential Smoothing Holt-Winter with Golden Section Optimization to Forecast Export Value of East Borneo Province," *Jurnal Matematika, Statistika Dan Komputasi*, vol. 18, no. 3, pp. 475–483, 2022, doi: https://doi.org/10.20956/j.v18i3.17492.

[30] D. D. Illeperuma and T. Rupasinghe, "Applicability of Forecasting Models and Techniques for Stationery Business: A Case Study from Sri Lanka," *International Journal of Engineering Research*, vol. 2, no. 7, pp. 449–451, 2013.

[31] J. S. Armstrong, "Illusions in regression analysis," *International Journal of forecasting*, vol. 28, no. 3. Elsevier, pp. 689–694, 2012. [Online]. Available: https://doi.org/10.1016/j.ijforecast.2012.02.001

[32] K.-Y. Chen, "Combining linear and nonlinear model in forecasting tourism demand," *Expert Systems with Applications*, vol. 38, no. 8, pp. 10368–10376, 2011, doi: https://doi.org/10.1016/j.eswa.2011.02.049.

[33] C. Mitrea, C. Lee, and Z. Wu, "A comparison between neural networks and traditional forecasting methods: A case study," *International journal of engineering business management*, vol. 1, p. 11, 2009, doi: https://doi.org/10.5772/6777.

[34] D. M. Miller and D. Williams, "Shrinkage estimators of time series seasonal factors and their effect on forecasting accuracy," *International Journal of Forecasting*, vol. 19, no. 4, pp. 669–684, 2003, doi: https://doi.org/10.1016/S0169-2070(02)00077-8.

[35] R. J. Hyndman and others, “The interaction between trend and seasonality,” *International Journal of Forecasting*, vol. 20, no. 4, pp. 561–563, 2004, doi: DOI: 10.1016/j.ijforecast.2004.03.005 ·
Source: RePEc.

[36] S. Ghosh, “Forecasting of demand using ARIMA model,” *American Journal of Applied Mathematics and Computing*, vol. 1, no. 2, pp. 11–18, 2020, doi: https://ajamc.smartsociety.org/.

[37] N. I. Sapankevych and R. Sankar, “Time series prediction using support vector machines: a survey,” *IEEE computational intelligence magazine*, vol. 4, no. 2, pp. 24–38, 2009, doi: https://doi.org/10.1109/MCI.2009.932254.

[38] N. Zhai, P. Yao, and X. Zhou, “Multivariate time series forecast in industrial process based on XGBoost and GRU,” in *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, IEEE, 2020, pp. 1397–1400. doi: https://doi.org/10.1109/ITAIC49862.2020.9338878.

[39] Y. Zhu, Y. Zhao, J. Zhang, N. Geng, and D. Huang, “Spring onion seed demand forecasting using a hybrid Holt-Winters and support vector machine model,” *PloS one*, vol. 14, no. 7, p. e0219889, 2019, doi: https://doi.org/10.1371/journal.pone.0219889.

[40] Y. A. Herrera-Jaramillo, J. C. Ortega-Giraldo, A. Acevedo-Amorocho, and D. Prada-Marin, “Colombian Coffee Price Forecast via LSTM Neural Networks,” *Technological and Industrial Applications Associated with Intelligent Logistics*, pp. 501–517, 2021, doi: https://doi.org/10.1007/978-3-030-68655-0_25.

[41] J. D. V. Henao and M. A. A. Dumar, “Modelado del precio del café colombiano en la bolsa de Nueva York usando redes neuronales artificiales,” *Revista Facultad Nacional de Agronomía-Medellín*, vol. 60, no. 2, pp. 4129–4144, 2007, doi: http://www.redalyc.org/articulo.oa?id=179914078016.

[42] T. Berhane, N. Shibabaw, A. Shibabaw, M. Adam, and A. A. Muhamed, “Forecasting the Ethiopian Coffee Price Using Kalman Filtering Algorithm,” *Journal of Resources and Ecology*, vol. 9, no. 3, pp. 302–305, 2018, doi: https://doi.org/10.5814/j.issn.1674-764x.2018.03.010.

[43] A. Rodríguez and M. Melgarejo, “Identification of Colombian coffee price dynamics,” *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 30, no. 1, 2020, doi: https://doi.org/10.1063/1.5119857.

[44] M. Jagadeesh, A. Jahnavi, H. Vinay, G. Abhishek, S. Abhishek, and A. S. Chikkalaki, “Export Competitiveness of Indian Coffee: Analysing Trade Potential in the Global Market”, doi: https://doi.org/10.9734/jsrr/2024/v30i92329.

[45] R. F. A. Duran, F. R. C. Sernaque, J. R. R. Sirlopu, and J. J. R. Moncada, “Forecasting the export competitiveness of Peruvian coffee in major importing countries usingautoregressive integrated moving average modeling,” *Revista Científica Pakamuros*, vol. 12, no. 3, pp. 126–137, 2024, doi: https://doi.org/10.37787/s7ztng79.

[46] S. M. Gómez, “Market Analysis and Entry Strategy for German Investors in the Specialty Coffee Segment of the Colombian Coffee Industry,” *Frontiers in Management Science*, vol. 3, no. 2, pp. 8–12, 2024, doi: doi:10.56397/FMS.2024.04.02.

[47] A. N. Temesgen, “Statistical Analysis of the Volatility of the Export Price of Coffee in Ethiopia,” 2017.

[48] J. C. Silva, M. C. Figueiredo, and A. C. Braga, “Demand forecasting: A case study in the food industry,” in *Computational Science and Its Applications–ICCSA 2019: 19th International Conference, Saint Petersburg, Russia, July 1–4, 2019, Proceedings, Part III 19*, Springer, 2019, pp. 50–63. doi: https://doi.org/10.1007/978-3-030-24302-9_5.

[49] C. Ingle, D. Bakliwal, J. Jain, P. Singh, P. Kale, and V. Chhajed, “Demand forecasting: Literature review on various methodologies,” in *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, 2021, pp. 1–7. doi: https://doi.org/10.1109/ICCCNT51525.2021.9580139.

[50] R. Priyadarshi, A. Panigrahi, S. Routroy, and G. K. Garg, “Demand forecasting at retail stage for selected vegetables: a performance analysis,” *Journal of Modelling in Management*, vol. 14, no. 4, pp. 1042–1063, 2019, doi: https://doi.org/10.1108/JM2-11-2018-0192.

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