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Research Article

Enhancing Predictions for Indian Coffee Exports with Hybrid Statistical and LSTM Models

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Abstract:

Accurate forecasting of Indian coffee exports is essential for optimizing supply chains, stabilizing prices, and mitigating market risks. Traditional statistical models like ARIMA and SARIMA struggle with capturing nonlinear dependencies and demand fluctuations, necessitating an advanced hybrid approach. This study proposes a Hybrid ARIMA-SARIMA-LSTM Forecasting Model (HASL-FM) that integrates statistical methods with deep learning for improved predictive accuracy. The objective is to enhance export forecasting precision by leveraging historical export data, macroeconomic indicators, and climate variables. The model employs ARIMA for linear trends, SARIMA for seasonal variations, and LSTM to capture complex, long-term dependencies. The proposed method is implemented in Python on an edge server (16–20 cores, 10TB–15TB storage) and evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 score. The dataset consists of Indian coffee export records, macroeconomic factors, and climate data. Experimental results demonstrate that HASL-FM significantly outperforms traditional models (ARIMA, SARIMA) and machine learning models (SVM, ANFIS), achieving the lowest RMSE (0.0256) and MAPE (0.0754), with the highest R^2 (0.9852). These findings confirm that AI-driven forecasting enhances accuracy, supporting producers, exporters, and policymakers in decision-making, resource allocation, and risk management. Unlike traditional models, HASL-FM effectively captures seasonal trends and nonlinear dependencies, leading to more stable trade and optimized market strategies. Future research could integrate global trade policies, sentiment analysis, and reinforcement learning to further enhance predictive capabilities.

1. Introduction

The coffee industry makes a substantial contribution to employment, trade, and GDP in significant coffee-exporting nations, such as India, and is one of the most popular drinks worldwide. ICO reports that coffee consumption continues to rise worldwide. to rise, with demand increasing by approximately 1.3% annually. This growth highlights the importance of effective forecasting techniques to anticipate demand trends and support strategic decision-making for stakeholders in the coffee industry[1].India is one of the leading coffee producers, with its exports reaching markets across Europe, North America, and Asia. Key importing nations, such as Italy, Germany, and Russia, have demonstrated a strong preference for Indian coffee due to its unique flavor profiles and sustainable production practices. However, fluctuations in international trade, economic uncertainties, and climate variability pose challenges to stable coffee exports[2]. The coffee industry is particularly susceptible to price volatility, making accurate demand forecasting essential for optimizing supply chain operations, stabilizing prices, and maximizing profitability for farmers and exporters[3].

Advanced technologies like ML, DL, and big data analytics have been brought about by the Fourth Industrial Revolution (4IR) and have the potential to completely transform demand forecasting techniques[4]. Forecasting using time series has made extensive use of conventional econometric models, among which are ARIMA and SARIMA[5]. However, because of their capacity to identify long-lasting trends and nonlinear correlations in data, deep learning models in particular, LSTM networks have become strong substitutes.[6].This study aims to develop a hybrid forecasting model that integrates ARIMA, SARIMA, and LSTM techniques to improve the accuracy of demand predictions for Indian coffee exports[7]. By leveraging historical export data, economic indicators, and seasonal trends, this research seeks to provide a robust predictive framework that enhances decision-making for coffee producers, exporters, and policymakers[8]. The insights generated from this study will help optimize production planning, mitigate risks associated with demand fluctuations, and ensure sustainable growth in India’s coffee export sector[9].

1.1 Research Motivation

The growing global demand for coffee and the volatility in international markets necessitate accurate forecasting for Indian coffee exports. Climate change, fluctuating prices, and evolving consumer preferences create challenges for producers and exporters. Traditional forecasting models struggle with nonlinear patterns, making machine learning approaches like LSTM essential for improved accuracy. This study develops a hybrid framework combining ARIMA, SARIMA, and LSTM to enhance demand prediction and support strategic decision-making.

1.2 Significance of the Study

This research benefits coffee producers, exporters, and policymakers by improving forecasting accuracy and mitigating market risks. Enhanced demand predictions will help optimize supply chain management and stabilize pricing strategies. The integration of AI-driven forecasting supports policy development and sustainability efforts in the coffee sector. Ultimately, this study contributes to India's global competitiveness and economic growth in the coffee trade.

1.3Recent Inventions and Challenges

The field of time series forecasting has seen significant advancements with recent innovations in ARIMA and SARIMA models, enhanced by machine learning and deep learning techniques. Hybrid models combining ARIMA/SARIMA with neural networks like LSTMs and deep learning frameworks have improved accuracy in forecasting complex datasets. Automated hyperparameter tuning using algorithms like Auto-ARIMA and Bayesian optimization has simplified model selection. However, challenges remain, including handling non-stationary and irregular data, computational complexity in large datasets, and adapting models to sudden market shifts. Overcoming these limitations requires integrating advanced statistical techniques with AI-driven approaches for more robust and adaptive forecasting solutions.

The key contributions of our paper is as follows:

- Introduces HASL-FM, a novel hybrid model combining ARIMA, SARIMA, and LSTM to improve the accuracy of Indian coffee export demand forecasting.
- Demonstrates superior performance of HASL-FM over traditional models (ARIMA, SARIMA) and machine learning models (SVM, ANFIS) in reducing forecasting errors.
- Utilizes historical export data, macroeconomic indicators, and climate variables to capture seasonal trends and nonlinear dependencies in coffee demand.
- Provides actionable insights for coffee producers, exporters, and policymakers to optimize production planning, mitigate risks, and enhance market competitiveness.
- Contributes to the evolution of AI-based forecasting in agricultural trade, promoting data-driven decision-making and future improvements in commodity export prediction.

The study is structured into five sections. Section 1 provides an introduction, outlining the research background and objectives. Section 2 presents a comprehensive literature survey, reviewing existing studies on demand forecasting and related methodologies. Section 3 defines the problem statement, highlighting key challenges in forecasting Indian coffee exports. Section 4 details the methodology, introducing HASL-FM, a novel hybrid model that integrates ARIMA, SARIMA, and LSTM for enhanced predictive accuracy. Finally, Section 5 discusses the results, evaluating the model's performance in forecasting demand for Indian coffee exports.

2. Related Works

Nguyen et al [10]work provides numerous major advances to the subject of predicting the use of coffee demand in Vietnam, notably via the implementation of gray forecasting models. Here are the important contributions that evaluation of Multiple Models: The paper presents and assesses three gray forecasting models: GM (1,1), DGM (1,1), and the gray Verhulst model (GVM). By comparing different models, the authors attempt to discover the best suited one for forecasting coffee consumption in Vietnam. Empirical Analysis: The study incorporates annual data on coffee consumption from 2010 to 2020, giving a strong empirical foundation for the analysis. This data-driven strategy boosts the dependability of the results. Identification of the Best Model: The findings reveal that the GM (1,1) model surpasses the other models in terms of accuracy, attaining the lowest average error of 2.93%. This conclusion is essential for regulators and stakeholders in the coffee business, since it indicates a trustworthy tool for future consumption projections. The research presents practical approaches to boost the forecast accuracy of the original gray model. This involves applying numerous transformations to the original series and employing centre parallel moving transformations to the accumulated generating operation (AGO) series, which may be advantageous for future forecasting applications. Practical Implications: By selecting the most accurate forecasting model, the research gives significant information for managers and policymakers in the coffee industry. This may assist in improved decision-making and strategic planning about coffee production and consumption in Vietnam. Contribution to current Literature: The research contributes to the current body of information on gray forecasting models by proving their application in a particular situation (coffee consumption in Vietnam) and evaluating their performance. This might motivate subsequent study in comparable topics or with alternative datasets.

Chen [11] research combines two machine learning approaches, multivariate linear regression and random forest algorithms, to create prediction models for C-type coffee futures prices and trends. It illustrates the relevance of C-type coffee futures in the worldwide market, offering benchmarks for future trading in China. The study involves a complete investigation of the coffee futures market, important variables impacting pricing, and the use of machine learning algorithms in price prediction. The article also provides strategies for improving the prediction models and presents a forecast on the future of the coffee futures market. The outcome of the models in long-term trend forecasts is substandard, suggesting the requirement for additional refining and the incorporation of more sophisticated technical and fundamental data to increase generalizability. The frameworks are not sensitive to peak values in short-term projections, which may restrict their usefulness.Motta et al [12] study evaluates and synthesizes available data on the use of Machine Learning (ML) in coffee production and marketing, concentrating on categorization activities such as flaws, roasting, maturity, and sensory characteristics of coffee beans and leaf illnesses. It examines trends in AI applications within coffee categorization and reveals research needs that may be addressed to better procedures in the coffee manufacturing chain. The paper presents a thorough account of ML approaches used for coffee categorization and stresses the role of AI start-ups in utilizing these techniques for problem-solving in agriculture. The present AI-based algorithms for coffee categorization primarily remain in experimental stages, lacking extensive practical application. Many models demonstrate a narrow emphasis, adapted to certain locations or coffee varieties, restricting their generalizability. There is a limited scope in determining finer traits such as roast degrees and maturation stages. The need for more broadly applicable models is stressed, especially in areas like aromatic profiling, which remain neglected. The article stresses the demand for bigger and more varied datasets to increase model performance.

Utilizing the Coffee Bean Dataset, which includes a large number of coffee bean variations, Hassan's [13] research uses various pre-trained convolutional neural network (CNN) architectures to classify images of coffee beans. Four fundamental steps make up the procedure: gathering data, training data, classifying data, and evaluating data. To ascertain how well models like "AlexNet, LeNet, HRNet, Google Net, Mobile V2 Net, ResNet (50), VGG, Efficient, Darknet, and DenseNet" perform in coffee classification, a comparative analysis is conducted. The study examines how selecting various previously trained models affects a coffee-type prediction technique's effectiveness. It investigates the impact of numerous state-of-the-art models being trained on total precision, learning time, and computational capabilities, such as VGG, ResNet, and MobileNet. For the advantage of coffee growers and processing units, the study recommends applying deep learning techniques and transferred learning to improve coffee systems of classification. The findings highlight how important model selection is for achieving higher accuracy and faster agreement in tasks involving coffee classification.

Farah and Ferreir[14] Research is useful. Diffusion or absorption of roasted coffee seeds from trees in the Rubiaceae family (genus Coffea, subgenus Eucoffea) produces the familiar and beloved beverage known as coffee. Two coffee species, C. arabica and C. canephora, are truly important in the global market, despite the fact that the National Center of Information on Biology (USA) has identified at least 124 species of the genus Coffee. Even though coffee's taxonomic categorization is somewhat complicated, the current section provides readers with an in-depth discussion of coffee botany, the plant, and the fruit while also assisting them in understanding the basic concepts involved in the production of freshly ground coffee beans.

Torga and Spers [15] applies the primary goals of the current section include evaluating perspectives for the global demand for coffee in both the present and the future, and to provide a greater awareness of available knowledge and data in such a way that every player of the chain may arrange themselves to be more profitable in the near future, preserving in mind the wider market that they will be placed into. This chapter is split into three parts: coffee manufacturing and delivery chain; coffee demand; and coffee pricing, differentiation, and marketing technique. The first stage is to synthesize what is already known about these themes, then aggregate pertinent data regarding global demographic and income development, as well as present and future possibilities to figure out how they relate to the world's demand for coffee. The primary findings at this point are that the world's population as well as revenue per capita are growing, which has a significant association with the consumption of coffee; additionally, the global population is also getting older, which is also favorable for coffee providers. In the previous 26 years, there has been a 67.9% surge in worldwide coffee consumption.

Hakim, Djatna, and Yuliasih [16] provides an example of To maintain their reputation and identity in the market, coffee companies must preserve the flavor and attributes of their product. Coffee's distinct process level has a significant impact on its flavor and aroma after brewing. As a result, consistent, consistent espresso roasting levels throughout the production stages are crucial. Throughout this study, we present a deep learning-powered rating system to help accurately observe the roasting process online and predict the roasted coffee bean's level of roasted. For into-demand portability use and assistance for categorizing insight on roasting degree, a proposed deep learning-based method for evaluating the standard of coffee roasting is integrated into Android-powered smartphones and tablets. Initially, the study produced a dataset with three separate categories for the coffee roasted process. According to the results, MobileNetV2 is the best candidate for use in determining roasting quality. Applying specific Android devices, the optimal inference time ranges among 44–50 ms while employing a CPU and 34–44 ms when using a GPU. Continuous surveillance while streaming services. quality assessment was shown to achieve an average of 97.75% accuracy, 96.44% recall, and 96.33% precision in the MobileNetV2 model. An overview of corresponding research on coffee forecasting and classification is provided in Table 1.

3. Problem statement

Although India dominates the market share in global coffee, its export sector is beset with overwhelming issues like price fluctuation, global warming, and evolving consumer preferences. Traditional techniques of demand forecasting are helpless to estimate demand accurately as they are incapable of forecasting nonlinear and sophisticated patterns[15].The inability to provide reliable demand forecasts causes inefficiency in production planning, supply chain management, and pricing policies and affects the profitability and viability of coffee exports. These gaps are bridged by this research through the design of a hybrid forecasting model combining ARIMA, SARIMA, and LSTM models with a view to improving forecasting accuracy and facilitating data-driven decision-making for the Indian coffee industry

4. Proposed hybrid hasl-fm model

HASL-FM is initiated with data collection, where export history, market trend, and drivers like macroeconomy and climate are gathered. Pre-processing involves making data immaculate by ensuring missing values, normalization, and stationarity testing using differencing. The data are input to three models, which include ARIMA, SARIMA, and LSTM. ARIMA identifies linear long-run patterns, SARIMA the same but for identifying seasonal patterns, and LSTM, a type of recurrent neural network with an architecture based on deep learning, identifies nonlinear relationships and long-run patterns. Having trained the models, they produce stand-alone predictions, which are tested using performance metrics such as accuracy, and F1 score, producing actionable insights and recommendations to enhance Indian coffee exports. The last step includes model evaluation where the optimal features of each of the models are put together to develop a more accurate and robust Indian coffee export forecast for optimizing supply chain planning and market strategies this is presented in Figure.1.

4.1 Data Collection

The historical production levels of coffee from 1998 to 2023, with some economic and environmental determinants of levels of production. The data set contains annual coffee production values along with corresponding average temperature, total rainfall, and world coffee price index, which affect yield and profitability, it also monitors policy and economic indicators like export policy score, GDP growth rate, and exchange rate (INR/USD), which are economic factors that can impact coffee trade and price. Taking all these factors together, coffee production trends can be contrasted with climate, market, and government policy trends

4.2 Data Preprocessing

In Data Pre-processing, raw data is cleaned and formatted for proper forecasting by addressing missing values, normalization of data, and stationarity adjustments. Missing values are handled using techniques such as interpolation, mean imputation, or forward/backward fill to maintain data integrity.

Normalization methods such as Min-Max Scaling or Standardization confirm the different variables (e.g., export values, weather) remain on the same scale, preventing bias during model training.

Min-Max Scaling Formula is given in eqn.(1)

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

here x' is the scaled value, x is the original value, x_{max} and x_{min}. are the minimum and maximum values in the dataset, respectively.

Standardization (Z-score normalization) Formula is given in eqn. (2)

$$z = \frac{x - \mu}{\sigma} \quad (2)$$

where Z is the standardized value, X is the original value, μ is the mean, and σ is the standard deviation of the dataset. To handle non-stationary data, transformations such as differencing, log transformation, or seasonal adjustment are applied to stabilize variance and improve model precision. These pre-processing steps enable properly processed inputs to be passed to ARIMA, SARIMA, and LSTM models, allowing HASL-FM to extract correct patterns and nonlinear relationships to accurately predict coffee exports.

4.3 Hybrid HASL-FM Model for Forecasting Demand for Indian Coffee Exports

Demand forecasting of Indian coffee exports is essential to streamline supply chains, pricing, and market positioning. The research incorporates ARIMA, SARIMA, and LSTM models to address linear and nonlinear time-series data patterns. The ARIMA model can be useful in short-term forecasts, while SARIMA augments ARIMA with the ability to handle seasonal patterns, which play a key role in crops like coffee that are exported. Hybrid HASL-FM Architecture is given in Figure.2.

4.3.1 Identification of Linear Long Term Pattern

ARIMA is a strong statistical approach used to predict time-series data, particularly the identification and modelling of trends of past coffee exports. The ARIMA model performs particularly well where seasonality has no dominant role to play and thus serves to be a powerful tool in the identification of long-term growth tendencies in Indian coffee exports. By analysing past demand, ARIMA can predict future export volumes so that stakeholders can make data-driven decisions regarding supply chain management, pricing, and foreign trade planning*[17]*.

ARIMA is composed of three primary elements: “Auto-Regressive” (AR), “Integrated “(I), and “Moving Average” (MA). The Auto-Regressive (AR) component represents the relationship between the present coffee export quantity and previous values. Order p specifies how many past observations affect the current. For example, if P=2 the current month's coffee exports rely on previous two months' export figures. The AR process is mathematically expressed in eqn. (3)

$$Y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \epsilon_t \quad (3)$$

here Y_t represents the coffee export demand at time t, ϕ_1 ϕ_2 are the AR coefficients, and ϵt is a random error term.

The Integrated (I) part ensures stationarity of the time series by removing trends by differencing. Differencing is conducted d times if there's a clear positive or negative trend in the data due to economic growth or climate change. This removes the trend in non-stationary coffee demand data and puts it into stationary form, with more precise predictions. The Moving Average (MA) component picks up on the relation between an observation and past forecasting errors. The order q is the number of errors to use in the past. If q=1the new forecast is adjusted by using the previous error. The MA process can be given in eqn. (4)

$$y_t=\mu+\theta_1\epsilon_{t-1}+\theta_1\epsilon_{t-2}+\epsilon_t \quad (4)$$

where μ represents the mean, θ_1 and θ_2 are the coefficients of MA, and ϵ_t are forecast errors.

By the use of these factors, the ARIMA model gives a reliable method of Indian coffee export forecasting that enables exporters, policymakers, and investors to predict future market trends and make successful decision-making strategies[18]. ARIMA Model is given in Figure 3**.**

4.3.2 Capturing Cyclical and Seasonal Patterns

The SARIMA model accounts for seasonal effects and hence it is of great use in forecasting Indian coffee exports. The demand for coffee has seasonal elements with cyclical repetition based on festive periods, climatic conditions, and importers' country choices. For example, in Italy, Germany, and the US, coffee is consumed mostly at winter celebrations such as New Year and Christmas, and could be less during the summer season. SARIMA covers these season dependences by including four season components: Seasonal Moving Average (Q), Seasonal Differencing (D), Seasonal Auto-Regressive (P), and the Seasonal Period (m). Mathematically, SARIMA is represented in eqn. (5)

$$SARIMA(p,d,q)\times(P,D,Q,m) \quad (5)$$

where $(p,d,q)$are the non-seasonal ARIMA parameters and (p,d,q) are the seasonal coefficients. P here represents the lagged seasonal demand effects, D eliminates recurring seasonal patterns by differencing, Q represents seasonal error variability, and mmm is the periodicity of the seasonality (e.g., m=12m = 12m=12 for monthly data on coffee exports). Because Indian coffee exports follow cycles, SARIMA takes into account yearly variations in demand accurately. SARIMA for Capturing Cyclical and Seasonal Patterns is presented in Figure 4.

For example, if Indian coffee exports have annual seasonality with demand depending on the exports of last year, and one lagged seasonal, seasonal differencing, and seasonal error corrections, a SARIMA model can be written in eqn. (6):

$$(1-B^m)^{\ D}\ Y_t=\Phi_p(B^m)Y_{t-m}+\Phi_Q(B^m)\epsilon_t \quad (6)$$

where B^m is the lag operator for seasons, $Y_{t-m}$is past values for seasons, and ϵt epsilon_ is the error term for seasons This model describes how past trends in seasons (for instance, last winter's coffee export trend) drive future demand so that supply chains and prices can be optimized. Through the addition of SARIMA, Indian coffee farmers can more accurately predict demand swings so that a stable presence in global coffee trade can be maintained [19].

4.4 Identification of Nonlinear Relationships

The LSTM architecture has been widely utilized in sequential data analysis and is widely used for time-series application. Here, the inputs are sequential elements of data in the form of time-series measurement or words forming a sentence. Since a particular input in the network's memory corresponds to a specific time step, hidden states serve as the network's memories, storing pertinent data form earlier time steps. In other words, the network can handle dependency in a sequence at a particular time step by using the input it gets as well as the hidden state from the previous time step. The network may comprehend the non-linear relationships present in the data by transforming the combined input and hidden state using additional activation operations such as sigmoid, tanh, or ReLU. The RNN is highly suited for applications like times-series prediction, natural language interpretation, and speech identification because of the recurring interactions within its latent states that enable it to retain historical context across time. However, the traditional RNN has challenges in handling "long-range dependencies" because of issues like vanishing gradients, which is alleviated by advanced architectures such as LSTMs and GRUs.

4.4.1 LSTM Prediction Model

The Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) that is designed to process sequential data effectively by maintaining and updating its internal memory (cell state) across time steps. This is achieved through three key gates: the input, output, and forget gates, which control how data is sent, updated, and stored across the network.

Forget Gate (f_t)

The forget gate chooses which elements of the prior cell state should be kept or deleted. Eqn. (7) is used to compute it.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{7}$$

Where W_f is the Weight matrix for forget gate,$[h_{t-1}, x_t]$: Concatenation of the previous hidden state and current input. b_f is the Bias term.σ is the Sigmoid activation function.

Input Gate (i_t)

The input gate determines the amount of fresh data that should be kept in a cell's state from the current input is givem in eqn. (8)

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$

Where W_i is the Weight matrix for input gate. b_i is Bias term. The sigmoid function σ controls how much new information is allowed into the cell state.

Candidate Cell State (C_t')

A candidate cell state is generated using the hyperbolic tangent function, which proposes new values for the cell state:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{9}$$

Where W_c is the Weight matrix for candidate state b_c is Bias term. tanh ensures the values are within the range [−1,1][-1,1][−1,1], enabling non-linearity and better learning capacity.

Cell State Update (C_t)

In eqn. (10), the effect of the input gate on the candidate state and the forget gate on the prior cell state are combined to calculate the updated cell state.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{10}$$

The LSTM can selectively maintain or alter data throughout lengthy sequences thanks to this method of recording.

Output Gate (o_t)

The output gate o_t chooses which portion of the updated cell state goes into the hidden state in eqn. (11)

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{11}$$

where W_o is the weight matrix for the output gate, and b_o is the bias term [20].

Hidden State Update (h_t)

Finally, the hidden state is updated by scaling the hyperbolic tangent of the new cell state with the output gate's activation is given in eqn. (12) LSTM Network Structure is given in Figure 5.

$$h_t = o_t \cdot \tanh(C_t) \tag{12}$$

4.5 Optimizer Adam Optimization Algorithm

The model updates its parameters using the Adam optimization algorithm, which adapts the learning rate dynamically for each parameter is given in eqn. (13)

$$\theta_t = \theta_{t-1} - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{13}$$

Where θ_t is the updated parameter at step t. where η is Learning rate . $\hat{m}_t$ is the bias-corrected first moment estimate (similar to momentum). is the bias-corrected first moment estimate $\hat{v}_t$ is the bias-corrected second moment estimate (variance of past gradients). ϵ is a small constant added for numerical stability.

Learning rate is a critical hyper parameter when training an LSTM model. Slow convergence and inefficient training result from a small learning rate (<0.001< 0.001<0.001). A high learning rate (>0.01> 0.01>0.01) brings instability, resulting in unreliable weight updates and poor model performance. Adam optimizer dynamically scales the effective learning rate of each parameter according to previous gradients, leading to faster convergence and improved stability [21].

Algorithm 1: Coffee demand data Prediction Algorithm
• $\boldsymbol{D_{Train}}$ → *Historical coffee demand data for training* • D_{Test} → *Test data for validation* • w → *Window size for LSTM sequences* • D_{Pred} → *Predicted coffee demand* ***Steps:***

Begin

Load Data:

Load the training dataset D_{Train}

Load the test dataset D_{Test}

Preprocessing:

Handle missing values using interpolation or forward fill

Normalize data for LSTM input using MinMaxScaler

ARIMA Prediction:

Identify parameters using ACF and PACF plots

Fit ARIMA model to D_{Train}

Predict demand D_{Pred} *using ARIMA*

SARIMA Prediction:

Identify seasonal parameters (p,d,q,P,D,Q,m)

Fit SARIMA model to D_{Train}

Predict demand D_{Pred} *using SARIMA*

LSTM Prediction:

Define LSTM model:

Input Layer*: Sequence of size www*

Hidden Layers*: LSTM units with activation functions*

Output Layer*: Single regression output for demand prediction*

Train LSTM model using D_{Train}

Predict demand D_(Pred) using LSTM

Evaluate Predictions:

Compute evaluation metrics for each model:

Mean Absolute Error (MAE)

$$MAE = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{y_i^p} - \boldsymbol{y_i^a})$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_i^p - y_i^a}{y_i^a} \right) \times 100\%$$

End

The suggested method for anticipating Indian coffee demand includes three advanced forecasting techniques—ARIMA, SARIMA, and LSTM. It starts off with preparing the data, where historic coffee demand data is prepared by resolving missing values, levelling for LSTM inputs, and establishing linearity for ARIMA and SARIMA modelling. The ARIMA model is set by determining its parameters (p , d , q) through ACF and PACF plots, representing linear trends in the data. The SARIMA framework extends ARIMA by integrating seasonal parameters (P , D , Q , m) to handle periodic patterns. Both models are fitted to the training dataset and assessed using metrics including MAE, RMSE, and MAPE. These older models provide stable baselines for time series forecasting.

The LSTM approach, employing deep learning, captures non-linear correlations and complicated time-dependent relationships in the data. Input patterns are produced utilizing a sliding window technique, transforming data into a 3D representation for the LSTM network. The model design includes LSTM layers with activation functions, preceding an extremely dense layer for regression output. Predictions from every simulation are examined, and the model with the lowest error metrics is selected for installation. The method ensures scalability and scalability by frequently updating the chosen predictive model with fresh data, making it an effective basis for forecasting coffee demand in the USA and other foreign markets.

5. Results and Discussions

The findings of this research indicate that the proposed Hybrid Forecasting Model HASL-FM outperforms traditional time-series forecasting methods in predicting Indian coffee export demand. Performance metrics, including RMSE, MAPE, and R^2, confirm that HASL-FM provides more accuracy compared to ARIMA, SARIMA, and other machine learning methods like SVM and ANFIS. The model effectively captures nonlinear and linear relationships in past patterns of export, macroeconomic statistics, and climatic factors and hence makes more precise demand forecasts. Comparative analysis shows it minimizes errors significantly if deep learning techniques are combined with statistical models, and hence the proposed framework is an efficient forecasting model for coffee producers, exporters, and policy-makers.

The findings suggest that AI-driven forecasting technologies hold promise for enhancing strategic decision-making, optimizing the supply chain, and mitigating risks that emanate from market uncertainty and making India globally competitive in the coffee trade.

5.1 Evaluation Results

The accuracy of the task has been estimated by examining predicting errors using two methods, namely MAE and MAPE. MAE is a measurement statistic that expresses the deviation between the projected and actual values. The total error is calculated using (14) in this case.

$$\text{MAE} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}} \left(\boldsymbol{y_i^p} - \boldsymbol{y_i^a}\right) \quad (14)$$

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{y_i^p - y_i^a}{y_i^a}\right) \times 100\% \quad (15)$$

Percentage of MAE is used in determine the precision of proposed model. Lower the value of MAPE indicates the model is performing better in prediction. In the above formula, predicted value is y_i^p, the actual value is y_i^a and N is the number of the predicted values in the dataset. The simulation uses ARIMA, SARIMA, and LSTM models to forecast Indian coffee export demand, integrating historical data, macroeconomic indicators, and climate variables. Data pre-processing includes handling missing values, normalization, and stationarity testing, with an 80-20 train-test split. The models are evaluated using MAE, RMSE, MAPE, and R^2, with Adam optimization used for LSTM training. Performance is compared against SVM, ANFIS, and MLR, running on a high-performance edge server. This is presented in Table 2.

Figure.6 shows how the gain ratio changes with varying learning rates for various iterations. The x-axis is iterations, and the y-axis is the gain ratio. Various colors of bars represent various learning rates (0.01, 0.001, 0.0001, and 0.00001). The pattern indicates that larger learning rates (0.01 and 0.001) produce a greater gain ratio, i.e., quicker learning, whereas smaller learning rates (0.0001 and 0.00001) indicate slower learning. It indicates that there is an optimalFigure 7 is a heatmap of correlation of the relationship among various features of coffee production. The gradient varies from blue (negative) to red (positive). Key observations are that there is a negative weak correlation (-0.2) between production and year, which means there is a gradual decline in production over years. Production is moderately positively related (0.29) to mean temperature, so increased temperature might be related to more coffee produced. Exchange rate and rainfall exhibit perceived correlation (0.43), possibly indicating economic and climatic interaction. Heatmap helps reveal strong interdependencies between variables that affect coffee production and can lead to better forecasting and decision making.Figure 8 shows the relationship between the Global Coffee Price Index and Coffee Production (tons). One point per data entry, showing how coffee production changes with price changes of coffee. The scattering of points indicates that there is no strong linear relationship between the two variables higher coffee prices do not result in higher production. This may be due to other factors outside of it such as climatic conditions, government measures, and production limits. The volatility shows that the production of coffee is exposed to various external forces apart from price.Figure 9 illustrates the correlation between coffee yield (in tons) and total rainfall (in mm). The red dots are individual observations, and the black trend line with a shaded confidence interval illustrates the overall trend. The nearly horizontal trend line suggests a weak or zero correlation between coffee yield and rainfall, implying that other factors may have a significant influence on coffee yield. The confidence interval, represented by the shaded region, indicates more variability in the predictions, especially at lower and higher levels of rainfall. Figure 10 illustrates the relationship between the Exchange Rate (INR/USD) and Coffee Production (tons). The red regression line illustrates a weak negative slope, indicating that when the exchange rate increases (INR value deprecates against USD), coffee production decreases. However, the dispersal of the data points and wide confidence interval (the shaded area) indicate a weak relationship, which implies other variables likely influence coffee production more. While currency movements might influence profitability on the export side and the price of inputs, they would not appear to be the sole determinant of production levels. Table 3 illustrates how various learning rates affect model performance, convergence rate, and stability. A higher rate of learning (0.01) provides a greater rate of convergence (1000 iterations) with a best gain ratio of 0.78 but is unstable, meaning that the model diverges or oscillates. A learning rate of 0.001 has the optimal trade-off, with a best gain ratio of 0.89, stable training, and convergence at 2000 iterations, and is thus best. Lower learning rates of 0.0001 and 0.00001 slow down convergence significantly (3000-5000 iterations), with decreasing gain ratios (0.72 and 0.55, respectively), but with greater stability. But an extremely low learning rate of 0.00001 makes training too stable and can lead to under fitting and longer training times. The table shows that 0.001 is the best learning rate, offering a good compromise between speed and stability for accurate LSTM-based forecasting in our coffee demand forecasting model. Learning rate is vital to successful model training; too large rate leads to instability, and too small reduces convergence. Figure 11 compare actual and projected production of coffee over a specified time period. The blue broken line indicates actual production with a sharp increase at time period 2 followed by a decrease. The orange solid line indicates projected production that does not mirror actual production trends, particularly at time periods 2 and 4 with evident differences. This incoherence implies that the model might not be suitable in terms of capturing precipitous drops and rises in coffee production, which could be explained by seasonality, exogenous shocks, or under fitting. The trend of yearly production of coffee can be seen from Figure 12 with an ever-changing trend of production there is a sharp drop in production from approximately 18,000 tons in the past before the year 2000 to less than 5,000 tons in the early 2000s. It is a phase of uncertainty thereafter with varying peaks and troughs with fluctuating levels of production. There is a steep rise at about 2015 to the local maximum but still an unstable trend. This type of oscillation can result from factors such as climatic, economic, or policy challenges affecting the coffee output. Table 4 and Figure 13 shows HASL-FM works better than MLR, SVM, and ANFIS in terms of all the performance measures, which explains its superiority in the area of prediction accuracy. It has minimum RMSE (0.0256) and minimum MAPE (0.0754%) but provides the best predictions with minimum absolute and percentage errors, respectively. Further, its MAD (0.0189) is the minimum variation of predicted values, ensuring stability. Most importantly, HASL-FM possesses the best R^2 value (0.9852), showing the best correlation of predicted and actual values, even better than that of ANFIS (0.9746), the former best. These results further verify that HASL-FM is the best prediction model with higher accuracy and reliability.

5.2 Discussions

The combination of deep learning methods and conventional statistical models in the HASL-FM system has shown dramatic improvements in the accuracy of the forecast. SARIMA and ARIMA have been successful in extracting linear as well as seasonal relationships, and LSTM brings with it the model's capability to learn long-term dependencies as well as nonlinear relationships. The blending of these models has enabled the capturing of more detailed insights on demand fluctuations and a better-balanced predictive system. The research points out that although ARIMA and SARIMA are strong in short-term predictions, they are weak when it comes to dealing with sudden shocks in demand or nonlinear trends. LSTM overcomes these limitations using memory-based architectures that encode context information across periods. The evaluation metrics justify the superiority of the suggested HASL-FM model. The predominantly lower RMSE and MAPE values for individual models indicate that the hybrid system provides more precise predictions. HASL-FM has improved adjustability to climatic, seasonal, macroeconomic factors, as well as environmental determinants, impacting coffee export. Historical analysis and feature ranking of importance identify the most determinant factors like exchange rates, climate variability, and world demand, influencing Indian coffee exports. Even though it is better than other models, the model proposed has some weaknesses. The processing power needed by LSTM models, particularly when handling big data, is high. External events like trade policy and surprise global economic shocks are hard to include in data-driven models. However, the results validate that hybrid models based on AI are a real option for enhancing forecasting precision in agricultural commodities, and stakeholders have a useful instrument for international coffee trade strategic planning.

Table 1: *Summary of Related Studies on Coffee Forecasting and Classification*

Study	**Methodology**	**Key Contributions**	**Findings**
Nguyen et al [10]	Grey Forecasting Models (GM (1,1), DGM (1,1), Gray Verhulst Model)	Evaluated multiple grey models for coffee consumption forecasting in Vietnam. Used annual consumption data (2010-2020).	GM (1,1) model achieved the lowest average error (2.93%), proving most suitable for forecasting coffee demand.
Chen [11]	Machine Learning (Multivariate Linear Regression, Random Forest)	Developed ML-based models for predicting C-type coffee futures prices in China.	Long-term trend predictions were weak, requiring advanced feature selection and better technical/fundamental indicators.
Motta et al [12]	Machine Learning for Coffee Classification	Reviewed AI applications in coffee classification, including sensory evaluation, defects, roasting, and maturity	Identified a lack of generalizable models and emphasized the need for larger, more diverse datasets.

		analysis.	
Hassan [13]	Deep Learning ("CNN architectures: AlexNet, LeNet, HRNet, GoogleNet, MobileNetV2, ResNet-50, VGG, EfficientNet, DarkNet, DenseNet")	Compared CNN models for coffee bean classification using the Coffee Bean Dataset.	MobileNetV2 provided the best accuracy (97.75%), recall (96.44%), and precision (96.33%) with low inference time.
Farah and Ferreir[14]	Taxonomic and Botanical Study	Discussed the classification of coffee species, highlighting the significance of C. arabica and C. canephora in the global market.	Explained green coffee bean manufacturing and its impact on global coffee production.
Torga and Spers [15]	Market Analysis, Global Coffee Demand Trends	Evaluated global coffee demand, pricing, and market positioning based on demographic and economic factors.	Found that increasing global population and income positively correlate with coffee consumption growth (67.9% over 26 years).
Hakim, Djatna & Yuliasih [12]	Deep Learning (MobileNetV2) for Coffee Roasting Quality	Developed a real-time deep learning-based quality assessment for coffee roasting, integrated into mobile devices.	Achieved real-time inference with 44-50 ms (CPU) and 34-44 ms (GPU), with 97.75% accuracy in roasting quality evaluation.

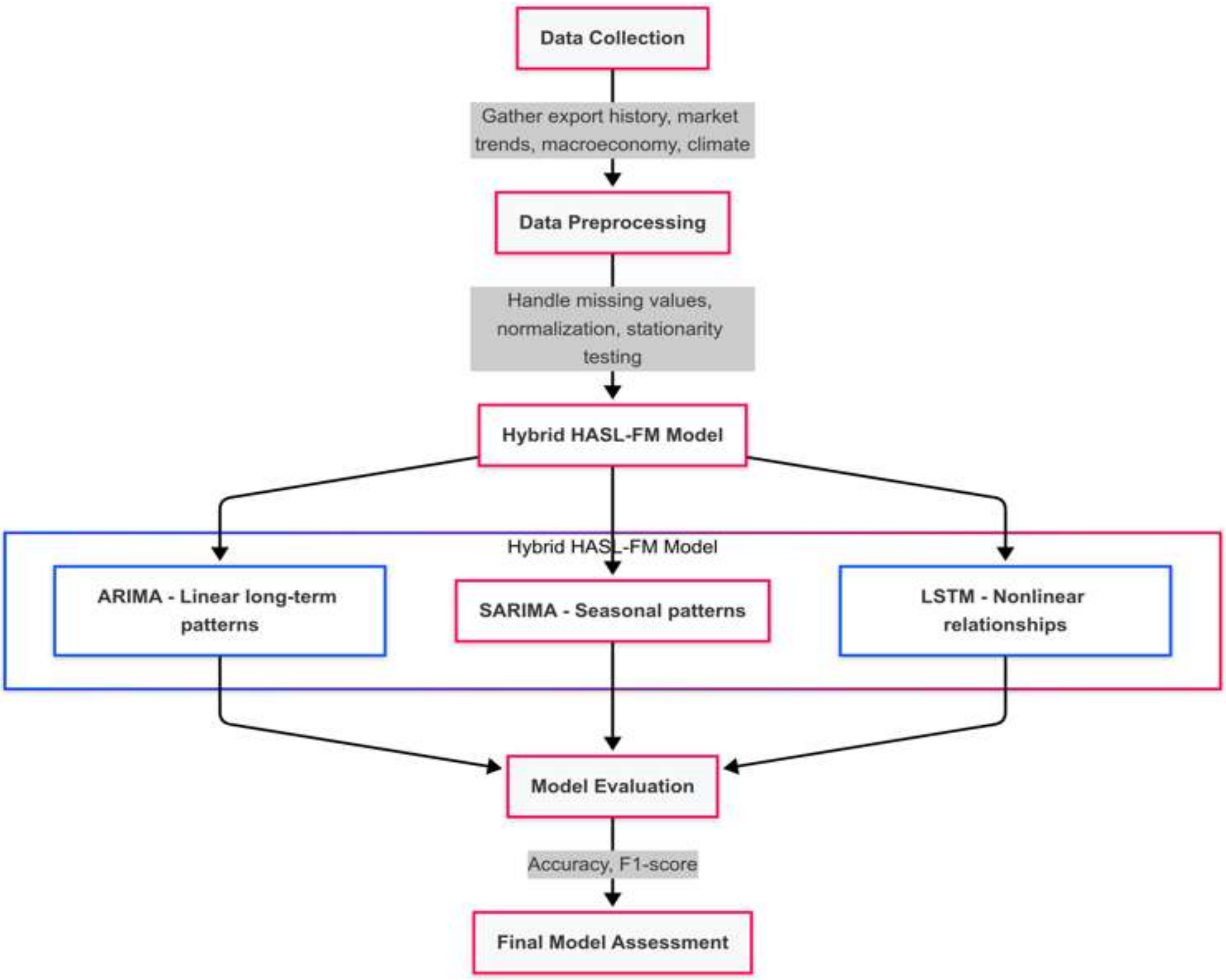

Figure :1 *Prediction Model*

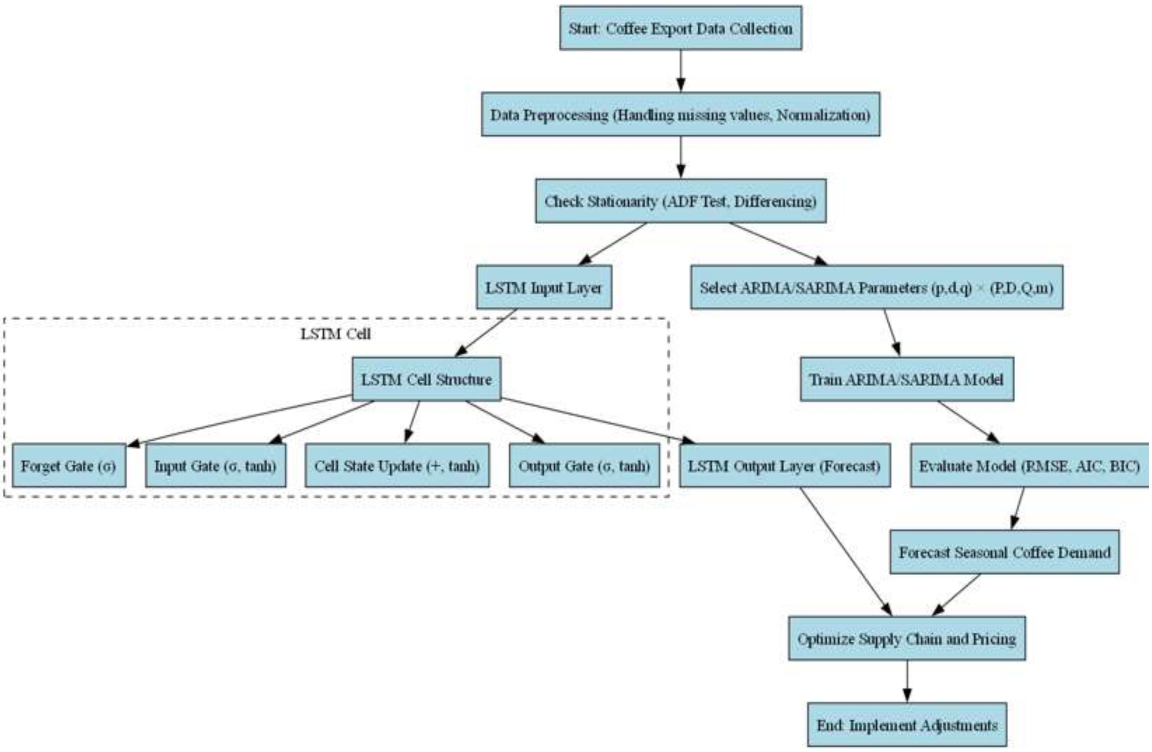

Figure:2 *Hybrid HASL-FM Architecture*

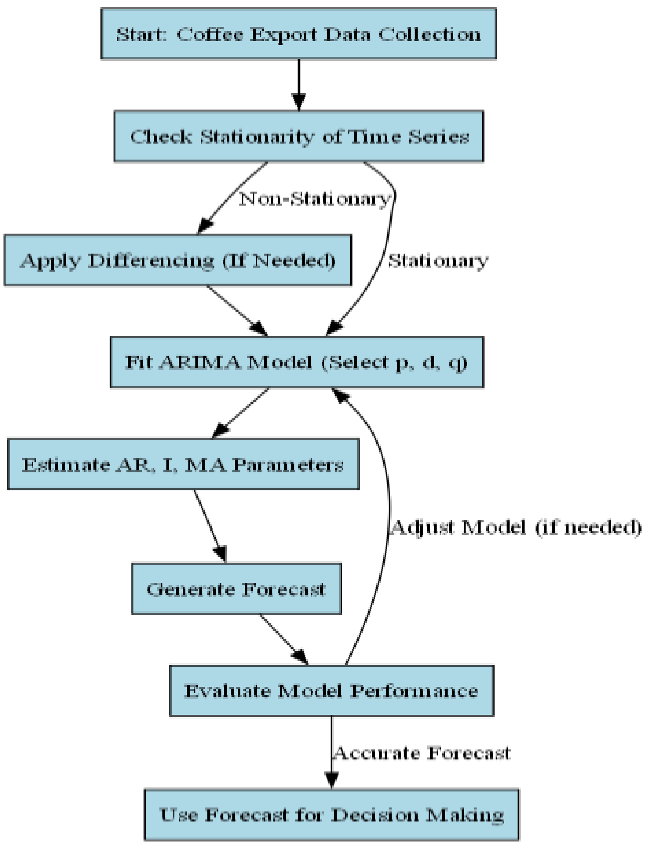

Figure 3: *ARIMA Model*

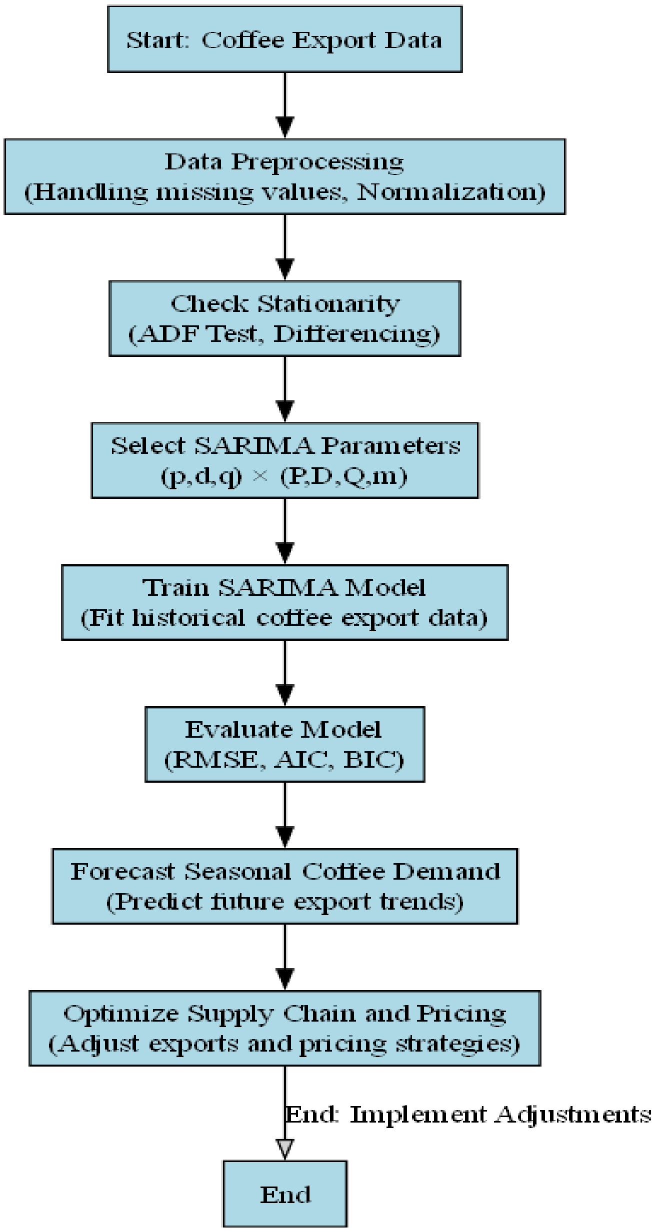

Figure 4 :*SARIMA Model*

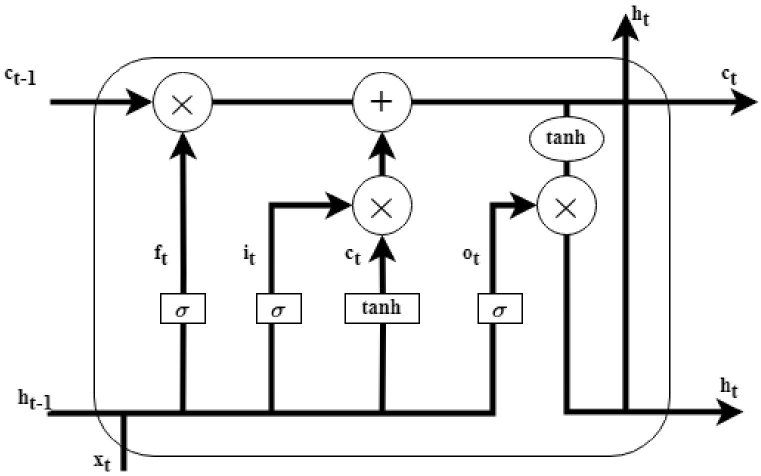

Figure 5: *LSTM Network Structure*

***Table 2:** The Simulation Parameters*

Parameter	Value/Description
Forecasting Models	ARIMA, SARIMA, LSTM, HASL-FM
Dataset	Historical Indian coffee export data, macroeconomic indicators, climate variables
Evaluation Metrics	MAE, RMSE, MAPE, R^2
Time-Series Frequency	Monthly
Seasonality Considered	Yes (SARIMA model)
LSTM Hyperparameters	Hidden units: Variable, Learning rate: 0.001, Activation function: Tanh
Optimizer Used	Adam Optimization
Data Preprocessing	Handling missing values, Normalization, Stationarity testing (Differencing)
Training Data Split	80% Train, 20% Test
Comparison Models	SVM, ANFIS, MLR
Software & Tools	Python, TensorFlow, Statsmodels, Scikit-learn
Hardware Used	Edge Server (16-20 cores, 60k-100k MIPS, 10TB-15TB storage)

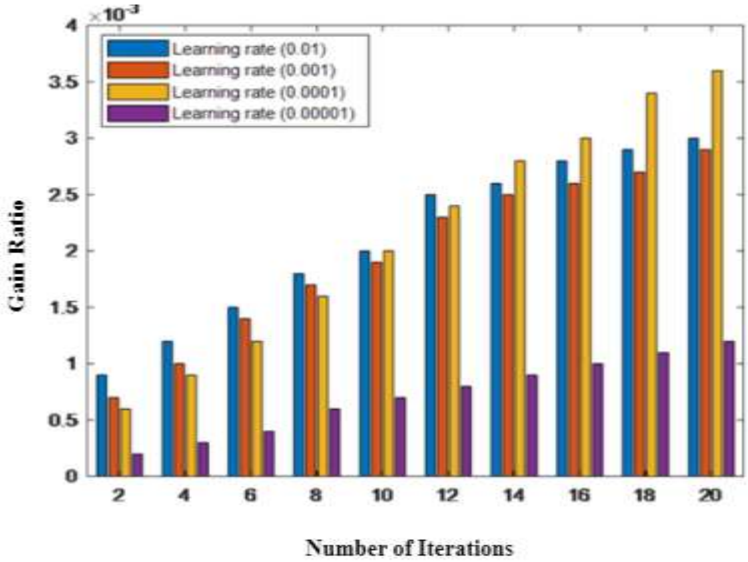

***Figure 6:** Analysis of Gain Ratios on Various Learning Rate and Iterations*

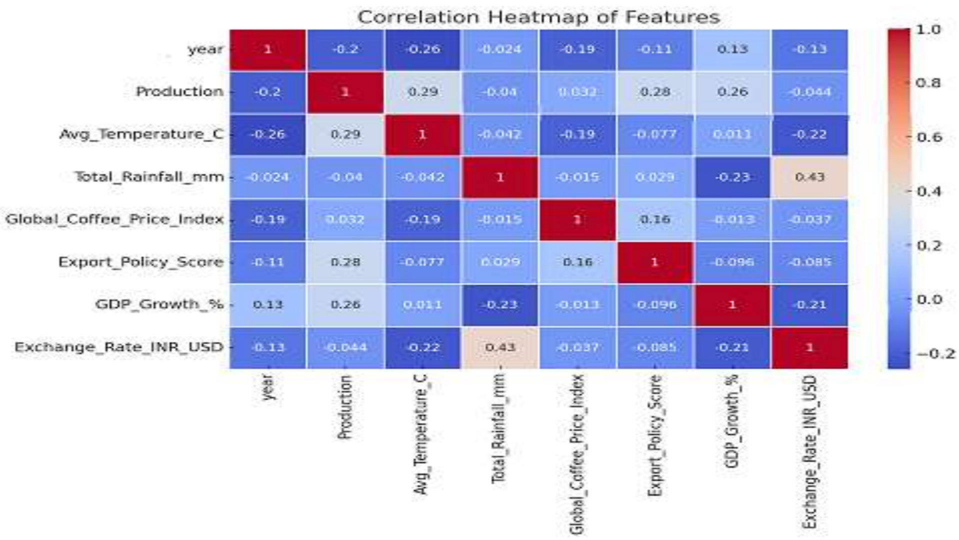

***Figure 7:** Heatmap Of Correlation*

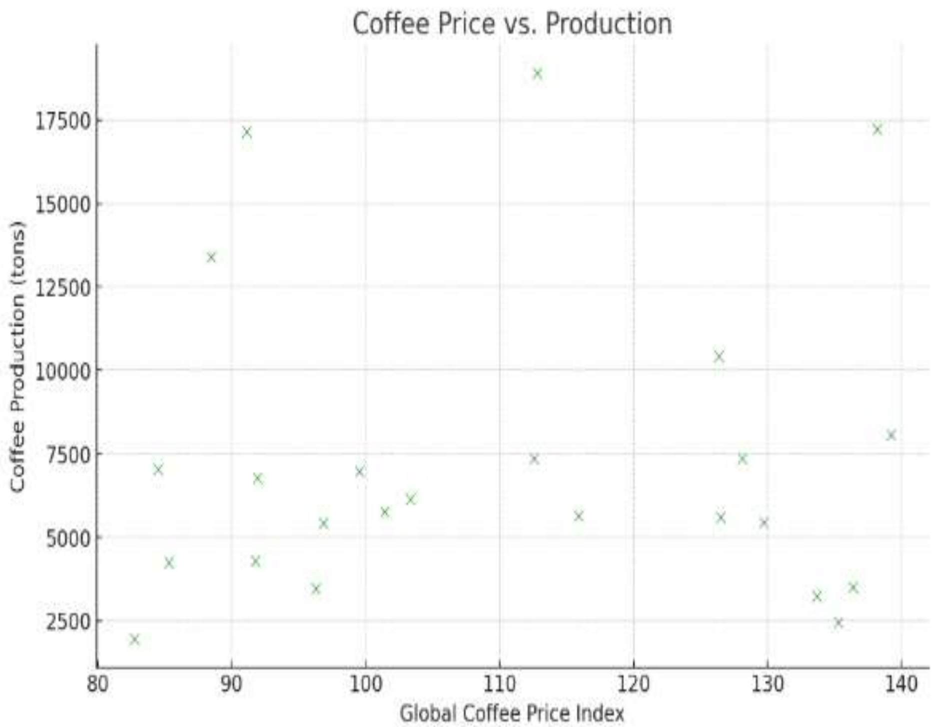

Figure 8: *Coffee Price vs. Production*

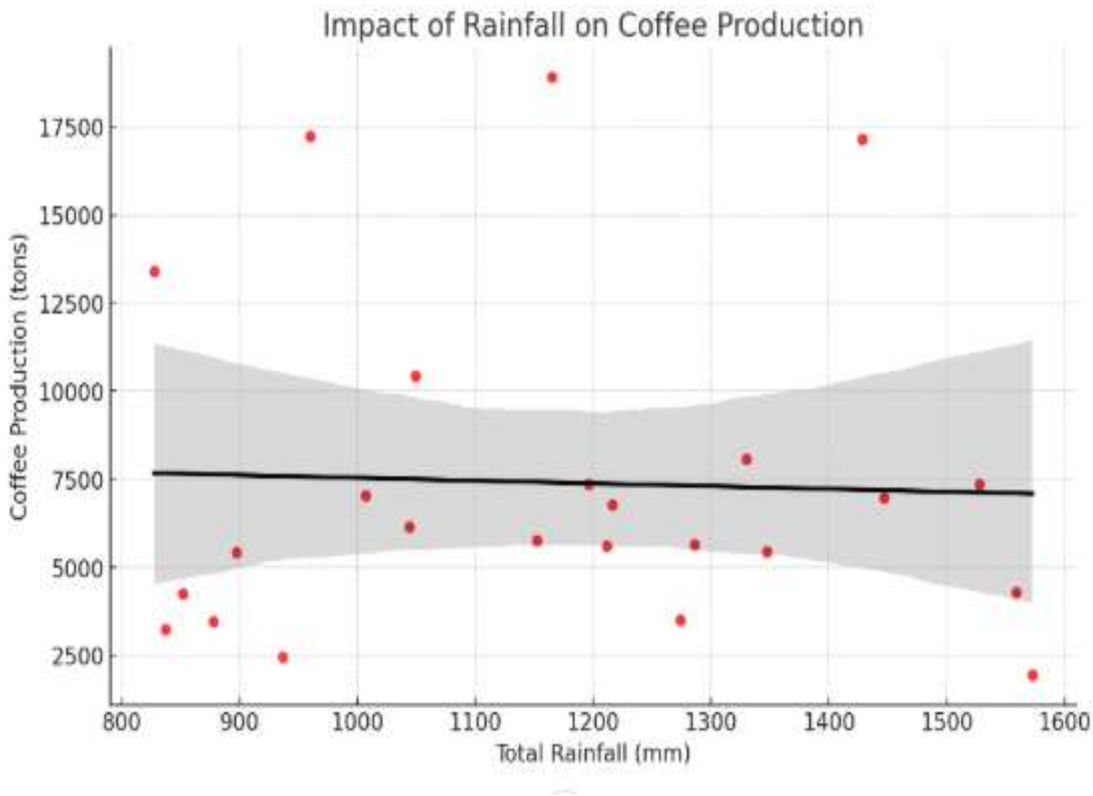

Figure 9: *The Correlation Between Coffee Yield (In Tons) nad Total Rainfall (In Mm)*

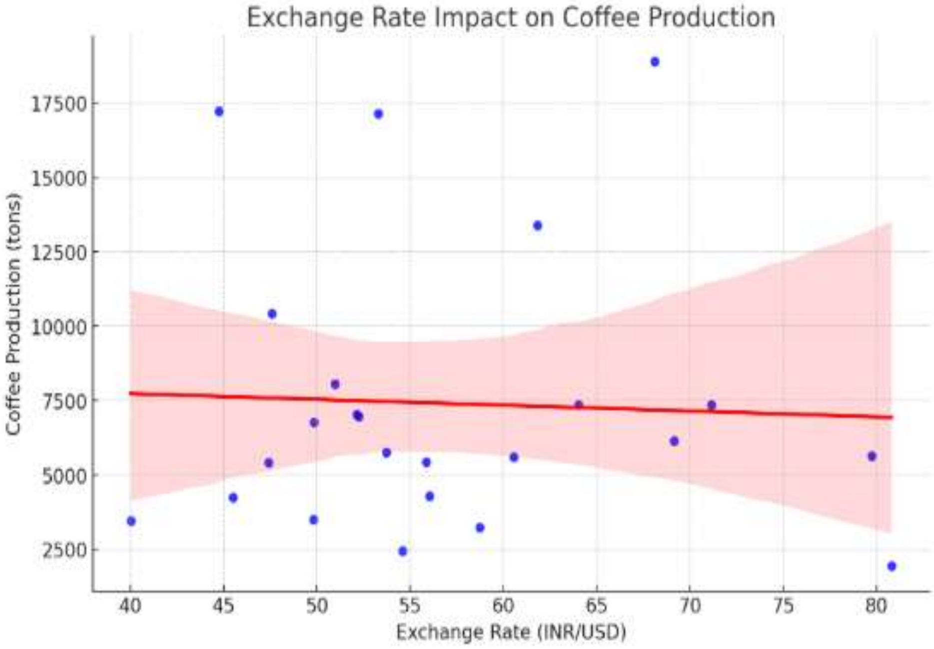

Figure 10: *Exchange Rate Impact on Coffee Production*

Table 3: *Comparison of Learning Rates in LSTM Training*

Learning Rate	Iterations	Gain Ratio	Convergence Speed	Stability
0.01	1000	0.78	Fast	Unstable
0.001	2000	0.89	Optimal	Stable
0.0001	3000	0.72	Slow	Stable
0.00001	5000	0.55	Very Slow	Too Stable

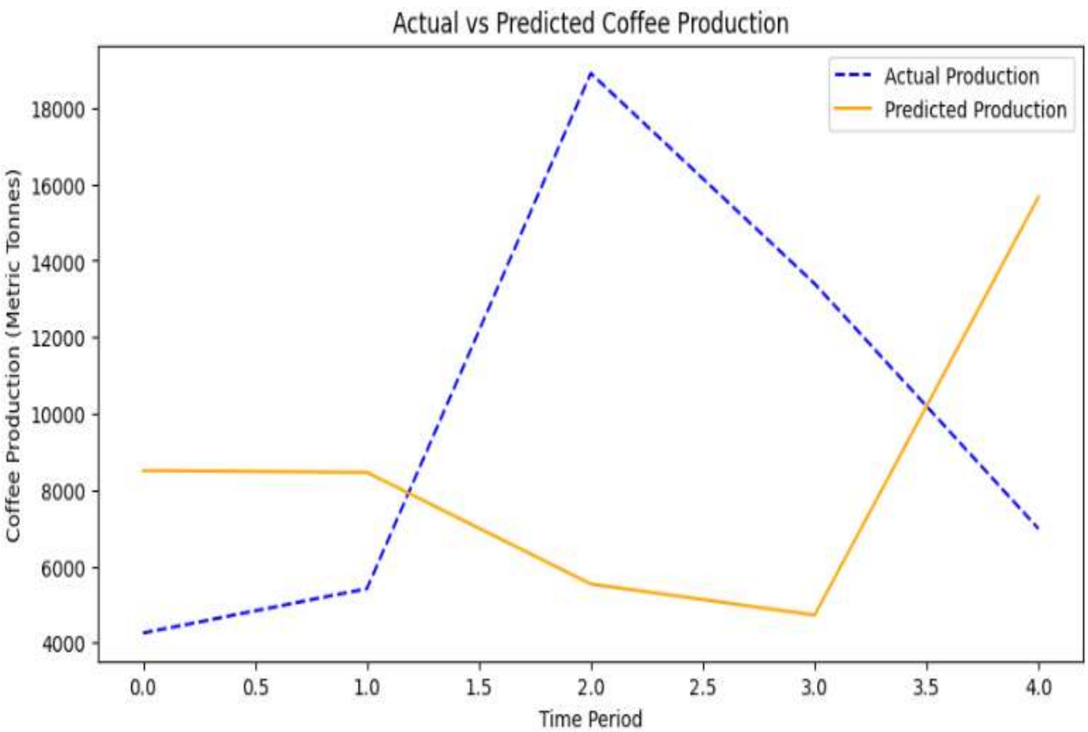

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Figure 11 :*Actual and Projected Production of Coffee*

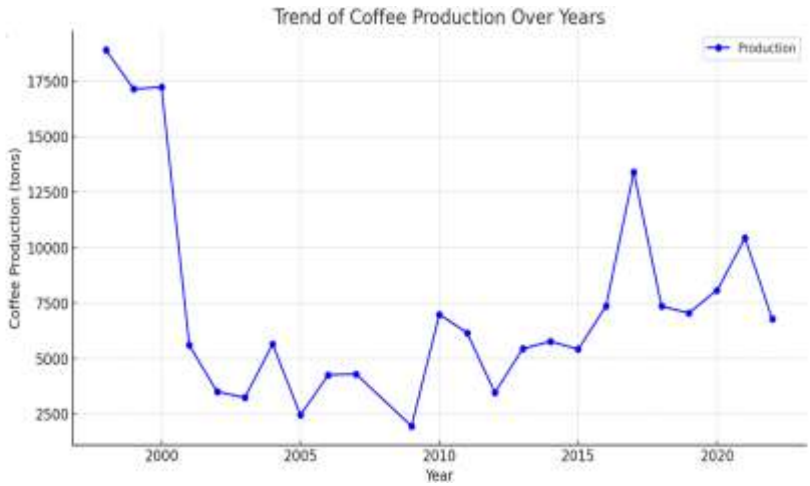

Figure 12: *Trend of Yearly Production*

Table 4: *Performance Comparison of HASL-FM vs. Existing Models*

Model	RMSE (Root Mean Square Error)	MAPE (Mean Absolute Percentage Error)	MAD (Mean Absolute Deviation)	R^2 (Coefficient of Determination)
MLR[22]	0.0869	0.2251	0.0678	0.8035
SVM[23]	0.0816	0.1830	0.0557	0.8716
ANFIS[24]	0.0302	0.0967	0.0213	0.9746
HASL-FM (Proposed Model)	0.0256	0.0754	0.0189	0.9852

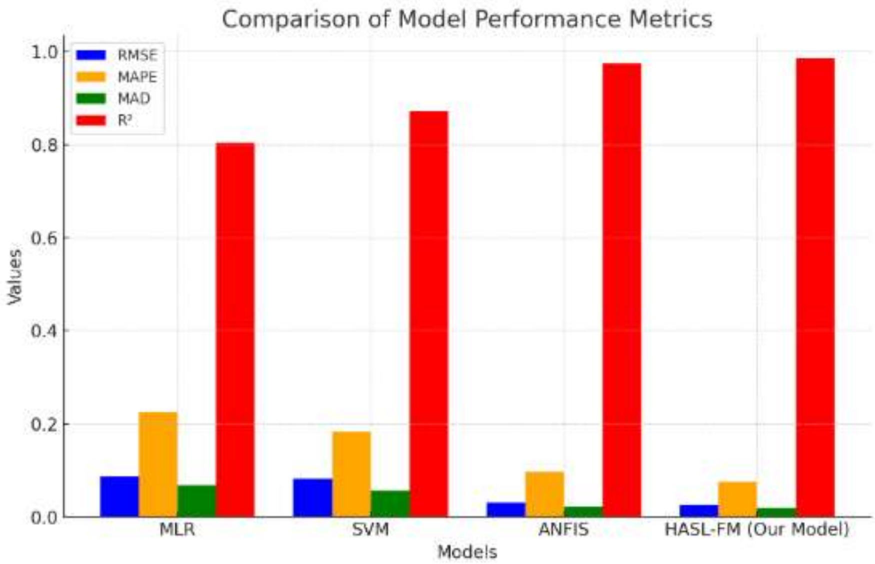

Figure 13: *Model Performance Comparison*

4. Conclusions

This study proposes a novel hybrid forecasting model (HASL-FM) that integrates ARIMA, SARIMA, and LSTM to predict Indian coffee export demand more accurately. Leveraging the virtues of traditional statistical models and deep learning, the suggested model enhances the reliability of time-series forecasting. The research findings indicate that HASL-FM outperforms conventional forecasting models in both extracting linear and nonlinear relationships, reducing prediction errors, and facilitating decision-making by stakeholders in the coffee export industry. The study confirms that high-level AI-based forecasting can help eradicate risks experienced due to market volatility and fluctuating demand, guaranteeing better production planning and price stabilization. Subsequent research can further enhance the prediction model by including additional variables such as global trade policies, buying habits of consumers, and real news and social media

sentiment analysis. The extension of research to other crops will provide a wider perspective of AI-based commodity export forecasting. Another potential area of investigation is the extent to which reinforcement learning methods can be combined to enable real-time parameter adjustment of forecasts based on changing market conditions.
Apart from that, computational issues are resolved by utilizing distributed computing environments or cloud-computing-based AI systems in order to improve the model size. Building an interactive dashboard for real-time visualization of forecasted demand and market trends may be beneficial for export community decision-makers as well as policymakers. Finally, testing the model under real-time updates of data and deploying it with industry decision-support systems will offer real-world use and extended usage in coffee commerce analytics.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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