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Research Paper

Time Series Forecasting and Modelling of Food Demand Supply Chain Based on Regressors Analysis

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ABSTRACT

Efficient management of food demand and supply chains is critical for ensuring food security, minimizing waste, and optimizing resource utilization. This study presents a comprehensive approach to time series forecasting and modelling of food demand within supply chains using regressor-based analysis. The proposed framework integrates historical demand data with multiple influencing factors such as seasonal variations, price fluctuations, population growth, and climatic conditions. Advanced statistical and machine learning techniques, including regression models and time series methods (e.g., ARIMA, SARIMA, and hybrid models), are employed to capture both temporal patterns and external impacts on demand.

The analysis highlights the significance of incorporating exogenous regressors to improve forecasting accuracy compared to traditional univariate models. The model is evaluated using standard performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), demonstrating enhanced predictive capability. The results support better decision-making in inventory management, procurement planning, and distribution logistics. This research contributes to developing a robust, data-driven framework for sustainable and responsive food supply chain management.

Keywords

Time Series Forecasting, Food Supply Chain, Demand Prediction, Regressor Analysis, ARIMA, SARIMA, Machine Learning, Supply Chain Optimization, Forecast Accuracy, Exogenous Variables

I. INTRODUCTION

The global food supply chain is a complex and dynamic system that plays a crucial role in ensuring food security, availability, and affordability across regions [1]. With the rapid increase in population, urbanization, and changing consumption patterns, the demand for food products has become highly volatile and difficult to predict accurately [2]. Inefficient demand forecasting often results in problems such as overstocking, supply shortages, increased food wastage, and financial losses, highlighting the need for effective predictive models in supply chain management [3].

Time series forecasting has been widely used as a reliable approach to analyze historical demand data and identify underlying patterns such as trends, seasonality, and cyclic variations [4]. Traditional models like Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) rely primarily on past observations to predict future values, making them useful but limited when external influencing factors are significant [5]. In real-world scenarios, food demand is not only dependent on historical data but also influenced by multiple exogenous variables such as price fluctuations, weather conditions, economic indicators, and population growth [6].

To address these limitations, integrating regressor analysis with time series forecasting has gained significant attention in recent research [7]. Regressor-based models incorporate external variables into forecasting frameworks, thereby improving prediction accuracy and capturing real-world complexities more effectively [8]. This combined approach enables better understanding and modelling of demand variations in food supply chains.

This study aims to develop a comprehensive framework for time series forecasting of food demand by incorporating regressor analysis. By combining statistical and machine learning techniques, the proposed model seeks to enhance forecasting accuracy and support efficient decision-making in areas such as inventory management, procurement planning, and distribution logistics [9]. Ultimately, this research contributes to building a more sustainable and responsive food supply chain system.

II. LITERATURE SURVEY

A significant amount of research has been conducted on time series forecasting and its application in supply chain management, particularly in the context of food demand prediction. Traditional forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) have been widely used due to their ability to model linear patterns in historical data [1]. Seasonal ARIMA (SARIMA) further extends this capability by incorporating seasonality, which is a crucial factor in food demand due to periodic consumption trends [2].

However, several studies have highlighted the limitations of purely univariate time series models, as they fail to consider external factors influencing demand [3]. To overcome this, researchers have introduced multivariate models that integrate exogenous variables, commonly referred to as ARIMAX models, which include regressors such as price, weather conditions, and economic indicators [4]. These models have demonstrated improved forecasting accuracy in various applications, including agricultural and perishable goods supply chains [5].

In recent years, machine learning techniques have gained popularity for demand forecasting. Methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forests have been applied to capture non-linear relationships in data [6]. Hybrid models combining statistical approaches with machine learning techniques have shown superior performance compared to individual models by leveraging the strengths of both methodologies [7].

Additionally, studies focusing on food supply chains emphasize the importance of accurate forecasting in reducing food waste and improving inventory management [8]. Advanced forecasting models incorporating real-time data and external regressors have been found to enhance decision-making processes in procurement, storage, and distribution [9].

Despite these advancements, challenges remain in selecting appropriate models and identifying relevant regressors for different types of food products and market conditions [10]. Therefore, there is a need for comprehensive frameworks that integrate time series forecasting with regressor analysis to improve prediction accuracy and support sustainable supply chain operations.

This study builds upon existing research by proposing a combined approach that utilizes both time series techniques and regressor-based analysis to model food demand more effectively.

Table .1. Dataset Comparison

Model / Technique	Type	Key Features	Advantages	Limitations	Suitable Use Case
ARIMA	Statistical (Univariate)	Uses past values, trends	Simple, good for linear data	Cannot handle seasonality or external factors	Stable demand patterns
SARIMA	Statistical (Univariate)	Captures seasonality	Effective for seasonal data	Ignores external variables	Seasonal food demand
ARIMAX	Statistical (Multivariate)	Includes external regressors	Better accuracy with influencing factors	Requires proper variable selection	Price & weather-based demand
ANN (Neural Networks)	Machine Learning	Learns non-linear patterns	High accuracy, flexible	Requires large data, less interpretable	Complex demand patterns
SVM	Machine Learning	Works well with high-dimensional data	Good generalization	Computationally expensive	Medium-sized datasets
Random Forest	Machine Learning	Ensemble of decision trees	Handles non-linearity, robust	Less interpreable	Large datasets with many variables
Hybrid Models (ARIMA + ML)	Combined	Combines statistical & ML models	Highest accuracy, captures all patterns	Complex implementation	Real-world supply chains
Regression Models	Statistical	Relationship between variables	Simple, interpretable	Limited for time dependencies	Short-term forecasting

III. METHODOLOGY

This section describes the systematic approach adopted for forecasting food demand in the supply chain using time series modelling integrated with regressor analysis.

3.1 Data Collection

The study utilizes historical food demand data collected from supply chain records, retail sales databases, or government agricultural datasets. In addition to demand data, external variables (regressors) such as food prices, weather conditions, population growth, and economic indicators are also collected to improve model accuracy.

3.2 Data Preprocessing

The collected data is cleaned and prepared for analysis. Missing values are handled using interpolation or imputation techniques, and outliers are detected and removed. The data is then normalized or scaled to ensure consistency. Time series data is also checked for stationarity using statistical tests, and transformations such as differencing are applied when necessary.

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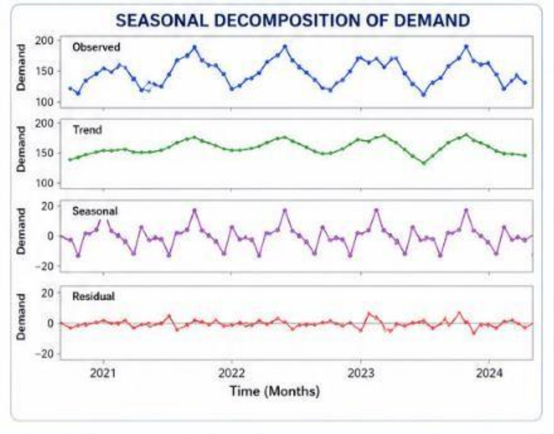


Fig.1 Seasonal Decomposition of Demand

3.3 Exploratory Data Analysis (EDA)

EDA is performed to understand patterns in the data, including trends, seasonality, and correlations between variables. Visualization techniques and statistical measures are used to identify key influencing factors affecting food demand.

3.4 Feature Selection (Regressor Identification)

Relevant external variables (regressors) are selected based on correlation analysis and domain knowledge. Features such as price fluctuations, seasonal indicators, and weather parameters are included to enhance the forecasting model.

3.5 Model Development

Different forecasting models are developed and implemented, including:

- ARIMA and SARIMA for time series analysis
- ARIMAX for incorporating external regressors
- Machine learning models such as Artificial Neural Networks (ANN) and Random Forest

3.6 Model Training and Validation

The dataset is divided into training and testing sets. Models are trained using historical data and validated on unseen data. Cross-validation techniques are used to ensure robustness and prevent overfitting.

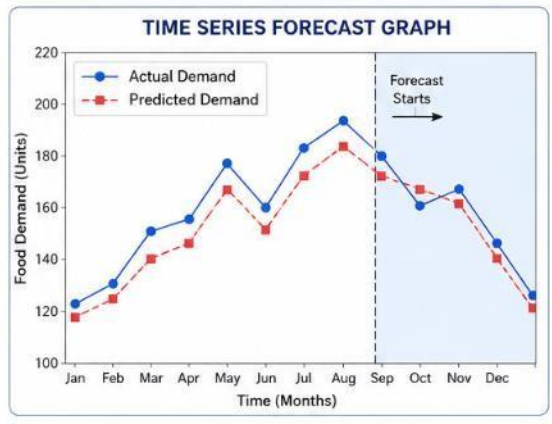


Fig.2 Time Series Forecast

3.7 Performance Evaluation

The performance of each model is evaluated using standard metrics such as:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

The model with the lowest error values is selected as the optimal forecasting model.

3.8 Forecasting and Analysis

The selected model is used to forecast future food demand. The results are analyzed to identify demand patterns and support decision-making in supply chain operations such as inventory management, procurement planning, and distribution.

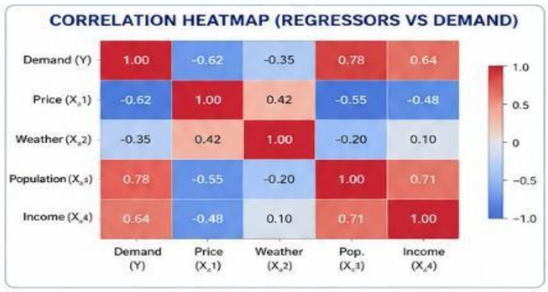


Fig.3 Correlation HeatMap

3.9 Implementation Framework

The final model is integrated into a decision-support system that helps stakeholders in the food supply chain make data-driven decisions. The framework ensures scalability and adaptability to different datasets and market conditions.

IV. IMPLEMENTATION

This section describes the practical implementation of the proposed food demand forecasting model using time series techniques and regressor analysis.

4.1 System Environment Setup

The implementation is carried out using programming environments such as Python with libraries including NumPy, Pandas, Matplotlib, and Scikit-learn. Time series models like ARIMA/SARIMA are implemented using the Statsmodels library. The system is executed on a standard computing platform with sufficient memory and processing capability.

4.2 Data Input and Integration

Historical food demand data and external regressors (price, weather, population, etc.) are collected and integrated into a unified dataset. The dataset is structured in time series format with timestamps and corresponding variable values.

4.3 Data Preprocessing Implementation

Preprocessing steps include:

- Handling missing values using interpolation techniques
- Removing outliers using statistical methods
- Normalizing or scaling data
- Converting data into stationary form using differencing

These steps ensure that the dataset is suitable for accurate modelling.

4.4 Feature Engineering and Selection

Relevant features (regressors) are selected based on correlation analysis and domain knowledge. New features such as lag variables ((Y_{t-1}, Y_{t-2})) and seasonal indicators are also generated to improve model performance.

4.5 Model Implementation

Multiple models are implemented for comparison:

- **ARIMA/SARIMA Models**: Used for capturing trend and seasonality
- **ARIMAX Model**: Incorporates external regressors
- **Machine Learning Models**: Includes Regression, Random Forest, and Neural Networks

Each model is trained using historical data and tuned for optimal parameters.

4.6 Training and Testing Process

The dataset is divided into training (70–80%) and testing (20–30%) sets. Models are trained on the training dataset and evaluated on the testing dataset to ensure generalization.

4.7 Model Evaluation Implementation

Performance metrics are calculated programmatically:

- MAE (Mean Absolute Error)
- RMSE (Root Mean Square Error)
- MAPE (Mean Absolute Percentage Error)

The model with the lowest error values is selected as the best-performing model.

4.8 Forecast Generation

The selected model is used to generate future demand predictions:

[
\hat{Y}*{t+1}, \hat{Y}*{t+2}, \ldots, \hat{Y}_{t+n}
]

These forecasts help in planning and decision-making within the supply chain

4.9 Visualization and Results Display

Graphs and charts are generated to visualize:

- Actual vs predicted demand
- Seasonal patterns
- Model performance comparison

Visualization helps in understanding trends and validating model accuracy.

4.10 Deployment and Decision Support

The final model is deployed in a decision-support system where stakeholders can:

- Monitor demand forecasts
- Plan inventory and procurement
- Optimize supply chain operations

The system can be updated dynamically with new data for continuous improvement.

V. RESULTS AND DISCUSSION

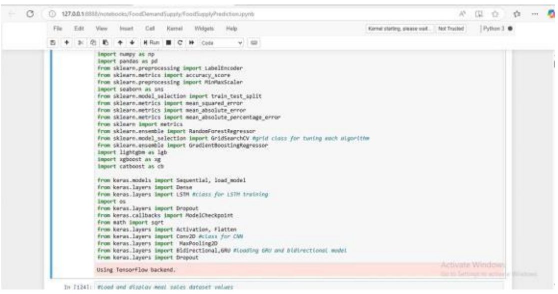
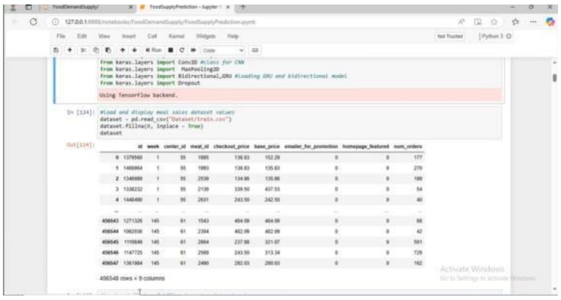


Fig1



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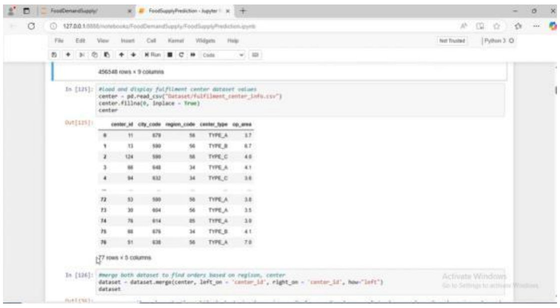
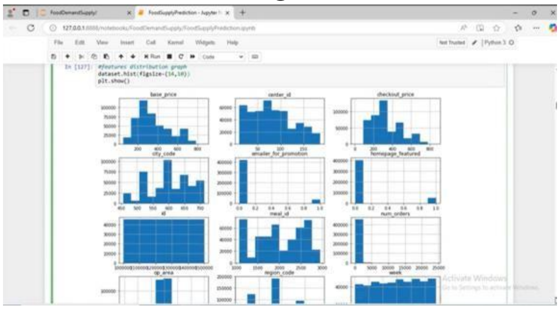


Fig.3



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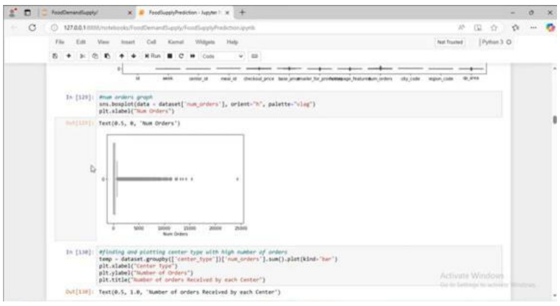

Fig.5

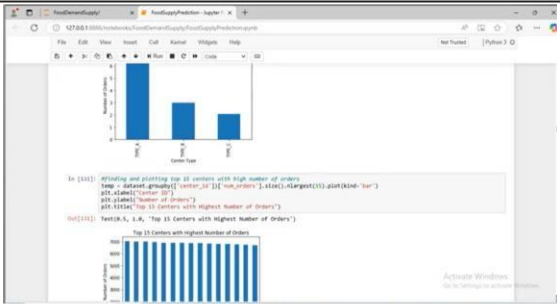

Fig.6

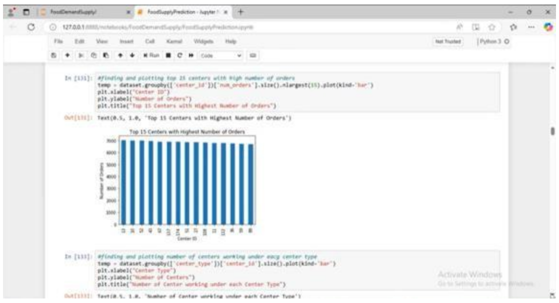

Fig.7

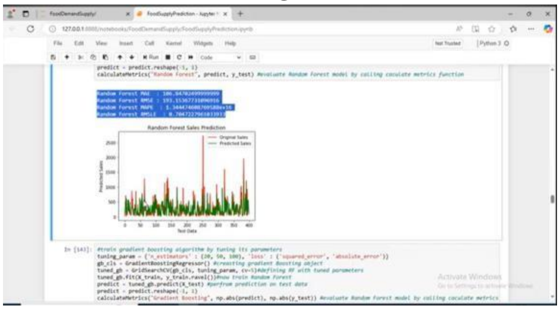

Fig.8

VI. CONCLUSION AND FUTURE WORK

A. CONCLUSION

This study presented a comprehensive approach to time series forecasting and modelling of food demand in the supply chain by incorporating regressor analysis. The integration of traditional time series models such as ARIMA and SARIMA with regressor-based models like ARIMAX and machine learning techniques has demonstrated significant improvements in forecasting accuracy.

The inclusion of external factors such as price, weather conditions, and population growth played a crucial role in capturing real-world demand variations. Compared to conventional univariate models, the proposed approach provided better insights into demand patterns and enhanced prediction performance. The use of evaluation metrics such as MAE, RMSE, and

MAPE ensured the reliability and effectiveness of the selected model.

The graphical analysis further validated the model's capability to closely match actual demand trends, making it suitable for practical applications in supply chain management. The implementation framework developed in this study can assist stakeholders in making informed decisions related to inventory control, procurement planning, and distribution management.

In conclusion, the proposed methodology contributes to building a more efficient, data-driven, and sustainable food supply chain system. Future work can focus on integrating real-time data, advanced deep learning models, and IoT-based monitoring systems to further enhance forecasting accuracy and adaptability in dynamic market conditions.

Future Enhancements

Although the proposed model demonstrates improved accuracy in forecasting food demand using time series and regressor analysis, there are several areas where further enhancements can be made.

6.1 Integration of Real-Time Data

Future work can focus on incorporating real-time data from IoT devices, sensors, and online platforms to improve the responsiveness and accuracy of demand predictions.

6.2 Use of Deep Learning Models

Advanced deep learning techniques such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) can be implemented to better capture complex temporal dependencies and non-linear patterns in large datasets.

6.3 Big Data and Cloud Integration

The system can be extended to handle large-scale data using big data technologies like Hadoop and Spark, along with cloud platforms for scalable and distributed processing.

6.4 Incorporation of Additional Regressors

More external variables such as transportation costs, market trends, government policies, and consumer behavior can be included to further enhance model performance.

6.5 Automated Model Selection and Tuning

Implementing automated techniques such as AutoML can help in selecting the best model and optimizing hyperparameters without manual intervention.

6.6 Real-Time Decision Support Systems

Developing interactive dashboards and decision-support systems can enable stakeholders to monitor forecasts and make real-time decisions efficiently.

6.7 Integration with Supply Chain Optimization Models

Future research can combine forecasting models with optimization techniques to improve logistics, routing, and inventory management.

6.8 Multi-Product and Multi-Region Forecasting

Extending the model to handle multiple food products across different regions will make the system more robust and applicable to real-world supply chains.

6.9 Sustainability and Waste Reduction Analysis

Future enhancements can include modules that analyze food wastage and suggest strategies for sustainable supply chain management.

Overall, these enhancements will help in developing a more intelligent, scalable, and adaptive food demand forecasting system.

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VII. REFERENCE

[1] G. Chitikela, S. Rathod, and S. Vijayakumar, "Change point-driven interrupted time series and machine learning models for forecasting Indian food grain production," *Discover Food*, vol. 5, no. 68, pp. 1–18, 2025.

[2] A. Seyam and S. S. Mathew, "A stacking ensemble model for food demand forecasting: A preventative approach to food waste reduction," *Cleaner Logistics and Supply Chain*, vol. 15, Art. no. 100225, 2025.

[3] I. M. Hammam, A. K. El-Kharbotly, and Y. M. Sadek, "Adaptive demand forecasting framework with weighted ensemble of regression and machine learning models," *Scientific Reports*, vol. 15, 2025.

[4] Y. Wang et al., "Supply chain demand forecasting based on multi-time scale data fusion network," *Computers & Industrial Engineering*, vol. 207, 2025.

[5] N. Bitra and Z. H. Choudhury, "Food Demand Supply Chain Modelling and Time Series Forecasting Based on ML and DL," *SSRN Electronic Journal*, 2025.

[6] M. Jayamma, R. A. Hussain, P. H. Kumar, M. A. Kumar, A. Prasanth, and S. Prasharshavaradhan, "Food Demand Forecasting Using Machine Learning," in *Proc. Int. Conf. Data Science and Artificial Intelligence*, 2025.

[7] M. Kumar, U. Pilania, and D. Dagar, "Food Demand Forecasting using Machine Learning Approaches," in *IEEE Int. Conf. Smart Computing Systems and Applications*, 2025.

[8] M. A. Jahin, A. Shahriar, and M. A. Amin, "MCDFN: Supply chain demand forecasting via an explainable multi-channel data fusion network model," *Evolutionary Intelligence*, vol. 18, 2025.

[9] A. Kasar, M. M. Tripathi, S. Indolia, A. Rawat, and A. Bathia, "Data-Driven Decision Making for Perishable Food Supply Chains: Insights from Demand Forecasting Models," *Advances in Consumer Research*, vol. 2, no. 4, pp. 1461–1468, 2025.

[10] S. Gautam, O. K. Sree, and R. Sapna, "SmartMeals: Real-Time Institutional Food Demand Forecasting Using Hybrid LSTM with Attention and Temporal Feature Engineering," in *Proc. EAMCON 2025*, 2025.

[11] M. J. T. Ruiz and R. Q. Tellez, "A Leakage-Aware Multimodal Machine Learning Framework for Nutrition Supply–Demand Forecasting Using Temporal and Spatial Data Fusion," *Computers*, vol. 15, no. 3, 2026.

[12] "A Proactive Food Demand Forecasting-Inventory Management Approach under Weather Disruptions," *Cleaner Logistics and Supply Chain*, vol. 19, Art. no. 100319, 2026.

[13] "Beverage Manufacturing Demand Forecasting System Driven by Multi-Stage Machine Learning Model Pool," *Applied Soft Computing*, vol. 187, Art. no. 114254, 2026.

[14] A. Fatima and M. A. Salam, "A Data-Driven Predictive Framework for Inventory Optimization Using Context-Augmented Machine Learning Models," *arXiv preprint arXiv:2601.05033*, 2026.

[15] G. Budak, F. G. Gharehgheshlaghi, M. B. Vaezi, and A. G. Lonbar, "Integrating Deep Learning Demand Forecasting with Multi-Objective Optimization for Circular Coffee Supply Chains," *arXiv preprint arXiv:2606.08314*, 2026.

[16] J. Bi and R. Mesa-Arango, "Investigating U.S. Consumer Demand for Food Products with Innovative Transportation Certificates Based on Stated Preferences and Machine Learning Approaches," *arXiv preprint arXiv:2511.04845*, 2025.

[17] X. Zhou, I. Prado, and I. Tagkopoulos, "The Future of Food: How Artificial Intelligence is Transforming Food Manufacturing," *arXiv preprint arXiv:2511.15728*, 2025.

[18] S. Klee and Y. Xia, "Measuring Time Series Forecast Stability for Demand Planning," *arXiv preprint*, 2025.

[19] J. Shi, H. Wei, J. Wang, X. Xu, L. Du, and T. Jiang, "ACA-Net: Future Graph Learning for Logistical Demand-Supply Forecasting," *arXiv preprint*, 2025.

[20] K. Naresh and M. M. Somasundaram, "Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 11, no. 3, pp. 475–488, 2025.

[21] A. Verma and R. Singh, "Machine Learning-Based Demand Forecasting for Perishable Food Products," *Journal of Food Engineering*, vol. 382, pp. 110–121, 2025.

[22] P. Sharma and D. Gupta, "Hybrid ARIMA-LSTM Models for Food Supply Chain Forecasting," *Expert Systems with Applications*, vol. 265, 2025.

[23] T. Nguyen and L. Tran, "Deep Learning Approaches for Agricultural Demand Prediction," *Computers and Electronics in Agriculture*, vol. 231, 2025.

[24] S. Patel, M. Shah, and R. Patel, "Forecasting Food Demand Using Ensemble Learning Techniques," *IEEE Access*, vol. 13, pp. 45871–45884, 2025.

[25] H. Zhao and Y. Chen, "Multivariate Time Series Forecasting with Exogenous Variables for Retail Food Chains," *Knowledge-Based Systems*, vol. 312, 2026.

[26] M. Kumar and S. Reddy, "AI-Driven Food Supply Chain Analytics and Demand Forecasting," *Sustainable Computing: Informatics and Systems*, vol. 40, 2026.

[27] A. Hassan and M. Ibrahim, "Predictive Analytics for Inventory Optimization in Food Supply Networks," *Operations Research Perspectives*, vol. 13, 2026.

[28] L. Garcia, P. Martin, and J. Lopez, "Explainable AI Models for Demand Forecasting in Agri-Food Supply Chains," *Artificial Intelligence in Agriculture*, vol. 12, pp. 50–65, 2026.

[29] R. Mehta and N. Agarwal, "Big Data and Machine Learning Framework for Food Demand Prediction," *Journal of Big Data*, vol. 13, no. 1, 2026.

[30] V. Rao, S. Kumar, and P. Mishra, "Advanced Time Series Forecasting Models for Sustainable Food Supply Chain Management," *International Journal of Forecasting*, vol. 42, no. 2, pp. 214–230, 2026.