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Demand Forecasting for Perishable Food Commodities Using Data Analytics

Advaita Menon[1], Midhir Nambiar[2], Aman Mishra[3,*], Aryan Tiwari[4], Aditya Kasar[5]

Abstract

This paper introduces a comprehensive study aimed at enhancing the forecasting of perishable food item demand. Focusing on solving the critical issue of waste management within the supply chain of food products, the research undertakes a comparative analysis of various machine learning models. The development of an optimized model that is capable of accurately forecasting the demand for perishable food items is the focus of this research. The research includes a review of the literature on demand, pricing, and production prediction studies carried out in India. It argues that machine learning algorithms can generate accurate forecasts and emphasizes the need for improved supply chain management to reduce waste in the perishable foods business. By underlining the need for modeling techniques in the optimization of supply chains for perishable items, this work increases the understanding of demand forecasting. Each entity involved in the supply chain can reduce waste and maximize inventory management with the help of the paper's insightful recommendations and proposed mechanism, thereby benefiting through a reduction in the cost of maintenance of the perishable food products.

Keywords: Data analytics, machine learning, regression, demand forecasting, supply chain, food waste, perishable food commodities

INTRODUCTION

Proper inventory management is a necessity in the supply chain, which is second to none [1]. The cost incurred by entities in the supply chain due to wastage of inventory, running out of stock, and ambiguities in demand and supply due to external factors is huge, especially in the perishable food industry. Around 30% of the wastage of fruits and vegetables is accounted for by poor infrastructure, 24% by transportation, and a huge amount of incorrect information shared by many intermediaries in the chain [2]. According to several studies, approximately 30–40% of the food in India goes to waste because of the discrepancy in supply chain mismanagement [2]. USD 750 billion worth of food weighing around 1.3 billion tonnes gets wasted every single year around the globe [3]. This mismanagement also results in wastage of water resources and the environment [4]. Accurately forecasting demand using machine learning has a major impact on streamlining supply chain processes, particularly perishable goods [5]. Therefore, our goal was to create a better demand forecasting model. This has the potential to provide significant benefits to several agricultural business sectors. This research is focused on food items like ladyfinger and tomato, which come under the "highly perishable category" with a shelf life of less than 2 weeks [6, 7].

***Author for Correspondence**
Aman Mishra
E-mail: mishraaman1777@gmail.com

[1-4]Student, School of Technology, Management & Engineering, NMIMS University, Navi Mumbai, Maharashtra, India
[5]Assistant Professor, School of Technology, Management & Engineering, NMIMS University, Navi Mumbai, Maharashtra, India

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Precisely predicting the demand for food items can help farmers, suppliers, store owners, and several intermediaries to appropriately stock their shelves and escape the situation of excessive or insufficient stock, which would help reduce approximately 18% of wastage caused by early or late harvest [2]. Moreover, an accurate image of demand patterns provided by a correctly adjusted model allows for efficient planning and coordination of production and distribution activities, thereby aiding in the coordination of the entire supply chain [1]. Accurate demand projections also contribute to the pricing stability in the perishable goods sector. Market volatility is one of the factors leading to a significant amount of food waste [3]. It is possible to prevent abrupt fluctuations in prices that could upset the market equilibrium by adjusting pricing strategies in real time in response to shifting consumer demand.

Stable pricing provides farmers and distributors with a consistent flow of income, which promotes the long-term stability and growth of the agricultural business in addition to providing consumers with peace of mind by enabling them to budget. Additionally, timely delivery of the proper quantity of fresh produce reduces transportation costs, supply chain efficiency, proper storage handling, and a reduction in the need for emergency supplies can be achieved with ease, which can contribute significantly to food waste reduction [2].

LITERATURE REVIEW

The supply chain of perishable goods in India suffers huge amounts of wastage now and then, according to a research paper around 18% of the total vegetables & fruits are wasted from the beginning of the harvest stage until they reach the customers. The absence of an integrated approach, accompanied by ineffective management of the supply chain, causes a huge loss of more than ₹440 billion per year.

This paper proposes an interactive digital platform that facilitates collaboration between the demand and supply sides of perishable food supply chains, focusing on integrating heterogeneous big data with AI-based forecasting methods to prevent food waste. This highlights the challenges in utilizing advanced forecasting methods, such as AI, owing to factors such as the differentiation between data-driven reliance and human judgment, as well as the integration of heterogeneous external data. This study emphasizes the novelty of the proposed platform architecture in combining heterogeneous data sources for AI-driven forecasting to prevent food wastage in the supply chain for perishable foods, leading to the inference that using AI-driven demand forecasting is necessary for the prevention of wastage [8].

This paper compares various machine learning based forecasting models for food demand in food catering services (FCSs) to reduce food waste. It includes a literature review on food waste (FW) and the types of approaches used in previous studies, both qualitative and quantitative. The models are based on casual and time series algorithms, considering variables such as the frequency of meals served, menus, features encompassing dates and weather, and the number of students expected to attend classes. The obtained results suggest that the Random Forest algorithm and long short-term memory (LSTM) recurrent neural network manufactured the most accurate predictions, an inference that is worked upon and modified as further literature review was done, based on the new knowledge acquired [9].

The international scientific community was concerned with models for predicting perishable food requirements that can boost economic gains and competition, and hence, conducted research. A literature review from 2013 to 2018 shows that soft computing techniques and time series constitute the best forecasting models for perishable food demand SMEs [10].

A study investigates the obstacles confronting Small Medium Enterprise (SME) wholesalers in precisely predicting the demand for fresh produce. It examines factors such as weather and holidays that contribute to high demand variability and the internal and external factors responsible for such variation. The research employs historical sales data from a UK-based SME wholesaler concentrating on the product “Milk.” From previous days searching for information about this issue, it was found that weather summary, cloud cover, and temperature are the most significant forecasters of demand, with monthly increasing correlations becoming more constant over time through correlation analysis and principal component analysis (PCA) analysis. This paper provides a rough idea of the variables for which data need to be collected and how important variables should be found through PCA [11].

One study focused on predicting the demand for perishable products using ARIMA (Autoregressive Integrated Moving Average) and LSTM methods. The quality of these products decreases with age, which, in turn, affects consumer satisfaction. The ARIMA method had a root mean square error (RMSE) value of 7.39% for Dataset1 and 34.29% for Dataset2, while the LSTM method had a reduced RMSE value in both datasets but showed overfitting; hence, it cannot be used for regular predictions. From the results obtained above, we can conclude that the ARIMA method performs better than the LSTM [12].

Food waste is a major problem, with a 20–60% loss in the supply chain. This study focuses on optimizing warehouse management by using machine learning to forecast the orders for perishable items and the use of the cloud to collect the dataset. Using the Random Forest regressor algorithm, the proposed model achieved an accuracy of approximately 75%, which helped retailers manage their buying and selling of goods with a profit [13].

This study proposes a novel algorithm to predict the demand for perishable farm products using the support vector machine (SVM) method. It generalizes well with improved performance and the assurance of a global minimum and is expected to be useful in forecasting perishable farm product demand. To enhance forecasting precision, fuzzy theory was employed to quantify the factors influencing sales forecasts by addressing real-world scenarios. Numerical experiments suggest that the fuzzy theory approach outperforms the radial basis function neural network, which works based on the relative mean error and FP [14].

This study suggests that the ARIMA (Autoregressive Integrated Moving Average) model provides good demand forecasts for perishable goods. The ARIMA model was used to predict the demand for perishable goods (onion, potato), and the forecasted values showed that the model was good but produced some errors owing to long-term prediction [15].

To improve availability and reduce losses, one paper suggests a Decision Support System (DSS) that forecasts the demand for perishable items using cluster analysis and multivariate ARIMA models with point-of-sale data. DSS employs article clusters showing similar intraday sales patterns, which helps in making precise top-down forecasts and reduces computational costs [16].

This paper proposes an ARIMA model that can predict the demand for vegetables (onion), but the model is only capable of predicting short-term data (month-wise/day-wise) rather than long-term data (year-wise). It was not perfect but was close enough to the actual data. The research paper further stated that the model could be used by any government organization, such as National Regional Comprehensive Organization Group (NRCOG) and Agricultural Produce Market Committee (APMC), to forecast the demand for vegetables (onion) [17].

The results of the study revealed that the ARIMA model had a higher MAPE of 43.14% after it was trained with 25 months of sales data for onions. The month-wise data caused the model to become confused and did not understand the demand trend properly. This is because ARIMA requires short-term data to understand trends and is viable only for short-term predictions [18].

This study conducted a systematic literature review of various machine learning models for predicting wheat demand and supply. It addresses the relationship between wheat production and human food supply, the rising demand for wheat, and factors affecting wheat output. It presents the findings of various predictive studies that utilized machine learning algorithms to forecast wheat demand, supply, and prices. The evaluation measures used in these studies, such as R2, RSME, MAPE, MSE, and accuracy metrics, are discussed to assess the predictive performance of the models. The important inference of this study was that demand forecasting with the help of machine learning models made more accurate forecasts than using simple traditional forecasting techniques (such as moving averages) and other neural networks (such as Artificial Neural Network (ANN) and recurrent neural networks (RNN)) [19].

This study compared the performance of different forecasting models, including ARIMA, based on the Box-Jenkins method, as well as a few machine learning algorithms such as LSTM networks, Support Vector Regression (SVR) regression, Random Forest regression, GBR boosting, and extreme GBR (XGBoost), focusing on specific vegetables selected for retailing. The results obtained indicate that machine learning methods such as LSTM and SVR outperform other models, thus implying their possible utilization in enhancing the demand prediction of perishable vegetables in India [20].

This study addresses various issues in estimating the demands of essential perishable items and focuses on the predictive analysis of a state-of-the-art inventory management system. The proposed model, which is a comparison of two-step models, uses a linear programming model and a reinforcement learning model to predict the order estimate of perishable products in the supply chain and identifies relevant features for estimating replenishment policies [21].

This study employs a novel approach integrating fuzzy MICMAC stands for Cross-Impact Matrix Multiplication Applied to Classification and total interpretive structural modeling (TISM) to address the significant issue of high food waste in the perishable produce supply chain, particularly in emerging markets, where these causal factors remain inadequately analyzed. This study identified 14–16 variables that represented the super-set of causal factors, highlighting issues such as the lack of scientific harvesting techniques and the presence of numerous intermediaries. It categorizes these causes into different levels, providing insights for improvement to enhance the competitiveness, efficiency, and profitability of food supply chains [22].

This study explores the challenges of predicting distorted demand in the supply chain, particularly due to the bullwhip effect, in which product demand information becomes distorted as it passes through the supply chain. They compared various machine learning and deep learning techniques, such as neural networks (NN), RNN, and SVM, with traditional forecasting approaches, including naïve forecasting, moving average, trend, and linear regression. Two datasets were used for their experiment, one of which was obtained from the simulation supply chain and the other from an actual Canadian Foundries order. The results suggested that the RNN and SVM demonstrated the best performance, but their forecasting accuracy did not significantly surpass that of the regression model [1].

This study focuses on the use of various machine learning approaches for predicting demand in the restaurant field business. This highlights the importance of accurate demand forecasting for optimizing resource management, reducing waste, and enhancing operational efficiency. This study explored several regression techniques for predicting food demand and optimizing storage. The results produced valuable insights into the application of machine learning techniques to address critical challenges in demand forecasting and sales optimization in the food industry, leading to the inference that techniques such as Random Forest and Gradient Boosting should be used to improve model accuracy [23].

This study addresses the critical challenge of accurate demand forecasting in the fresh-food retail sector. It introduces advanced machine learning and deep learning techniques, which include LSTM networks, Feedforward neural networks (FNN), extreme Gradient Boosting (XGBoost), Prophet, and Transformers, to predict daily retail orders. The study incorporates these models to identify temporal patterns, trends, and long-term dependencies in a sales dataset, aiming to optimize supply chains and reduce costs due to food wastage and stock runouts, thereby improving customer satisfaction. This research utilizes seven years of sales data and evaluates the performance of the above-mentioned models using the Normalized Mean Absolute Error (NMAE) metric approach. The results suggest that all models performed well, with XGBoost demonstrating a slight performance edge. While the previous paper suggests the use of the Gradient Boosting technique, this paper helps us finalize the exact technique to obtain better results [24].

Therefore, keeping in mind the problems, issues, and other factors related to perishable goods, the main objective of this project is to support farmers and wholesalers by proposing a model to forecast the demand for highly perishable food items that would help them with efficiency and cost reduction.

RESEARCH METHODOLOGY

Problem Statement

The goal of this research is to implement multiple regression models to reduce the margin of error, in essence, the mean absolute percentage error (MAPE) in demand forecasting of perishable food items to improve prediction accuracy and analyze and compare all the models to derive a conclusion as to which model is best suited for our application and data available. The perishable food category considered in this study is “highly perishable,” and two food items, ladyfinger and tomato, were used. We used secondary data for this research, being able to find data for both tomato and ladyfinger since 2018 from the official database of the Ministry of Agriculture and Farmers Welfare, Government of India [25]. The model tries to forecast the demand for ladyfinger and tomato in various markets with different population densities.

Developing Hypothesis

Based on our comprehensive research, we were able to build the following hypothesis for our research (Figure 1).

- *H1:* At least one independent variable has a significant impact on the MAPE value of the demand forecasting models.
- *H2:* The quantity of highly perishable food item arrivals varies significantly across months.
- *H3:* There is a significant difference in the MAPE values of the same models used for different product datasets.
- *H4:* The ranking of models according to the MAPE values of different models changes with changes in the product.

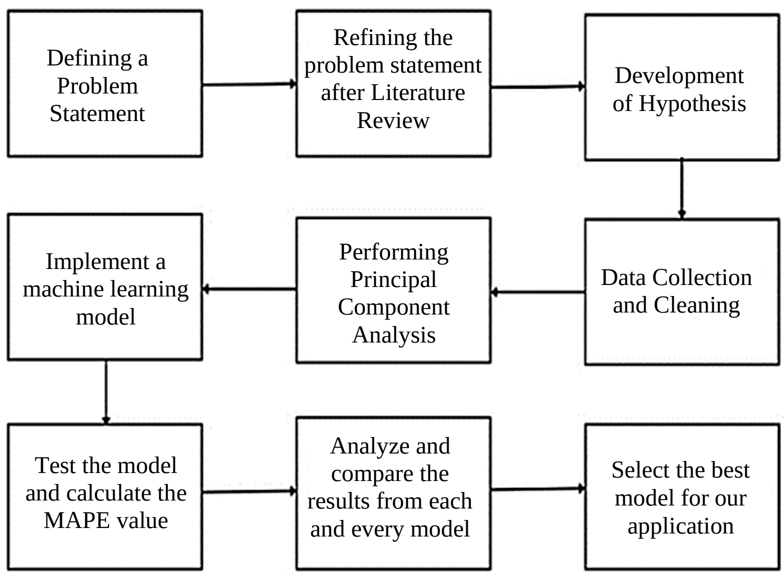


Figure 1. Research methodology.

Data

To obtain accurate data for the models to provide precise results, we banked on government resources for it. The data used in this research were obtained from an Indian government website for agriculture. The data used for this purpose were collected from 16 different markets of Maharashtra within a time frame of six years, in essence, from 2018 to 2023. The data collected was made consistent by performing a data cleaning process and treatment of outliers. Demand for any commodity in a geographical area might depend on many demographic factors, of which population is the most important; however, this factor was not included in our data. Thus, a new parameter, strata, was added by implementing a stratified sampling technique that considered population density as a constraint for deciding the strata for a given market. Eventually, the parameter market was replaced by the newly added parameter strata. Lastly, the data were split into 80–20% proportions for training and testing purposes, making the data ready to be fed into the model.

Principal Component Analysis

Principal component analysis is generally used to reduce the dimensionality of data while preserving important information. In this process, less relevant features are discarded to reduce dimensionality. Thus, it aids in the feature-selection process. Thus, we used PCA to select important features of the data. Hence, we were able to determine the most significant parameters from our data to be used in our machine learning models. By performing PCA, we found that all parameters in our data passed the 95% significance test.

Implementation of Models

As per the research methodology, we developed several machine learning models using the training data and tested them on our testing data to calculate the MAPE value to be used for comparative analysis.

ARIMA

Time series data forecasting requires a wide range of models known as ARIMA models. Generally, these models are identified using the ARIMA (p, d, q) notation, where p represents the autoregressive model order, d is the difference degree, and q denotes the moving average model order. These models attempt to forecast future values using past information after creating a non-stationary time series by differentiating them. The subsequent models will then project these future values through “auto” correlations and the moving averages over residual errors in the data.

SARIMA

SARIMA is also known as seasonal ARIMA or seasonal autoregressive integrated moving average (SARIMA). It is a variant of ARIMA that is specifically intended to deal with univariate time series data with a seasonal component. It has three additional parameters compared to the seasonal period hyperparameter for specifying autoregression, differencing, and moving averages in the seasonality adjustment of the model.

Multi-Linear Regression

The goal of this statistical technique is to determine the degree and nature of the relationship between a single dependent variable (Y) and several independent variables (X); this is known as regression. A regression line is drawn with such a slope that the sum of the distance of each point from the line is minimal. We performed multiple linear regressions on the given data by taking eight independent variables as inputs and one independent variable as the output.

Polynomial Regression

It is an extension of multi-linear regression, with the relationship between the independent variables (X) and dependent variable (Y) being of nth degree. This means that the regression line drawn to have a minimum distance from each data point should not be straight but can be a parabola or hyperplane corresponding to the degree of the relationship. Thus, the cubic equation yields the best degree of relationship when we apply the brute-force method to obtain the optimum degree for our given data.

Lasso Regression

This is a type of regularization technique that uses shrinkage. It attempts to shrink the data values towards the mean value. It adjusts the cost or loss function with a penalty and is also known as L2 regularization. A penalty was added, which was equivalent to the absolute value of the magnitude of the coefficients. L2 uses the sum of the squares of the coefficients to be multiplied by the penalty. Alpha (α) represents a penalty term that denotes the degree or amount of shrinkage (or constraint) that will be implemented in the equation, which is calculated using brute force.

Ridge Regression

Ridge regression is a technique for estimating multiple regression model coefficients in situations where the independent variables have a high degree of correlation. It uses a regularization technique to adjust the cost or loss function with a penalty. The regularization used here is ridge regularization, which is also known as the L1 regularization technique. L2 uses the absolute value of the coefficients to be multiplied by a penalty. Alpha (α) represents a penalty term that denotes the degree or amount of shrinkage (or constraint) that will be implemented in the equation, which is calculated using brute force.

Random Forest Regressor

A Bagging or Bootstrap Aggregating Ensemble Learning technique involves training multiple models on random subsets of training data. The predictions from the individual models were then combined, typically by averaging. The individual models used in Random Forest are decision trees. On this facet, it may seem that Random Forest is used for classification purposes only, but to bust out this myth, below is the working of the Random Forest regressor. The Forest comprises several randomly drawn decision trees. Tree prediction was performed in parallel. For regression, it takes the individual independent variable as a decision node which is then given to another decision node consisting of another independent variable criteria and outputs a decision i.e. dependent variable based on it. The prediction of individual trees was averaged, and the final output value was obtained. Using brute force, the number of trees was set to 100. We used 42, which is a standard number that is used everywhere as an unwritten norm.

XGBoost

XGBoost is an ensemble learning-boosting method. Boosting builds sequential models with maximum accuracy thereby converting weak learners into strong ones. It is possible to fit the models using any arbitrary differentiable loss function and gradient descent optimization procedure. The model's gradient is minimized upon fitting in a neural network, hence its name "gradient boosting." A powerful open-source implementation of this technique is XGBoost or eXtreme Gradient Boosting.

COMPARATIVE ANALYSIS

A comparison of the MAPE values produced by all the above models when tested on the testing data is shown below.

From Tables 1 and 2, we can infer that for our data and application, the Random Forest regressor produced the lowest MAPE value, followed by XGBoost and polynomial regression. However, the execution time for XGBoost was less than that for Random Forest. Thus, there can be a trade-off between time and error depending on whether the application is critical.

From Figure 2, we can derive an inference to reject the Null Hypothesis for H1, as the graphs in Figure 2 clearly show that there is greater demand in the later months, thereby confirming the seasonal influence on the demand for food products. PCA of the data helps us understand that all the variables are significant considering the Level of Significance to be 95%, hence, inferring rejecting the null hypothesis for H2. This research leads us to reject the Null Hypothesis for H3 because, with the product change, a significant change can be seen between the MAPE values in Tables 1 and 2.

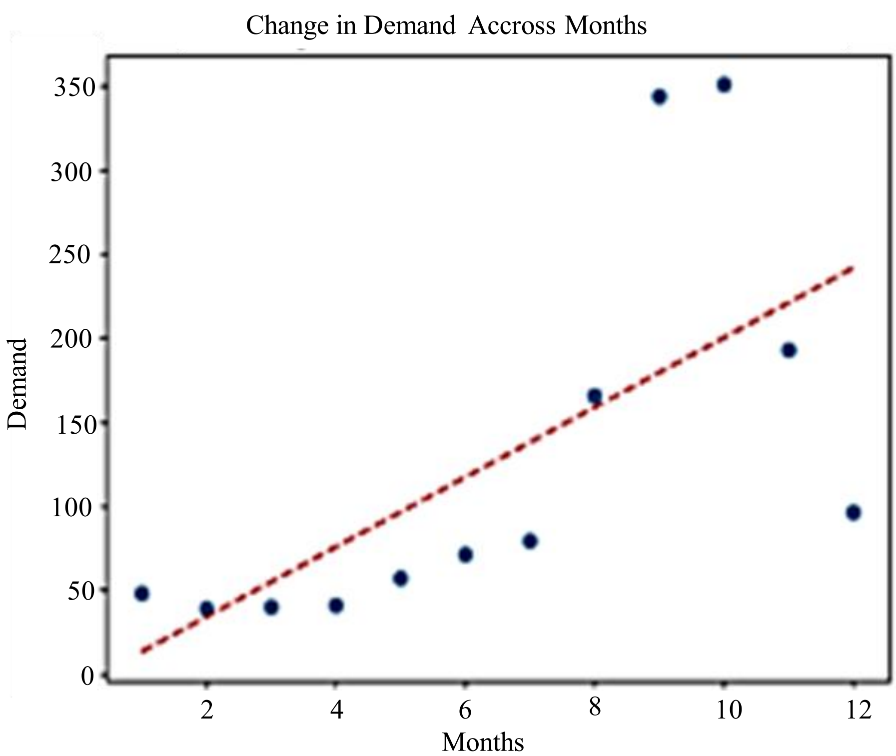
However, the ranking of the models in both tables (Tables 1 and 2) did not change, leading us to accept the null hypothesis for H4.

Table 1. Comparison of MAPE value of models for tomato data.

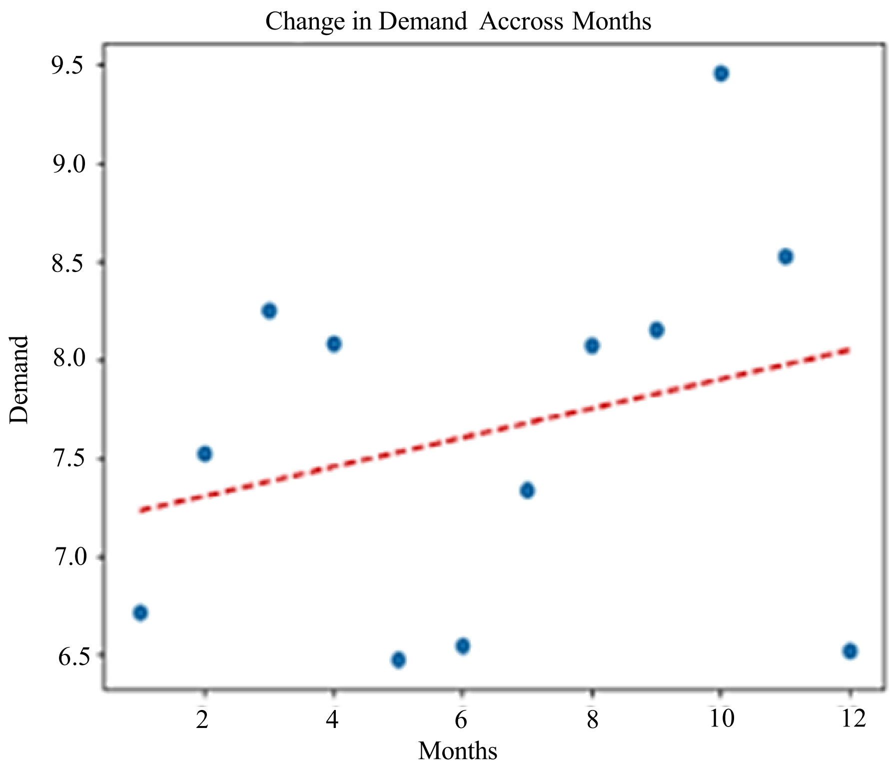
Models/Metrics	MAPE values
ARIMA	86.11
SARIMA	39.43
Linear regression	29.97
Ridge regression	29.97
Lasso regression	29.93
Polynomial regression	21.93
XGBoost regressor	8.40
Random Forest regressor	3.36

Table 2. Comparison of MAPE value of models for ladyfinger data.

Models/metrics	MAPE values
ARIMA	56.32
SARIMA	25.11
Linear regression	1.53
Ridge regression	1.53
Lasso regression	1.53
Polynomial regression	1.17
XGBoost regressor	0.81
Random Forest regressor	0.68



(a) Demand v/s Month for Tomato



(a) Demand v/s Month for Lady finger

Figure 2. (a) and (b) Graphs show the change in demand across months for tomatoes and ladyfinger.

CONCLUSION

In this study, through a comparative analysis of various machine learning models, we conclude that the seasonal impact on the demand for perishable food commodities is significant over the yearly cycle. However, the quality of vegetables is not a major contributor to demand. By considering the time-accuracy trade-off, we propose that using the Random Forest regressor or XGBoost model for demand prediction of perishable food commodities can help in developing effective supply chain strategies. This approach can also support data-driven decision-making to address the problem of food waste in India due to supply chain issues.

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