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Data-Driven Decision Making for Perishable Food Supply Chains: Insights from Demand Forecasting Models

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Machine Learning, Supply Chain, Food Waste, Regression, Perishable foods, Demand Forecasting

ABSTRACT
In recent years, food supply chain has gained considerable attention as compared to other supply chain systems. This can be attributed to the fact that fresh food products are perishable items which inherently has very short shelf life. Further, manual estimation of demand of these products often leads to demand underestimation and overestimation, which adversely affects revenues of the retailer. Therefore, effective demand forecasting can help to reduce food wastage as well as financial losses. The primary objective of this research is to investigate advanced machine learning models such as Random Forest Regressor, XGBoost, and Polynomial Regression, for improving demand forecasting accuracy. In this work, we have specifically considered highly perishable items such as ladyfinger and tomato. Performance of the proposed models are evaluated on six years of market data from Maharashtra, India, using the Mean Absolute Percentage Error (MAPE) metric. Findings indicate that the Random Forest Regressor achieves the highest accuracy, reducing forecasting errors and enabling better decision-making in inventory and resource management. The proposed approach provides valuable insights for stakeholders, including farmers, distributors, and retailers, to minimize waste, optimize inventory, and ensure sustainable supply chain practices.

1. INTRODUCTION

Recent studies have shown that perishable food supply chain is a challenging process. The underlying causes are short product shelf life, wastage of inventory, products getting out-of-stock and unstable market demand. Such challenges often increase the overall cost involved in the supply chain of perishable food items. Research indicates that approximately 30% to 40% of food products end up as waste in India due to supply chain mis-management (Negi & Anand). Globally, food waste amounts to nearly 1.3 billion tonnes annually, with an estimated value of USD 750 billion (Sahoo et al., 2023).

Poor food supply chain management remains a global issue due to multiple factors contributing to the problem. Approximately 30% of total food waste stems from poor infrastructure such as unfavorable storage conditions, and poor preservation methods. Additionally, 24% of food waste is caused by poor transportation systems including delays and lack of temperature control logistics (Negi & Anand, n.d.). Additionally, a huge portion of food waste arise from incorrect information shared by intermediaries in the supply chain and miscommunication regarding demand forecast. Such mismanagement leads to spoilage, over or under production of perishable food items and wastage of water resources (Mithun Ali et al., 2019) , which ultimately increases the overall cost.

Thus, to address this critical issue, machine learning algorithms can be employed to accurately forecast the demand of perishable goods (Feizabadi, 2022). Therefore, in this work, we propose a model which has the potential to provide significant benefits to several agricultural business sectors. In this research, our primary objective is to forecast the demand of two food items which are classified under “highly perishable category” due to shelf life of less than two weeks (Indore et al., 2016; Thole et al., 2021). Accurate prediction of demand for perishable items can support the farmers, store owners, intermediaries and suppliers to avoid over or under prediction of stocks. This will ultimately reduce around 18% wastage of food products caused by early or late harvest (Negi & Anand, n.d.).

Moreover, an accurate image of demand patterns provided by a correctly adjusted model allows for the efficient planning and coordination of production and distribution activities, hence aiding in the coordination of the entire supply chain (Carbonneau et al., 2008). Accurate demand projections also contribute to pricing stability in the perishable goods sector. Market volatility is one of the factors that lead to a significant amount of food wastage (Sahoo et al., 2023). It is possible to prevent abrupt fluctuations in prices that could upset the market's equilibrium by being able to adjust 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 peace of mind by enabling them to budget (Kasar et al., 2025). Additionally, with timely delivery of the proper quantity of fresh produce reduction in transportation costs, supply chain efficiency, proper storage handling, and a reduction in the need for emergency supplies can be achieved with ease that can contribute hugely towards food wastage reduction (Negi & Anand, n.d.). Major contribution of this research are as follows:

(i) This work propose predictive machine learning models which can minimize the financial losses in perishable food supply chain.

(ii) Vegetable under highly perishable category contribute to significant financial losses, thus, in this work, the proposed models target two highly perishable items i.e., ladyfinger and tomato.

(iii) To evaluate performance of the proposed model, mean absolute error (MAE) is employed as evaluation metric, in order to validate its predictive efficacy.

Remainder of the paper is structured as follows, Section II illustrates the existing literature in this domain, Section III presents the proposed research methodology, Section IV demonstrates the obtained results and discussions.

2. LITERATURE REVIEW

The supply chain of perishable goods in India suffers huge amounts of wastage every 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. This absence of having an integrated approach, accompanied by ineffective management of the supply chain, causes a huge loss of more than ₹440 billion per year (Kasar et al., 2025).

The paper proposes an interactive digital platform, facilitating collaboration between demand and supply for perishable food supply chains, focusing on integrating heterogeneous big data with AI-based forecasting methods to prevent food waste. It highlights the challenges in utilizing advanced forecasting methods, such as AI, due to factors like the differentiation between data-driven reliance and human judgment, as well as the integration of heterogeneous external data. This paper 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 of perishable foods, leading to the inference that for prevention of wastage, using AI-driven demand forecasting is a must (Birkmaier et al., 2023).

In order to minimize food waste, the study compares different machine learning-based forecasting models for food demand in food catering services (FCSs). It includes a literature review on food waste (FW) and the types of approaches used in previous studies like qualitative & quantitative. The models take into account variables including the quantity of meals served, the menu, date-related features, weather-related features, and the anticipated number of students attending lessons. They are based on casual and time series algorithms. The results suggest that random forest algorithm & long short-term memory (LSTM) recurrent neural network produced the most accurate predictions, an inference that is worked upon and modified as further literature review was done, based on the new knowledge acquired (Rodrigues et al., 2024).

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 2013-2018 shows that soft computing techniques and time series constitute the most effective forecasting models of perishable food demand in small medium enterprises (*Models for Predicting Perishable Products Demands in Food Trading Companies*, n.d.).

A paper investigates the obstacles confronting Small Medium Enterprise (SME) wholesalers in precisely predicting demand for fresh produce. It examines such factors as weather and holidays that contribute to high demand variability, and internal and external factors responsible for such variation. The research employs historical sales data from a UK-based SME wholesaler concentrating on product "Milk". From previous days of searching information about this issue, it was found out that weather summary, cloud cover & temperature are the most significant forecasters of demand with monthly increasing correlations becoming more constant by time through correlation analysis and PCA analysis. This paper provides us with a rough idea on the variables for which data needs to be collected and how we should find important variables through PCA (*Investigating-the-Demand-for-Short-Shelf-Life-Food-Products-for-SME-Wholesalers*, n.d.).

One paper focuses on predicting the demand for perishable products using ARIMA and LSTM methods, it is known that the quality of these products decreases with age, which in turn affects consumer satisfaction. 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 smaller RMSE value in both datasets but showed overfitting, hence cannot be used for regular predictions. From the results obtained above, we can say that the ARIMA method performs better than LSTM (Azzam et al., 2023).

Food wastage is a major problem, with 20-60% lost in the supply chain. This paper focuses on optimizing warehouse management by using machine learning to predict the orders for perishable products 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 profit (Kumar et al., 2021).

The paper proposed a novel algorithm to predict the demand for perishable farm products, using the support vector machine (SVM) method. It generalizes well with an improved performance, and the assurance of global minimum, and is expected to excel in forecasting perishable farm product demand. To enhance forecasting precision, fuzzy theory is employed to quantify factors influencing sales forecasts, addressing real-world scenarios. Numerical experiments suggest that the fuzzy theory approach outperforms the radial basis function neural network, which works on the criteria of relative mean error, day absolute error & FP (Du et al., 2013).

The paper 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) day-wise and the forecasted values showed that the model was pretty good but produced some errors due to long-term prediction (*Inderscience Publishers - Linking Academia, Business and Industry through Research*, n.d.).

In order to improve availability and reduce losses, one paper suggests a Decision Support System (DSS) that forecasts perishable items' demand using cluster analysis and multivariate ARIMA models with point-of-sale data.The DSS employs article clusters showing similar intra-day sales patterns, which helps in making precise top-down forecasts and reduces computational costs.(Huber et al., 2017).

The paper proposes an ARIMA Model, which was able to predict the demand for vegetables (onion), but the model was only capable of predicting short-term data (month-wise/day-wise) rather than any long-term data (year-wise). It wasn't exactly perfect but was close enough to the actual data. The research paper further said that the model could be used by any government organizations like NRCOG and APMC to forecast the demand for vegetables (onion) (Sankaran, 2014).

The results of the paper reveal 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 get confused and not understand the trend of the demand properly. This is because Arima requires short-term data to understand the trends, and is only viable for short-term prediction (Shukla et al., n.d.).

A thorough evaluation of the literature on different machine learning models for forecasting wheat supply and demand was done in this research. It discusses the variables influencing wheat yield, the growing demand for wheat, and the connection between wheat production and the provision of human sustenance. It displays the results of several forecasting experiments that forecasted wheat supply, demand, and pricing using machine learning algorithms. It discusses the evaluation measures used in these studies, such as R2, RSME, MAPE, MSE, and accuracy metrics, to assess the predictive performance of the models. The important inference coming out of this paper was that Demand forecasting with the help of machine learning models made more accurate forecasts rather than using the simple traditional forecasting techniques (like moving average, etc) and also other neural networks (like ANN, RNN, etc.) (Almbaidin & Etaiwi, 2023).

The paper compared the performance of different forecasting models, which included ARIMA, based on the Box-Jenkins method as well as a few machine learning algorithms such as LSTM networks, 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 like LSTM and SVR outperformed other models, thus implying their possible utilization in enhancing the demand prediction of perishable vegetables in India (Priyadarshi et al., 2019).

The paper addresses various issues in estimating the demands of essential perishable items and focuses on predictive analysis of an end-to-end inventory management system. The proposed model, which is a comparison of two-step models, using linear programming and reinforcement learning predicts the order estimate of perishable products in the supply chain and identifies relevant features for estimating replenishment policies (Sakhare & Kulkarni, 2022).

The critical problem of high food waste in the perishable produce supply chain, especially in emerging countries where these causative elements are still not fully understood, is addressed in this research using a unique technique that integrates fuzzy MICMAC and total interpretative structural modelling (TISM). The study identified 14-16 variables that represented the super-set of causal factors, highlighting issues such as the lack of scientific harvesting techniques along with the presence of numerous intermediaries. It categorizes these causes into different levels, providing insights for improvement to enhance the efficiency, competitiveness, and profitability of food supply chains (Balaji & Arshinder, 2016).

The bullwhip effect, in which product demand data becomes skewed as it moves through the supply chain, is one of the main reasons why it is difficult to predict distorted demand in the supply chain. They contrasted several machine learning and deep learning methods, like support vector machines (SVM), recurrent neural networks (RNN), and neural networks (NN), with more conventional forecasting methods, such as linear regression, trend, moving average, and naïve forecasting. They employed two datasets for their experiment: one from a real Canadian Foundries order, and the other from the simulated supply chain. The results suggested that RNN and SVM demonstrate the best performance, but their forecasting accuracy does not significantly surpass that of the regression model (Carbonneau et al., 2008).

The use of different machine learning techniques for restaurant demand forecasting is covered in the article. It highlights how crucial precise demand estimation is to improving operating efficiency, cutting waste, and managing resources optimally. In order to forecast food consumption and optimise storage, the study investigates a variety of regression algorithms, including Random Forest and Gradient Boosting. The paper offers insightful information about how machine learning methods can be applied to solve important problems in the food industry's demand forecasting and sales optimisation, which leads to the conclusion that methods like Random Forest and Gradient Boosting should be applied to increase model accuracy (Pandey et al., 2023).

In a paper, the crucial problem of precise demand forecasting in the retail fresh food industry is discussed. It presents cutting-edge deep learning and machine learning methods, such as Prophet, Transformers, eXtreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM) networks, and Feedforward Neural Networks (FNN), to forecast daily retail orders. In order to optimise supply chains and lower expenses associated with food waste and stock-outs, the study uses these models to find long-term dependencies and temporal patterns/trends in sales data. This improves customer satisfaction. The research utilizes seven years of sales data and evaluates the performance of above-mentioned models using the NMAE metric approach. Results suggest that all models perform well, with XGBoost demonstrating a slight edge in performance. While previous paper suggests the use of Gradient Boosting technique, this paper helps us finalize the exact technique to be used to get better results (Bozdogan & Alptekin, 2023).

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

3. RESEARCH METHODOLOGY

Problem Statement

The goal of this research is to implement multiple regressive models to reduce the margin of error in essence 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 suitable for our application and data available. The perishable food category considered in this study is “Highly Perishable”, and two food items: Ladyfinger and Tomato are thus used. We made use of secondary data for this research, being able to find data of both Tomato and Ladyfinger since 2018 from the official database of Ministry of Agriculture and Farmers Welfare, Government of India (Ministry of Agriculture and Farmers Welfare, n.d.). 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 work.

H1: There is a significant impact of at least one independent variable on the MAPE value of 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 data.

H4: The ranking of models to the MAPE values of different models changes with the change in the product.

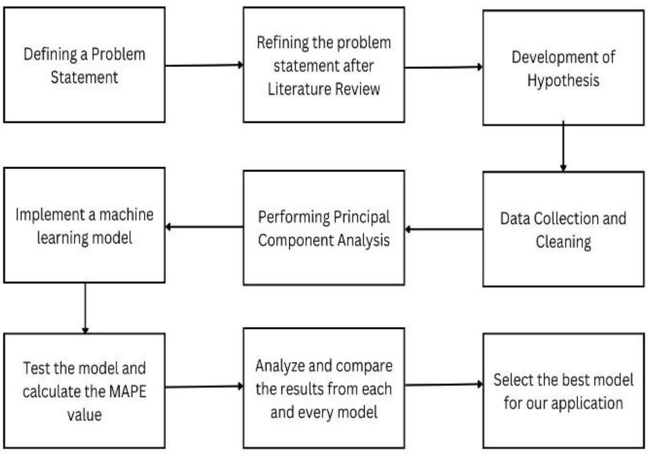


Fig 1: Research Methodolgy

Data

To have accurate data for the models to provide precise results, we banked on the government resources for it. The data used for this research was hence, taken from an Indian government website for agriculture. The data used for this purpose was collected from 16 different markets of Maharashtra within the time frame of 6 years, in essence, from the year 2018 to 2023. The data collected was made consistent by performing the data cleaning process and treatment of outliers. Demand for any commodity in a geographical area might depend on many demographical factors, out of which population is the most important, however, this factor was not included in our data. Thus, a new parameter named strata was added by implementing a stratified sampling technique that took population density as a constraint for deciding the strata for a given market. Eventually, the parameter market was replaced by this newly added parameter strata. Lastly, the data was split in 80% - 20% proportion for training and testing purposes respectively, making the data ready to be fed into the model.

Principal Component Analysis

A common method for lowering the dimensionality of data while maintaining crucial information is Principal Component Analysis (PCA). In this process, less relevant features are discarded to reduce the dimensionality. Thus, it helps in the feature selection process. Thus, we used Principal Component Analysis to select the important features of the data. Hence, we were able to find out the most significant parameters from our data to be used by our machine learning models. By performing PCA, we found out that all the parameters in our data passed the 95% significance test.

Implementation of Models

In accordance with the research methodology, we used the training data to create a number of machine learning models, which we then evaluated on our testing data to determine the MAPE value that would be utilised for comparative analysis.

Arima

Time series data forecasting, requires a wide range of models that are known as ARIMA models. The ARIMA (p,d,q) notation is typically used to identify these models, where p stands for the autoregressive model order, d for the difference degree, and q for the moving average model order. In this case, these models try to forecast future values using past information after creating a non-stationary time series by differentiating it. These future values will then be projected by the following models using "auto" correlations and moving averages over the data's residual errors.

Sarima

Seasonal Autoregressive Integrated Moving Average (SARIMA) is another name for seasonal ARIMA. It is a type of ARIMA designed especially to handle univariate time series data with a seasonal component. It has three additional parameters as compared to the seasonal period hyperparameter for specifying autoregression, differencing and moving average in the seasonality adjustment of the model.

Multi-Linear Regression

Finding the strength and type of the link between a single dependent variable (Y) and multiple independent variables (X) is the aim of this statistical method, which is called regression. The slope of a regression line is chosen so that the total distance between all of the points and the line is as small as possible. Using eight independent variables as inputs and one independent variable as the outcome, we conducted Multiple Linear Regression on the provided data.

Polynomial Regression

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

Lasso Regression

It is a type of regularization technique that uses shrinkage. It tries 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 is added which is equivalent to the **absolute value of the magnitude** of the coefficients. L2 uses the sum of squares of coefficients to be multiplied by the penalty. Alpha (α) represents a penalty term that denotes the degree/amount of shrinkage (or constraint) that will be implemented in the equation, which has been calculated by brute force here.

Ridge Regression

In multiple-regression models with highly correlated independent variables, ridge regression is a technique for estimating the coefficients. The cost or loss function is adjusted with a penalty using a regularization technique. The regularization used here is Ridge regularization also known as the L1 regularization technique. L2 uses the absolute value of coefficients to be multiplied by the penalty. Alpha (α) represents a penalty term that denotes the degree/amount of shrinkage (or constraint) that will be implemented in the equation, which has been calculated by brute force here.

Random Forest Regressor

One Bootstrap or Bagging Aggregating Ensemble learning method is Random Forest. Several models are trained using random selections of the training data in the bagging approach. The individual models' projections are then aggregated, typically through averaging.

The individual models used in Random Forest are Decision trees. On the facet, it may seem that Random Forest is used for classification purposes only, but to bust out this myth, below is the working of Random Forest Regressor. The Forest comprises several randomly drawn decision trees. The prediction for trees is done 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 is averaged and a final output value is obtained. Using brute force, the parameter of the number of trees was set to 100. We have used 42 which is a standard number 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 learners. 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 called 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

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

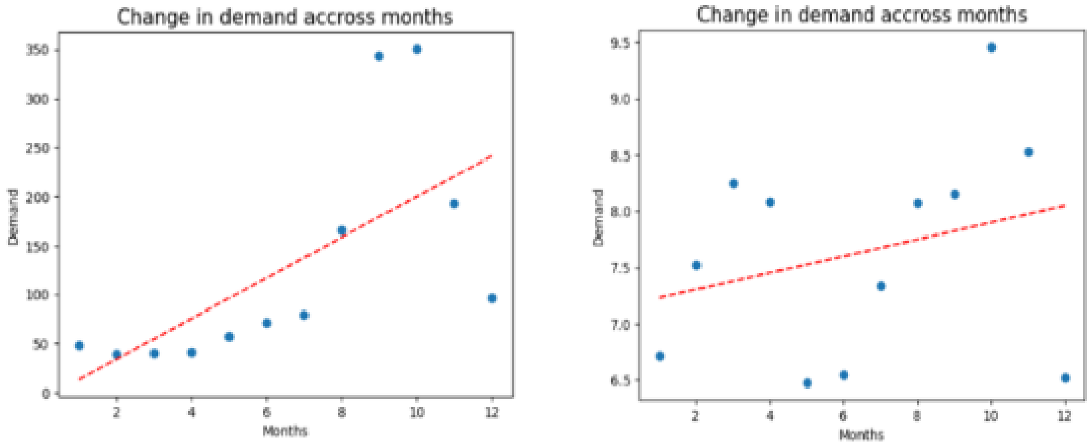
Models/Metrics	**MAPE values**
ARIMA	86.11
SARIMA	39.43
Linear Regression	29.97
Ridge Regression	29.97
Lasso Regression	29.93
Polynomial Regression	21.93
XGBoost Regressor	8.40
Random Forest Regressor	3.36

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

4. RESULTS

From Table 1 and Table 2, we can infer that for our data and application, the Random Forest Regressor produced the least MAPE value followed by XGBoost followed by Polynomial Regression. However, the execution time for XGBoost was lesser than that of Random Forest. Thus, there can be a time and error trade-off depending on whether the application is critical or not.



(a) Demand v/s Month for Tomato **(b) Demand v/s Month for Ladyfinger**

Fig 2: Graphs showing the change in demand across months for Tomato and Ladyfinger

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

However, the ranking of the models in both the tables, Table 1 and Table 2, does not change leading us to accept the Null Hypothesis for H4.

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