Forecasting and Modelling of Food Demand Supply Chain using Machine Learning

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Abstract

This paper presents a comprehensive software solution for addressing the challenges associated with predicting and managing the demand and supply of food in a dynamic environment. The system leverages machine learning algorithms, including XGBoost, LightGBM, and SARIMA, to provide accu- rate demand forecasting and optimize inventory and distribution by modelling supply chains. The user-friendly interface allows administrators to interpret machine learning model outputs and make informed decisions, while the historical data module provides essential access to past trends and patterns for training and validating machine learning models. The paper discusses the system's key features, such as demand forecasting, inventory management, data analytics dashboard, and fulfillment center allocation, and outlines the nonfunctional requirements, including performance, safety, security, and software quality attributes. The proposed solution aims to provide valuable insights for stakeholders in the food industry, ultimately contributing to more efficient and informed decision- making in the management of food demand and supply chains.

Keywords: Time Series Forecasting, Machine Learning, Demand Forecasting, Supply Chain Management, Food Industry, Inventory Management

I. INTRODUCTION

Food demand prediction has become critical issue for both businesses and continuos development. Business aspects are mainly related to improving the manufacturing, supply chain processes, inventory cost reduction, and customer satisfac- tion. Continuous development issues are mainly related to food loss and waste, and they have been drawing much attention in recent years. Due to the consumer's varying and increasing needs and competitiveness among the companies, most of the companies in today's market are shifting their focus to demand forecasting for the demand-supply chain management. Demand forecasting is beyond the scope of any decision planning, as they directly impact a company's profitability. Inaccurate prediction of demand can either cause too large inventory, which can results in a high risk of wastage and high costs to pay or too little inventory, leading to out-of stocks which will make company to look after services from its competitors when they failed to meet customers needs. For these reasons, the use of demand forecasting methods is one of the most fundamental components of the strategic planning. Traditional data science forecasting models, such as multiple regression, gradient boosting are applied in food demand prediction.

The prevention of food waste is one of the most important worldwide issues, especially in the continuous development. The amount of food wasted is not geographically specific lo- cation but it correlates with the country's development. Wasted food is defined as food that is unconsumed or discarded by the retailer because of its colour or appearance. Some products delivered to the store are never sold because of the expiration date on the label or damage. Demand forecasting importance becomes noticeable as its outcome is used by many subdivi- sions in the company that is Purchasing department may come up with their plan of short investment and the operation de- partment can manage their plan of purchasing the required raw materials, machinery, and labor in advance. Therefore, the forecasts are beneficial and their high accuracy has the potential to improve demand-supply chain management, and reduce wastage.

A. MOTIVATION

For meal delivery companies, a big challenge is managing how much food to make without wasting ingredients that can spoil quickly. This makes it super important to predict how much food people will order accurately [1]. Predicting demand means turning a problem about time into one about figuring things out. Right now, there are lots of different ways to predict demand, using both simple and more complicated methods. In the past, people mostly used simple methods like Linear Regression or Random Forests for short-term predictions. But now, there are newer methods like Extreme Gradient Boost- ing Regressor[Light Gradient Boosting Machine Regressor (LightGBM) [3] and Gradient Boosting Regressor (XGBoost) that work better, especially when we have lots of different kinds of information to consider.

B. PROBLEM DEFINITION

The client is a meal delivery service operating in multiple cities, each with several delivery centers. To minimize food waste, they need a reliable model to predict future order vol- umes so they can stock the right amount of ingredients. Since most ingredients need weekly replenishment and can spoil quickly, planning procurement is crucial. Accurate demand forecasts also help in staffing the centers efficiently. To forecast demand for the next 10 weeks, they'll use:

1) Past sales data for a specific meal at each center.
2) Meal details like category, subcategory, current price, and discounts.
3) Information about delivery centers, including region and city codes.

C. NOVELTY OF THE WORK

The originality of this study lies in the exploration of lag features and Exponentially Weighted Moving Average (EWMA) for enhancing prediction accuracy. Extensive ex- perimentation was conducted to identify the most effective parameters for each model. This paper aims to evaluate the ability of three distinct models : Gradient Boost, LightGBM, and XGBoost through comparative analysis.

D. CONTRIBUTIONS

This article aims to utilize machine learning regressors to forecast the number of meals for the subsequent 10 weeks. The significant contributions of this study are as follows:

1) Application of boosting algorithms such as XGBoost, LightGBM, and Gradient Boost, chosen for their ver- satility in handling both categorical and numerical fea- tures.
2) Integration of lag and Exponentially Weighted Moving Average (EWMA) features, selected for their robustness in analyzing historical data and facilitating accurate forecasting.
3) Evaluation of prediction performance metrics, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which yielded values of 172.37 and 158.48 for one model, and 91.41 and 86.41 for another model, respectively.

II. LITERATURE REVIEW

Forecasting demand of any commodity is one of the most important aspects to prevent wastage in any form.Recent stud- ies demonstrated the practical application of LSTM and SVM models to analyze various factors. By enhancing predictive capabilities for sales and minimizing food wastage machine learning approaches to address supply chain issues effectively [1].The significance of accurate demand forecasting in the e- commerce industry and the increasing application of machine learning approaches, such as NAR and LSTM models.The solution which aims to solve the challenge of using statistical machine learning models like VAR to predict the production of crops and livestock [2].A novel algorithmic approach to address the challenges which is related with stochasticity and uncertainty in food delivery operations in online food deliv- ery, operations management [3].A hybrid approach combines ARIMA and NARNET models to forecast coconut prices, leveraging their strengths to capture complex patterns and im- prove forecasting accuracy. Performance of the hybrid model against individual models are evaluated [4]. The growing trend of utilizing machine learning methods that is CNN and LSTM, for predicting crop yields highlights the possible of these tech- niques in agricultural yield forecasting [5].The study compares ARIMA, ANNs, and SVR models for electricity demand and price forecasting, proposing a hybrid model to the enhance accuracy by improving prediction in energy sector.Predicting the prices of four key Nigerian food items using the ARIMA model, emphasizes the importance of accurate price forecast- ing to make less overproduction and underproduction losses [6].The ARIMA model combined with R-programming for food price forecasting, addresses the challenges of food price management in Nigeria [7].The use of hybrid CNN-GRU based probabilistic model for developing a highly accurate demand forecasting model for the retail industry [8].Machine learning based model is used to predict food sales accurately by leveraging the Random Forest Regression algorithm which predicts the sales for perishable goods [9].Temperature data using machine learning techniques emphasizes potential supe- riority of supervised machine learning models over traditional statistical approaches offers insights powerful alternative to traditional statistical methods [10].The contribution to the field of food industry by providing a robust and reliable tool for demand forecasting, by benefiting companies' intelligent man- agement systems for rational control of inventories and food production by reducing food waste [11].A secure monitoring system using IoT, RFID, and WSN to enhance the security of perishable food supply chain processes during transportation for food safety [12]. The challenges such as overfitting and vanishing gradients, proposes solution to enhance performance potential of RNNs in capturing complex patterns [13].To make less losses and improve the efficiency of online order fulfillment by the use of penalty functions to assess model risks and potential benefits [14].The blockchain contributes to the field of supply chain management by providing a framework for forecasting demand, efficient resource allocation [15].The importance of food material management to reduce losses related with overproduction and underproduction [16].ARIMA model to forecast consumption for various food materials, demonstrating its effectiveness in enhancing decision-making and reducing financial losses. ARIMA, Holt-Winters, and neural networks for forecasting the prices of 11 are evaluatded efficiently [17].Accurate demand forecasting for fresh foods, particularly bread, in Indonesia, proving the influence the store of classification and seasonal factors on sales forecasting [18]. Using the ARIMA method to predict daily sales, to help franchise businesses in reducing waste and optimizing inventory management for perishable goods by [19].Utilized novel method for predicting relief food demand after natural disasters using SVM and factor selection techniques [20].

III. DATA ANALYSIS AND PREPROCESSING

In this section, we present our proposed methodologies, beginning with an overview of the existing and derived fea- tures, followed by an outline of the preprocessing techniques employed.

A. Dataset Description

The ”Food Demand Forecasting” dataset, provided by Gen- pact, an American professional services firm, contains weekly order data spanning 145 weeks for 50 different meals. This dataset is organized into three separate files, comprising a total of approximately 450,000 entries and 15 distinct features. These features are described below:

1) Weekly Demand Data: This file contains historical records of sales numbers for specific meals at various centers. The details included are:

a) id: A unique identifier for each order.
b) week: The week number, ranging from 1 to 145.
c) meal id: A unique identifier for each meal.
d) center id: A unique identifier for each fulfillment center.
e) checkout price: The final price of the meal after applying discounts, taxes, and delivery charges.
f) base price: The original price of the meal as listed on the menu.
g) emailer for promotion: Indicates whether an email was sent to promote the meal (0 for no, 1 for yes).
h) homepage featured: Indicates whether the meal was featured on the website’s homepage (0 for no, 1 for yes).
i) num orders: The number of orders received.

2) fulfilment center info.csv: This file provides informa- tion about each fulfillment center, including:

a) center id: The identifier for each fulfillment center.
b) op area: The service area of each center (in square kilometers).
c) city code: The postal code associated with each city.
d) center type: The type of fulfillment center (type A, type B, type C).
e) region code: A unique code for each region.

3) meal info.csv: This file contains details about each meal, including:

a) meal id: The identifier for each meal.
b) category: The type of meal (e.g., beverages, snacks, soups).
c) cuisine: The cuisine type (e.g., Indian, Italian).

B. Dataset Analysis

Fig. 1. Order per region

The Fig 1 represents the total number of orders for each region code.Each bar shows corresponding to a specific region code and its height representing the number of orders in that particular region. The region code 56 shows that it has the highest number of orders, reaching approximately 60,000,000 orders.Where the region 34 it has the second-highest number of orders, which is reaching approximately 20,000,000 orders and region code with 77 has notable number of orders, which is slightly above 10,000,000 orders while remaining relatively fewer orders much less than major region.

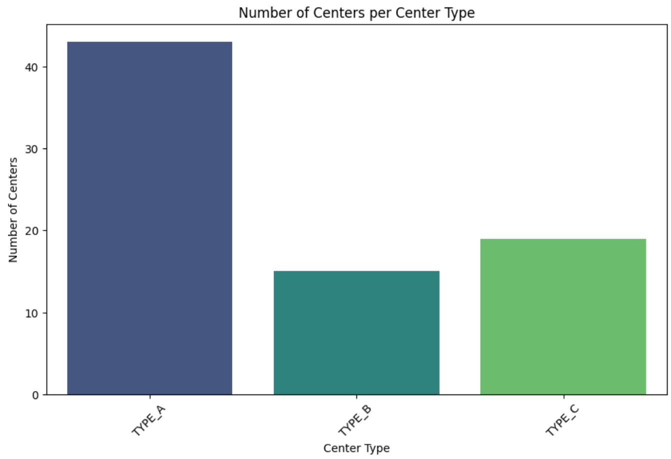

Fig. 2. number of center per center type

The Fig 2 represents the number of centers for each center type. Each bar indicating to a specific center type and its height represents the number of centers of that type. The Center Type TYPE A has the highest number of centers, which is reaching above 40 centers, TYPE B Center Type has less centers compared to TYPE A center reaching above 10 centers, while center TYPE C has the moderate number of centers reaching approximately 20 centers.

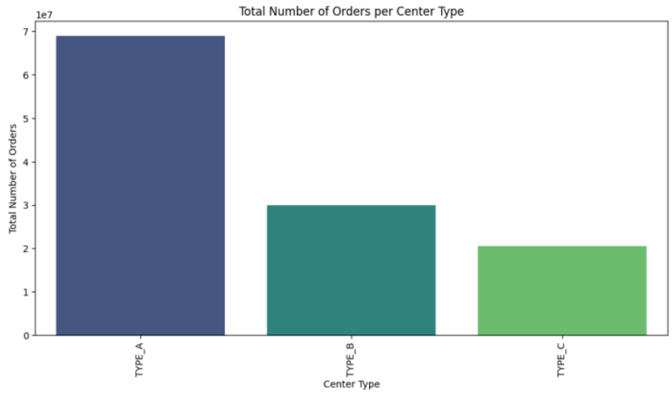

Fig. 3. order per center type

The Fig 3 represents the total number of orders for each center type having center type TYPE A , TYPE B, TYPE C where TYPE A centers handles the most of the orders, which is followed by TYPE B and then TYPE C centers.

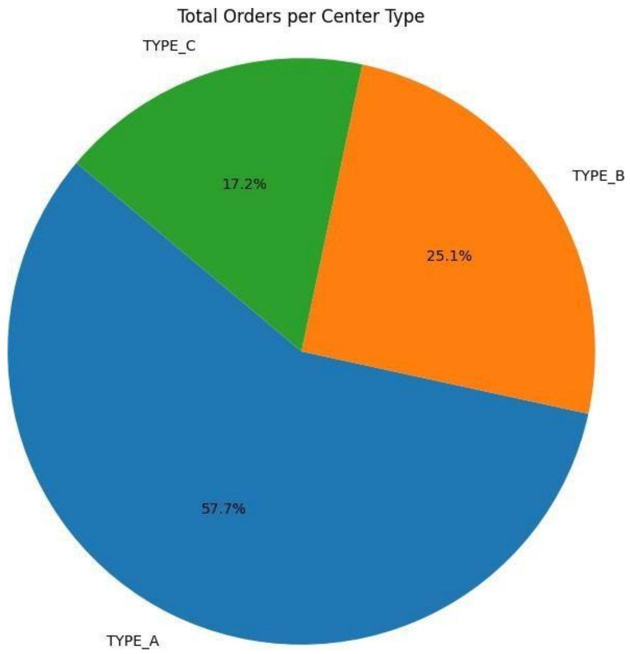

Fig. 4. order per center pichart

The Fig 4 representing the distribution of total orders amongs the three different center types that is center type TYPE A , TYPE B, TYPE C where the majority of orders are handled by TYPE A centers that is more than half of the total orders (57.7%) , TYPE B centers contributing moderately which is handling over a quarter of the total orders (25.1%) and TYPE C centers handling the smallest portion of the total orders 17.2%.

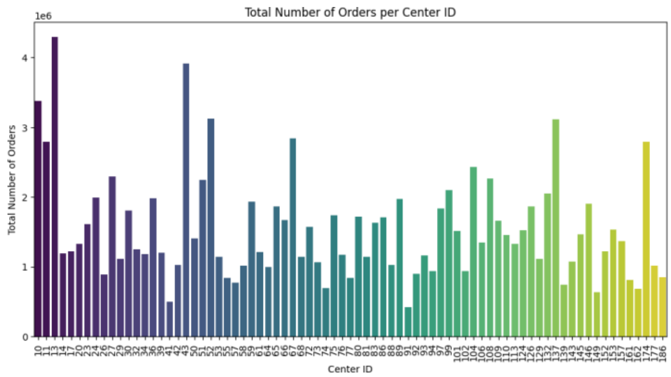

Fig. 5. order per center id

The Fig 5 representing the differences in number of orders across different centers highlighting the specific centers that handles large order of volumes, where the center ID 13 which has the highest number of orders which is exceeding 4,000,000 other high order centers are in range between 2,000,000 orders each to less than 4,000,000. There are several centers with orders which are ranging between 1,000,000 to 2,000,000, other Center IDs shows fewer volume of orders less than 1,000,000 order

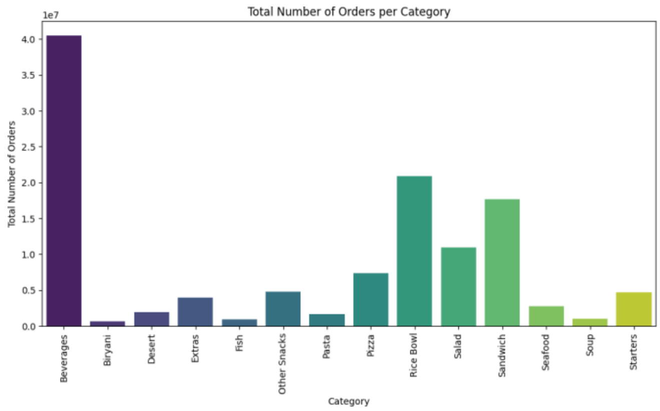

Fig. 6. order per category

The Fig 6 highlights the huge popularity of beverages compared to all other categories.It indicates that Rice Bowl, Sandwich, and Salad are also relatively popular but it is significantly less than the Beverages.The beverage has the highest number of orders which is close to 40,000,000. Rice bowl ranges with orders between 5,000,000 to 10,000,000 where the Sandwich and Salad follows them behind. The categories like Pizza, Other Snacks, and Pasta have average order of volumes which is ranging between 1,000,000 to 5,000,000 orders and the others has the lowest order of volume below 1,000,000 orders.

The Fig 7 highlights the popularity of Italian cuisine comparing with the other cuisines indicating that Thai cui- sine is also popular but significantly less than Italian close to 4,000,000, Indian cuisine has average volume of orders 3,000,000 while the Continental has the lowest 2,000,000 orders

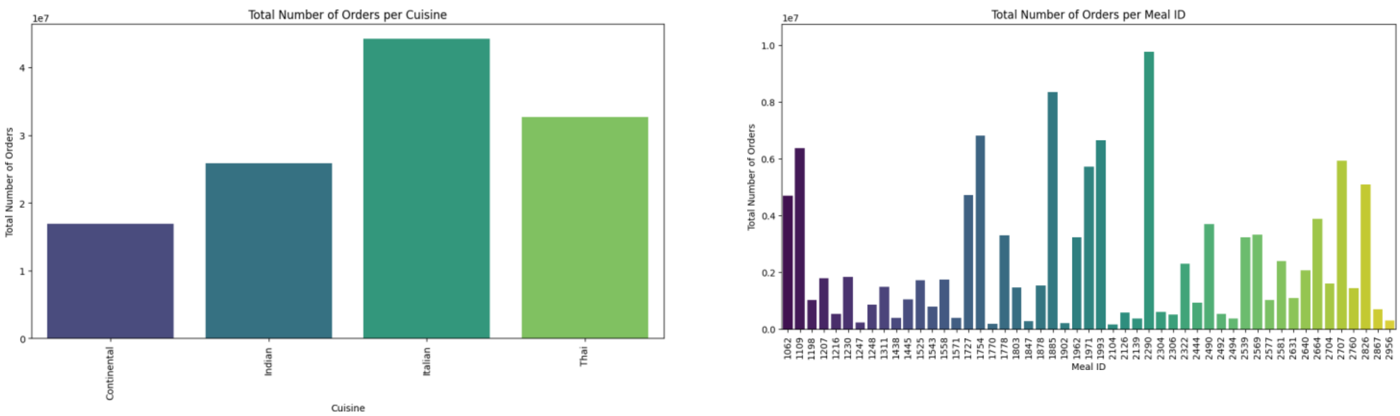

Fig. 7. order per cuisine

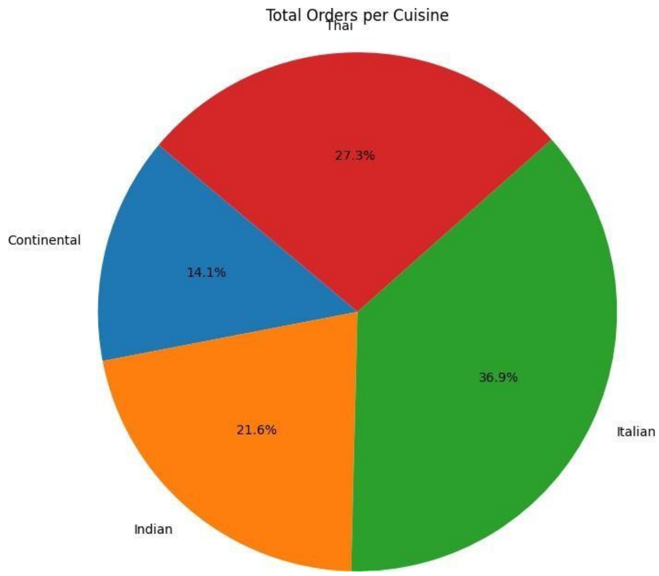

Fig. 8. order per cuisine pichart

The Fig 8 shows the distribution of orders amongs the different types of cuisine, with each portion of the pie chart which is representing a different cuisine category. Italian cuisine occupies the largest volume of orders 36.9% , Thai has 27.3% of the total orders, Indian has the 21.6% of the total orders and Continental representing 14.1% of the total orders.

The Fig 9 shows the distribution of orders across different meal IDs, highlighting that which meals are ordered the most and the least. The meal ID 2290 is having the highest number of orders , Meal IDs such as 1778, 2104, and 2707 moderate numbers of orders showing less than 2290 meal ID and others are having lower numbers.

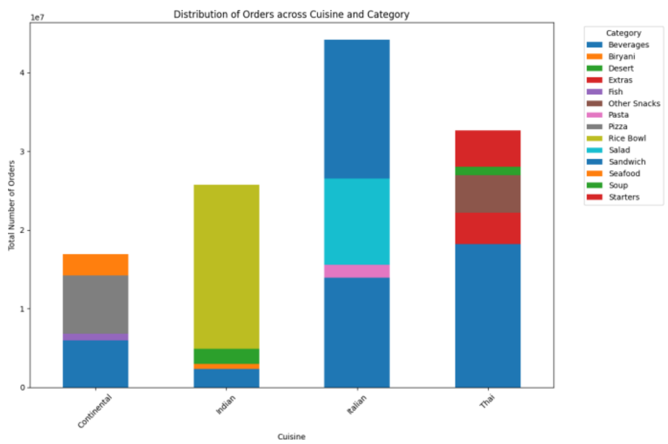

Fig. 10. Distribution of Orders across Cuisine and Category

The Fig 10 shows the distribution of orders across different cuisines and categories, highlighting the most popular cate- gories within each cuisine. By displaying the total number of orders for each cuisine further it is broken down by category. Continental Cuisine total orders were 20 million where sandwiches and beverages are the major category .In Inidan Cuisine total orders were 30 million where the rice bowl is the most popular.In Italian Cuisine total orders were 40 million where salad and beverages are the major category and Thai Cuisine orders are above 30 million, starters is having notable presence in Thai

The Fig 11 is the matrix scatter plot which visualizes the relationships between multiple numerical variables.The num orders variable is highly skewed showing that the most of the centers having low number of orders while with few centers having significantly higher numbers. There are notice- able clusters and patterns in the scatter plots, particularly in the base price vs. center id plot, where distinct vertical bands indicates that the certain centers are having consistent base prices and There are no clear linear relationships between the variables in the scatter plots.

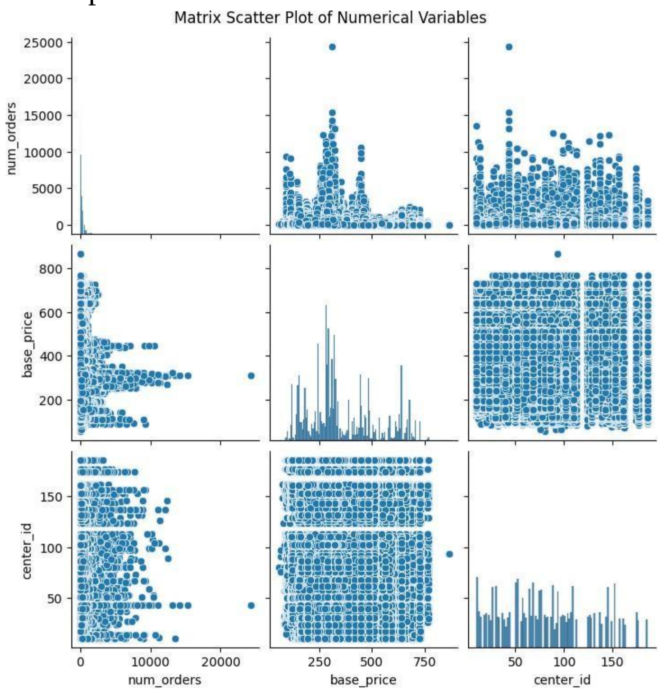

Fig. 11. Matrix Scatter Plot of Numerical Variables

C. Data preprocessing techniques

1) Numerical Features : The dataset contains numerical features with varying scales, and many of these features exhibit a pronounced right-skew. To reduce skewness, quantile or power transformations can be applied, which adjust the distribution to be more normal. However, since the data already follows a normal distribution, standardizing the data is more appropriate for scaling purposes than normalization.
2) Categorical Features : There are two methods for con- verting categorical features into numerical ones: Label Encoding and One-Hot Encoding. Label Encoding as- signs a unique integer to each category based on al- phabetical order. On the other hand, One-Hot Encoding creates additional features for each unique value in the categorical feature, which can be memory and energy- intensive, especially with a large number of features. Given the already substantial number of features in the dataset, Label Encoding is preferred for its efficiency.

IV. METHODOLOGY

A. Machine Learning Models

In our study, we applied three machine learning models Gradient Boost, LightGBM, and XGBoost—for predicting food demand :

In this section, the aim is to describe the forecasting methods. The models used in the proposed system are Gradient Boost, Extreme Gradient Boosting Regressor(XGBoost) and Light Gradient Boosting Machine

Regressor (LightGBM). These models are used for demand forecasting and inventory management. The XGBoost and LightGBM models are the gradient boosting frameworks that uses decision trees as base learners. They are known for their high accuracy and efficiently handling large datasets. These models are trained on historical data on food demand and inventory levels, which is accessed through the historical data module. The historical data is essential for training and validation of machine learning models, which allows them to learn from past data, trends and patterns.

The outcome of these models are used to predict the quan- tity of food orders expected in the upcoming weeks and to forecast stock needs for selected food items for specific time periods before it get expired, such as weekly forecasts. These predictions are used to optimize inventory and distribution by modeling supply chains and to allocate customer orders to fulfillment centers. Overall, the models used in the project are designed to provide accurate insights to optimize stock levels and order fulfillment, which finally contributes to more efficient and informed decision-making process in the man- agement of food demand and supply chains. The Following key components are :

1) Demand Forecasting: The system uses machine learning techniques that is Gradient Booost, XGBoost and Light- GBM to predict the quantity of food orders that is expected in the upcoming weeks based on historical data analysis and machine learning models. This feature is of high priority and critical for the effective management of stock levels.
2) Inventory Management: Efficient management of raw material inventory is prioritized to meet forecasted up and down demands, reduce waste, and minimize storage costs. The system uses machine learning techniques to predict stock needs for selected food items for specific time periods, such as weekly forecasts.

The proposed system is web application which provides restaurants with an builtin platform to effectively manage the inventory. It consists of three core module, each method optimizes different part of the overall process of inventory control.The initial page represents the login and signup page which allows users to access the web application.It provides secure and user-friendly interface for both new and existing users. The food demand forecasting module is designed to help restaurants in predicting future food orders for at least upcoming 10 weeks. This part of the application requires users to enter inputs to 11 distinct features which includes the category of food, number of weeks ,checkout price,base price,city code,region code,operational area etc. By using Machine learning algorithms like XGBoost, LightGBM, and Gradient Boosting, the forecasting tool analyzes the provided data to produce predictions. These forecasts helps restaurants to plan their inventory more effectively, ensuring that they can meet customer demand, minimize waste, and maintain optimal stock levels. By expecting future orders restaurants can make informed decisions that will enhance their operations and customer satisfaction. The Inventory Management module is used for administrator to oversee and control stock levels. This module of system provide comprehensive tools to monitor food orders and track inventory usage in real-time. Center owner can view detailed information about each order, includ- ing its status and the amount of inventory utilized. This real-time tracking helps to prevent stock outs and over stocking, by ensuring that inventory is managed cost-effectively and that waste is minimized. By maintaining inventory, restaurants can ensure that they always have the necessary ingredients on hand to meet customer demand while optimizing their storage and procurement processes.

Fig. 12. Distribution of Price

The Fig 12 shows analysis of distribution of checkout price, base price, and number of orders received by count of number of customers.

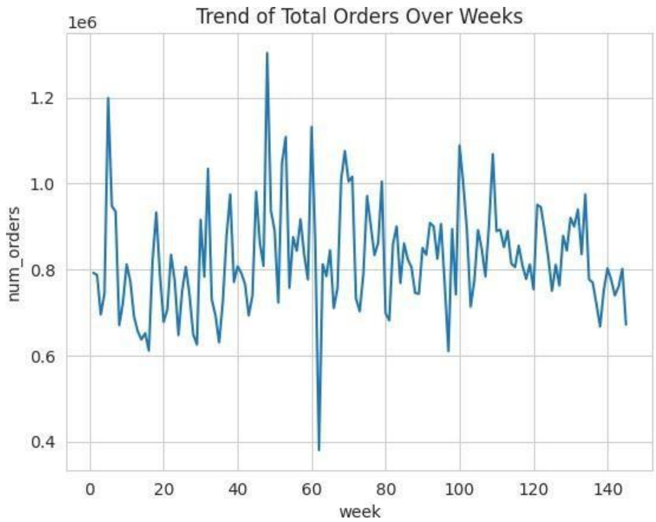

Fig. 13. Trend of orders over the week

The Fig 13 represents analysis of the trend of total number of orders over the weeks. Here the number of orders are increasing and decreasing over weeks.

The Fig 14 illustrates the architecture of the system. It is carefully crafted to utilize machine learning for predicting and modeling food demand and supply chain behavior. It starts by merging various datasets containing meal details, fulfillment center information, and historical demand data, laying the groundwork for analysis. Following this, data is prepared for analysis through thorough cleaning, transformation, and exploratory analysis to ensure accuracy. Then, trends and anomalies are identified to understand how demand fluctuates.

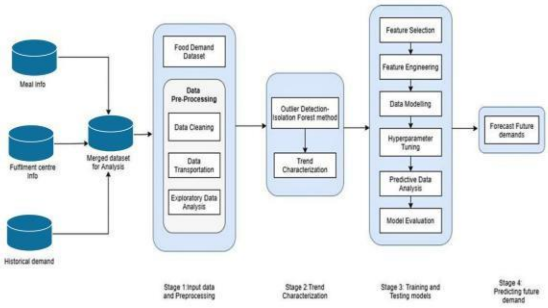

Fig. 14. Architecture Diagram

Next, machine learning models are trained and tested, refining their performance through techniques like feature selection, engineering, and evaluation. Finally, these models are de- ployed to forecast future demand, providing actionable insights for effective decision-making in the food supply chain.

A. Models

The proposed system uses 3 machine learning models that is Gradient Boost, Extreme Gradient Boosting Regres- sor(XGBoost) and Light Gradient Boosting Machine Regres- sor (LightGBM). These models are used for demand forecast- ing and inventory management.

- XGBoost and LightGBM are gradient boosting frame- works that uses decision trees as base learners. They are known for their high accuracy and efficiency in handling large datasets.In proposed system these models are used for demand forecasting and inventory management.
- Xgboost is well known for its robustness and high performance, is used to capture complex patterns and trends in historical sales data. It is widely used because it efficiently cuts down on running time by parallel and distributed computing and handles the NaN values in the dataset.

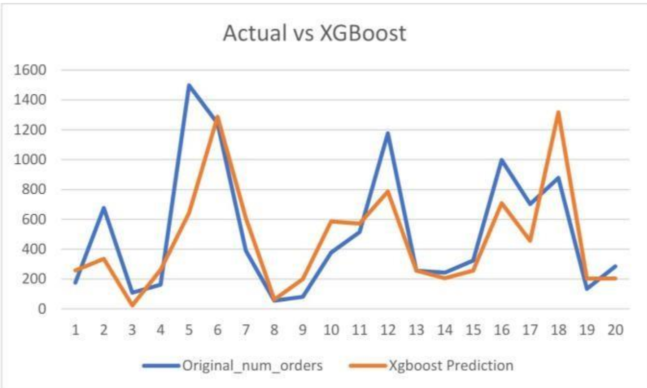

Fig. 15. Xgboost Prediction

The Fig 15 Represents the actual number of orders with the predictions of XGBoost model. Here the Blue Line indicates the actual number of orders and Orange Line indicates XGBoost model predicted number of orders. XGBoost prediction is following the trend of the ac- tual number of orders with some variation in degrees of accuracy.The model captures the changing patterns and fluctuations of the actual order data and tends to underestimate at particular peaks such as instances 1, 3, 9, 18 and overestimate in other areas.

- The Light GBM algorithm performs well in proposed system , is an optimization of the original Gradient Boosting Algorithm. It works on the same principles as the boosting algorithm but, unlike its parent algorithm, it grows the decision trees using a leaf-wise policy. It is designed for fast and efficient training. It is well-suited for handling large datasets and is widely used in industry.

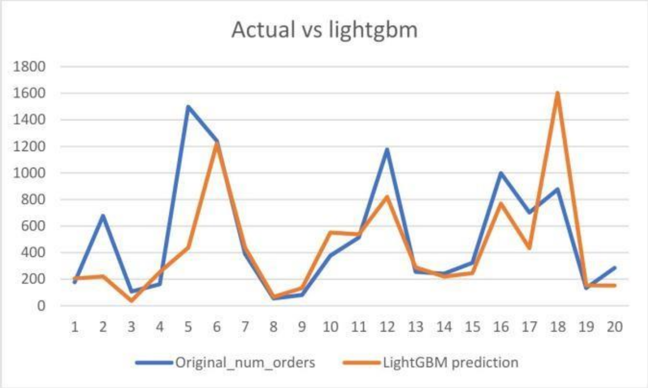

Fig. 16. Lightgbm Prediction

The Fig 16 shows the comparison of the actual number of orders with the LightGBM predictions model.Here the Blue Line indicates the actual number of orders and Orange Line indicates Lightgbm model predicted number of orders where Lightgbm closely follows the trend of actual orders with good alignment.

- Gradient Boosting Machine are based on the concept of combining a group of weak learner or base learner regression trees with gradient boosting regression to create robust forecasting models.By using this approach, the error rate of weak learned models is decreased.

The Fig 17 shows comparison between actual data values with predicted values produced by Gradient Boosting model.The blue line (actual values) shows increase in values from point 1 to point 5, reaching at point 5. It is then gradually decreasing to near 0 at point 8, increases again to another at point 12, and then shows another top at point 18. The orange line (predicted values) follows the similar trend but tends to smooth out some of the extreme fluctuations.

The Fig 18 shows the comparison of actual data values with predicted values from three different machine learning models.It compares the performance of three predictive models that is XGBoost, LightGBM, and Gradient Boosting against the actual number of orders. The actual data is represented by the blue line showing fluctuations with sharp apex and troughs. LightGBM represnted by the gray line results to provide the closest predictions to the actual data, often matching the apex and troughs more accurately while comparing with other. XGBoost is represented by the orange line and Gradient Boosting by yellow line which also follows the general trend of the actual data but with tending to smooth out the fluctuations more than LightGBM. Here it is been observed that the overall LightGBM prediction model results to perform the best in terms of closely matching the actual data values.

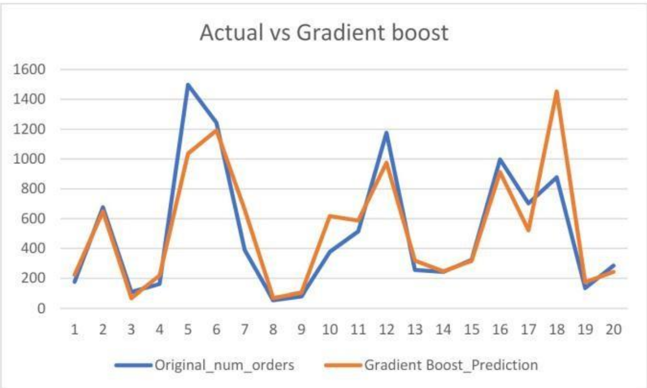

Fig. 17. Gradient Boosting Prediction

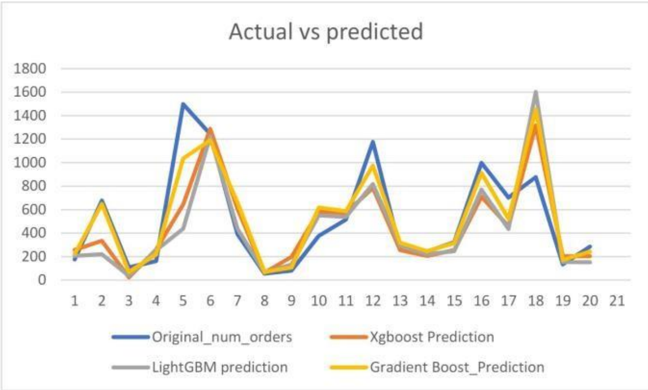

Fig. 18. Models prediction

B. Web Application

Web application provides a user-friendly platform for restaurants to track inventory and forecast food demand ef- fectively. It is designed to streamline operations and improve decision-making. This application consists of five separate sections, each providing its own functionality:

1) Web interface: This section serves as the gateway to the entire system, including buttons or options for logging in, registration, services and "About Us" page. The user- friendly navigation bar allows users to access all these sections easily. This interface provides a comprehensive overview of the system structure in a general way.

2) Login/Register: The login and registration page allows users to enter a username and password or email address to access the system. New users can register through the registration page. This section is important because it provides secure access to the inventory management and forecasting modules. After successfully logging in or registering, the user will be redirected to the following sections of the application.
3) Forecast Dashboard: This section allows users to enter various parameters such as variety, cuisine, week, case price, and base price to forecast food demand. After entering the required information, users can click the "Prediction" button to view the prediction results. The dashboard displays food demand forecasts for specific weeks, using multiple algorithms to ensure accuracy.
4) Inventory Management Dashboard: Accessible only to administrators, this section provides complete details about customer orders, including total customers, total orders, orders delivered orders, future orders, canceled orders and orders in progress. Admins can also view detailed information about each customer, including name, order history, and most recent order details. This dashboard is essential for updating inventory records and managing customer relationships effectively.
5) Create Customer/Product: This module allows adminis- trators to add new dishes and customers to the system. To add a new dish, admins can enter the dish type, dish name, and price. To add a new customer, the required fields are name, phone number, email, and address. This feature ensures the system is always updated with the latest menu items and customer information.

TABLE I COMPARISON STUDY OF MODELS

Metric	XGBoost		LightGBM	
	Original	*Predicte*	*Original*	*Predicte*

		d		***d***
RMSE	205.31	172.37	194.68	158.48
MAE	106.17	91.41	104.49	86.41

As shown in Table I it effectively compares the performance of XGBoost and LightGBM models using RMSE and MAE metrics where the LightGBM outperforms XGBoost in both RMSE and MAE metrics, it has a better predictive perfor- mance.

CONCLUSION AND FUTURE SCOPE

The proposed system highlights the importance of food demand forecasting in the today's food industry. This system focuses on effective demand supply chain management, in- ventory cost reduction and customer satisfaction. Inaccurate demand prediction can lead to either excess inventory which can result in waste or insufficient inventory result in outoff stock. This system uses machine learning techniques such as Gradient Boost, XGBoost and LightGBM to provide valuable insights for stakeholders in the food industry which aims to optimize inventory management and predict food demand modeling supply chains.

The dataset used in system don't have large enough seasonality feature such as account for the date, month or any holidays.Without these factors, it was difficult to capture any trend or seasonality. Also, there was no mention of any event (like special discount or occasion) which may be able to explain sudden spikes of the target variable.In future by having external factors and variable will be able to predict the volume of orders including events and applying advanced technique.

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