Forecasting Food Demand in Supply Chains: a Comprehensive Comparison of Regression Models and Deep Learning Approaches

Shilpa Katikar, Vikas Maral, Nagaraju Bogiri, Vilas Ghonge, Pawan Malik and Suyash Karkhele

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Shilpa M Katikar[1], Vikas B Maral[2], Nagaraju Bogiri [3],Vilas D Ghonge[4]
Pawan S Malik[5], Suyash B Karkhele[6]
[1,2,3,4,5,6] BRACT's Vishwakarma Institute of Information Technology, Pune, India
shilpa.katikar@viit.ac.in,vikas.maral@viit.ac.in,nagaraju.bogiri@viit.ac.in,
vilasghonge77@gmail.com, pawan.22220010@viit.ac.in, suyash.22110828@viit.ac.in

Abstract

Effective forecasting and modeling in food demand supply chains are critical to minimizing waste, reducing costs, and ensuring product availability. This paper explores a comprehensive approach to forecasting food demand by leveraging regression-based models for analysis. We investigate how various machine learning regressors can predict food demand more accurately by examining key supply chain factors such as seasonal trends, price fluctuations, and consumer behavior. The study implements and compares multiple regressors to assess their performance in predicting demand. Metrics Evaluation is done by predicting various models which are Ensemble Learning Models and Neural Network Models to calculate the model's accuracy. By doing prediction, we identified that Gradient Boosting and XGBoost have overall good accuracy in forecasting and it has provided optimized solutions in the supply food chain. This research mainly focuses on using the best modeling techniques which will help the end users to make proper decisions and bring efficiency in food demand management.

Index Terms

Deep learning, predictive modeling, seasonal trends, consumer behavior analysis, demand volatility, supply chain efficiency, ensemble methods, feature engineering, data-driven decision-making, logistics optimization, perishability management.

I. Introduction

Effective demand prediction plays a vital role in food supply chain due to the perishable nature of food products and the volatility in consumer demand. In contrast, to industries with products that last longer and have demand changes,such as the food sector confronts obstacles. The quality of product restricts storage duration. The unpredicted elements like variations,favoritism, for specific regions and abrupt market fluctuations can greatly impact consumer interest. So the inaccurate predictions may cause drastic impact on the production and wastage of inventory or insufficient output resulting in customer needs and potential loss of earnings.

The complexity of food supply networks mostly encompass participants,that are from suppliers to merchants underscore the importance of utilizing predictive approaches. Traditional forecasting techniques, such as moving averages or simple linear regression, often fail to capture the interdependencies and non-linear patterns in food demand data. Modern machine learning algorithms have become tools that can manage amounts of data efficiently and accurately predict outcomes by analyzing various factors such, as past trends in demand, marketing campaigns, price changes and external influences, like weather conditions and holidays.

Regression models are widely used in this scenario because they excel at representing variables and managing connections, in the data set. Sophisticated machine learning techniques such as Random Forests and Gradient Boostings have shown their effectiveness in understanding these connections. These models can handle linear patterns and interactions among features in time series datasets successfully. They are particularly useful for predicting outcomes in supply chain settings due to their capacity to account for long-term dependencies.

This paper presents overall in-depth study and comparison of these regression models for forecasting food demand in supply chains. A real-world dataset is used for the comparison of various regression models' performance and search for a model with better performance in demand prediction. Several commonly used evaluation indexes, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), are selected to assess the performance of each model.

Apart from the comparison of forecasting errors, this research also investigates the impacts of feature selection and external factors on the accuracy of predicted results by different regression models with an expectation to provide some useful guidelines for applications in food supply chain. The most important thing is that we advocate applying advanced machine learning techniques to improve efficiency, sustainability and responsiveness in managing food supply chains under demand uncertainty.

A. Motivation

The motivation to conduct this study is the central importance of accurate demand forecasting in a food supply chain management by the fact that food products are perishable and consumer demand is volatile. Many classical forecasting techniques are often not able to model the complexities of food demand, which can be driven by factors like seasonality, regional preferences or even external effects as weather conditions. But if forecasts are too high or too low overproduction waste will occur or missing sales can happen when underestimating production.

With the food supply chain becoming increasingly complex, advanced machine learning techniques such as Random Forest, Gradient Boosting, XGBoost and CatBoost can provide a potential solution as these models are capable to deal with large data sets, extract complicated patterns and are not affected by non-linear relationship between demand data. This study aims to compare and benchmark those advanced regression models in food demand forecasting and provides an understanding on their feasibility of practical implementation in real-world supply chain settings. Highlighting that accurate forecast allows waste reduction, inventory optimization and sustainability improvement in the food sector.

B. *Problem Definition*

The task is to develop a demand prediction model for a meal delivery service with multiple locations and fulfillment centers. The client will use the order forecast for the next 10 weeks in making plans for procurement and staffing, so it is crucially important this forecast is as accurate as possible. Most of the raw materials needed to prepare meals are perishable and need to be ordered weekly; hence, minimizing waste by ordering close to actual sales and ensuring there are no shortages require an accurate estimate of how many meals will be ordered in future weeks.

The main challenge lies in estimating how many orders will be placed in coming weeks based on the given predictors, which include meal characteristics (category, subcategory, cuisine, price, and discount) with historical sales data as well as details about fulfillment center (region and city). Accurate demand forecasting will help the client optimize procurement planning, stock the appropriate amount of raw materials, and schedule the necessary staff for meal preparation and delivery, thus improving operational efficiency and minimizing food wastage.

The model will be trained on the following data:

- **Historical Sales Data**: The number of sales of each specific meal at various fulfillment centers.
- **Meal Features**: Attributes of the meals, including their category, subcategory, price, and any available discounts.
- **Fulfillment Center Information**: Details about the fulfillment centers, including region and city codes.

II. Literature Survey

Accurate demand prediction is very important factor for handling the supply network, specially in industries handling perishable goods like meals. Effective call for forecasting allows organizations to optimize stock, reduce waste, and make certain well timed deliveries. Various techniques, along with statistical strategies, device studying algorithms, and deep gaining knowledge of fashions, had been explored inside the context of food demand forecasting.

Zhang et al. (2022) [1] Emphasize the significance of ensemble studying strategies in improving call for forecasting, specially for agricultural merchandise. They discover how incorporating outside factors like climate and local choices complements the predictive power of fashions. Such strategies are important for food demand forecasting, wherein outside elements strongly have an effect on patron behavior and income patterns.

Nguyen et al. (2023) [2] Talks about the software of reinforcement studying for dynamic food demand forecasting. By constantly updating the forecast model as new records turns into to be had, this method lets in for real-time variation, which is important for industries in which demand is noticeably risky, which include the meals delivery industry.

Recent advances in deep studying have additionally caused the development of models that could seize greater complex patterns in call for information. *Liu et al. (2022)* [3] looked at the use of CNNs combined with LSTMs for time series forecasting in meals supply chains. This hybrid model takes benefit of CNNs for feature extraction and LSTMs for shooting temporal dependencies, enhancing prediction accuracy inside the presence of non-linear demand patterns.

Another promising method is using transformer-based models.*Yang et al. (2022)* [4] explore the Transformer architecture for call for forecasting, demonstrating its superiority in managing lengthy-variety dependencies and complicated seasonal trends. Transformer models are specially appropriate for food call for forecasting, in which seasonal patterns and lengthy-term trends want to be captured effectively.

Li et al. (2023) [5]introduce a singular hybrid model that integrates XGBoost and LSTM for demand forecasting in meals deliver chains. This version combines the strengths of gradient boosting and deep gaining knowledge of to deal with both brief-time period fluctuations and long-time period dependencies in call for records.

Furthermore, *Cheng et al. (2023)* [6] make use of Graph Neural Networks (GNNs) for meals call for forecasting in multi-region situations. They take a look at highlights how GNNs can version the interdependencies between exceptional locations within the meals supply chain, improving the accuracy of forecasts with the aid of thinking about the interactions between various factors.

Wang et al. (2023) [7] cognizance at the application of switch mastering for meals demand forecasting, mainly in instances wherein historic statistics is constrained. By moving expertise from similar domains, their technique extensively improves forecasting accuracy, making it a treasured tool for emerging food markets with scarce statistics.

Khan et al. (2023) [8] explore the integration of sentiment analysis from social media statistics into food demand forecasting models. Their examine demonstrates how customer sentiments derived from social media structures can offer treasured insights into call for fluctuations, mainly in fast-shifting industries like meals transport offerings.

Shen et al. (2023) [9] suggest a multi-modal technique that integrates climate facts, economic signs, and social factors for food call for forecasting. Their model demonstrates stepped forward accuracy by incorporating external statistics assets, that is critical in shooting demand fluctuations that arise because of seasonal, monetary, or societal adjustments.

Lastly, *Zhao et al. (2023)* [10] look at the capacity of AutoML for meals demand forecasting. Their study exhibits that automatic device getting to know fashions can reap aggressive performance with much less human intervention, making them a promising answer for groups with limited information technology sources.

III. Methodology

A. Data Analysis and Preprocessing

The "Food Demand" data published by the international service company Genpact contains 145 weeks of weekly order data for 50 different food products. These files are divided into three files with 15 different characteristics, totaling approximately 450,000 files, as described below:

1) **Weekly_Data**: This includes historical records of food sales at various fulfillment centers. The dataset provides the following details

Feature	**Description**
Record_ID	Unique identifier for each order.
Week_Number	Week numbers are between 1 to 145.
Food_ID	Unique identifier for each meal.
Center_Code	Unique identifier for each fulfillment center.
Final_Price	Final price of the meal after applying discounts, taxes, and delivery charges.
Initial Price	The base price of the meal as listed in the menu, before any discounts.
Email_Promotion	shows that the promotional email was sent for the meal (0 means- no , 1 means- yes).
Homepage_Highlight	shows that the meal was featured on the homepage (0 means- no, 1 means- yes).
no_orders	Indicates that the number of orders recieved for particular food

TABLE I: Descriptions and Features of Weekly Demand Data

2) **fulfillment_center_info.csv:** In this dataset the details include about each fulfillment center. The following features are included:

Feature	**Description**
Center_Code	Unique identifier for each fulfillment center.
operational_area	The service area covered by the center (in km^2).
urban_code	Indicates the pin code which associated with each city.
location_type	The type of fulfillment center (type_A, type_B, type_C).
zone_code	Unique identifier for the region in which the center is located.

TABLE II: Features of the Fulfilment Centre

3) **meal_info.csv:** This dataset contains data about each meal. It contains the following features:

Feature	**Description**
Food_ID	Unique indentity for each food.
Meal_Type	meal type like..snacks, soups.
Culinary_Style	Culinary of the meal like.. Indian , Itallian.

TABLE III: Information Features about Meal

B. Single-Variable Analysis

This section examines each feature individually, considering both categorical and numerical variables. Histograms are used to visualize the distribution of each feature.

As shown in Fig. 1, the ”no_orders” feature predominantly ranges between 0 and 1000, although a tail extends beyond 20,000, indicating potential outliers. Box plots, shown in Fig. 2 and Fig. 3, highlight these extreme values, which could distort the analysis.

A significant outlier in the ”no_orders” feature is detected in Fig. 2 and Fig. 3. This anomaly likely stems from a data entry mistake and is excluded from the dataset to ensure it does not impact the accuracy of the analysis.

Fig. 4 illustrates the distribution of total orders across various center types. Type_A centers account having most or highest orders, while Type_C centers register the fewest. However, Fig. 5 reveals an anomaly: center 13, a Type_B center, recorded the highest number of orders.

The breakdown of orders by region is provided in Fig. 6. Region 56 stands out due to its exceptionally high order volume compared to other zone.

As seen in Fig. 7, beverages emerge as the most popular food category, while biryani records the least number of orders. food ID 2290 is identified as the most-ordered food, as shown in Fig. 8. Interestingly, the order volumes across different food IDs exhibit little variation in most cases.

Fig. 9 highlights City 590 as the leader, with 18.5 million orders—significantly more than Urban zone 526, which recorded 8.6 million orders.

Finally, Fig. 10 presents the weekly order trends. Week 48 had the highest order volume, whereas week 62 recorded the lowest.

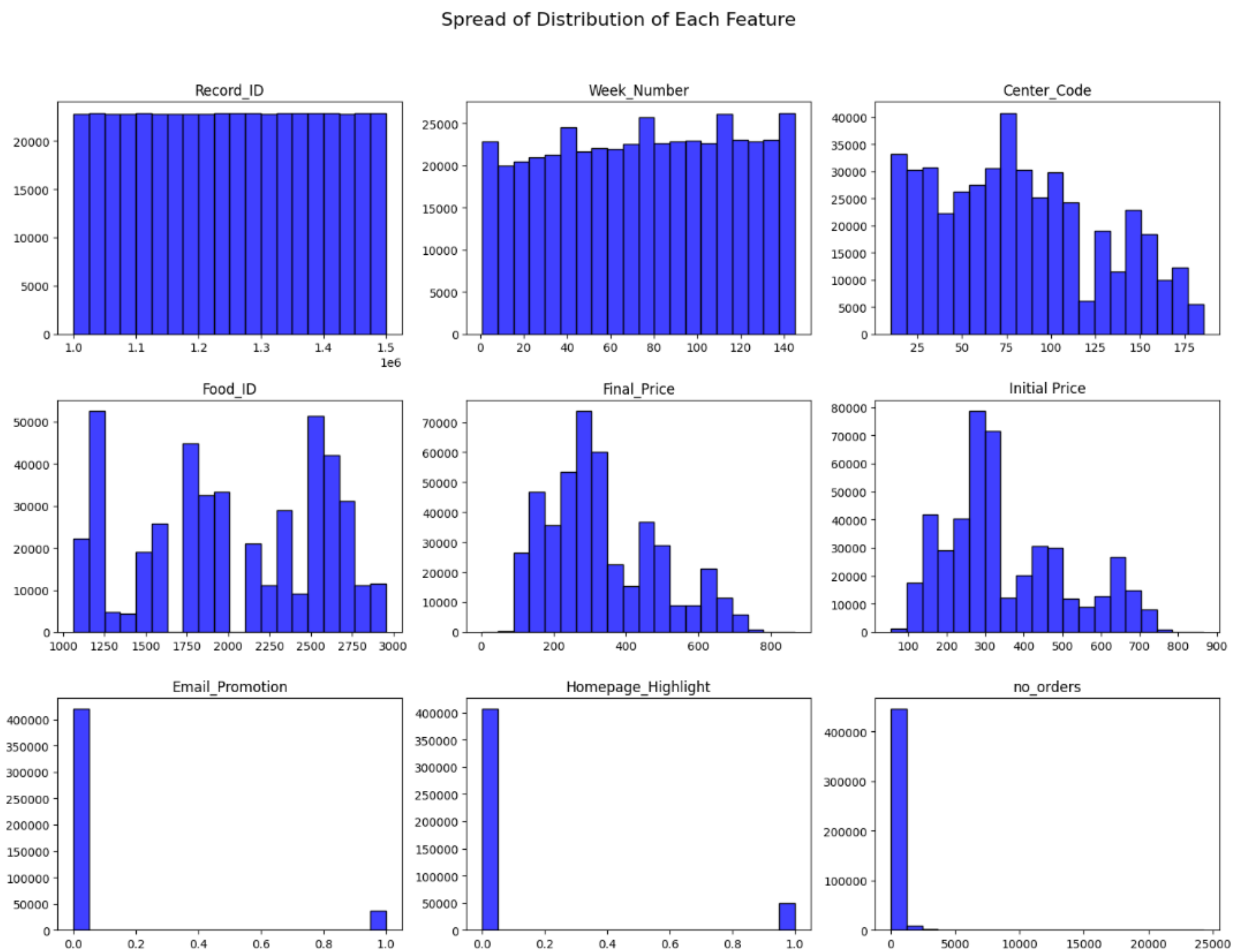

Fig. 1: Each feature’s distribution.

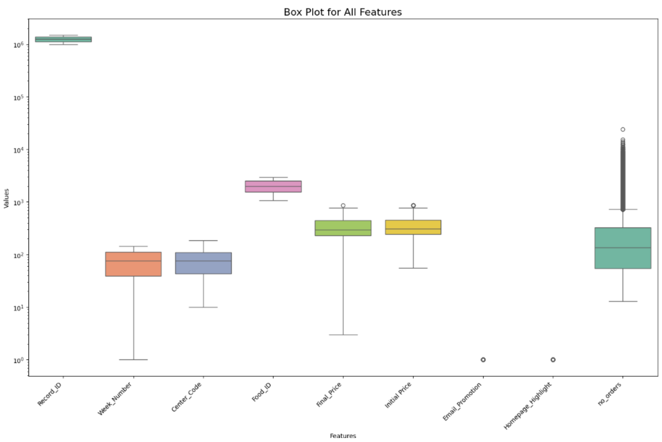

Fig. 2: Boxplot for every characteristic.

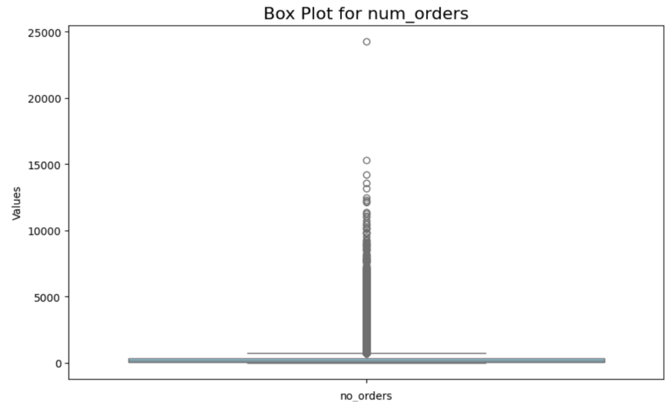

Fig. 3: The "no_orders" feature's outlier is displayed in a box plot.

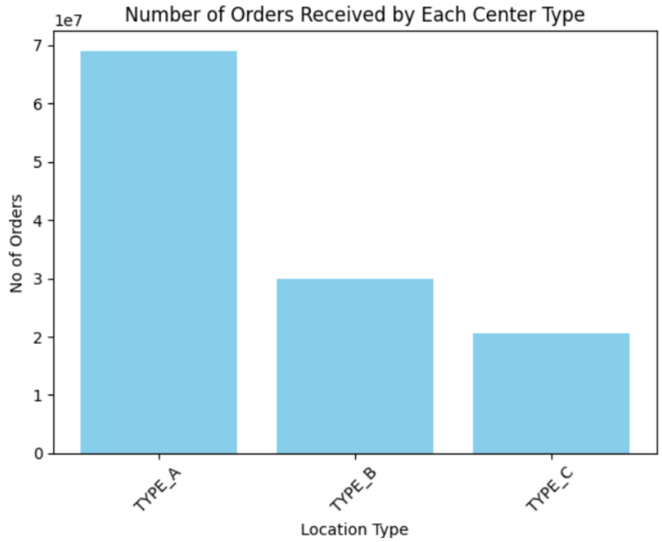

Fig. 4: The number of orders received by each location or center.

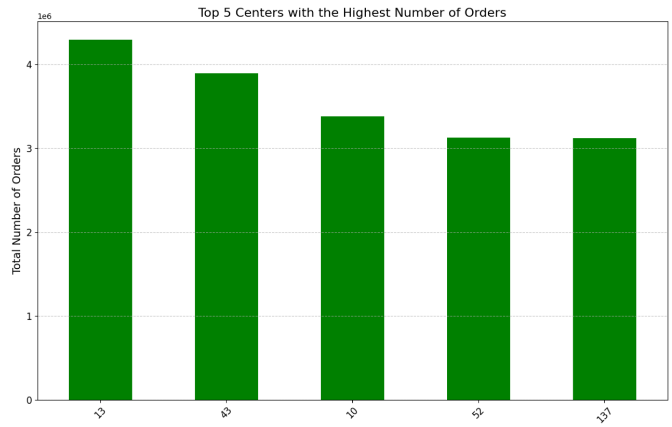

Fig. 5: Center 13 (Type_B) logged the maximum orders.

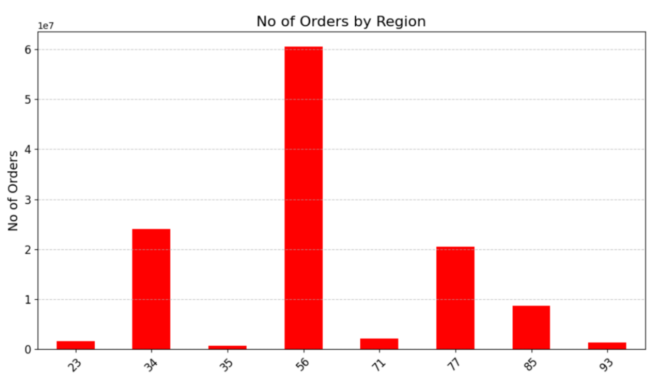

Fig. 6: The count of orders received across each region.

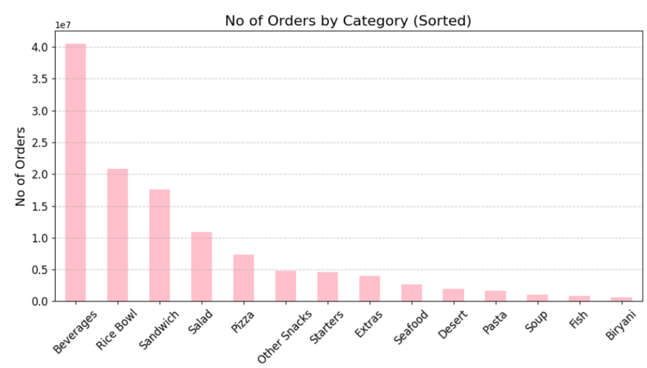

Fig. 7: The count of orders for each food category.

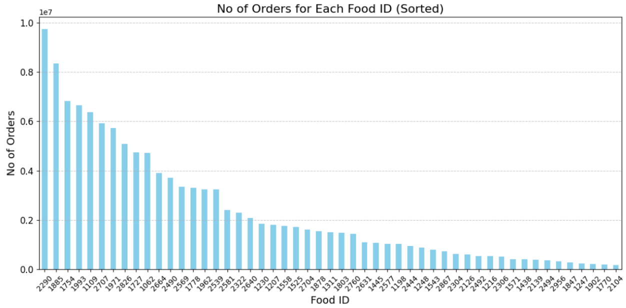

Fig. 8: The count of orders for various food IDs, with a focus on food ID 2290.

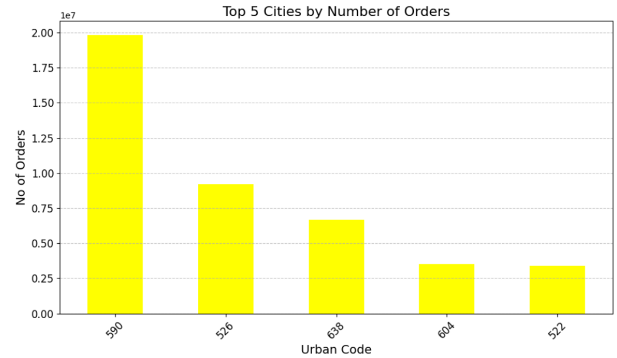

Fig. 9: The total count of orders by urban zone, with urban 590 leading in order volume.

Fig. 10: The weekly count of orders received.

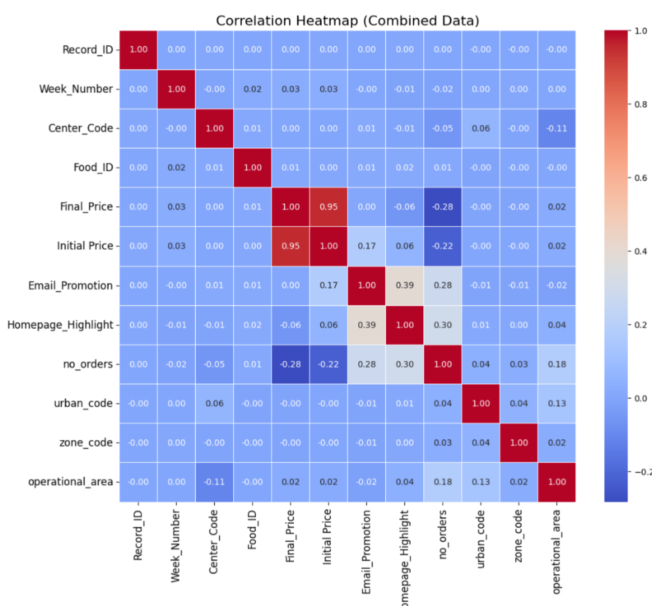

Fig. 11: The correlation heatmap showing the relationships between various features.

C. Multivariate Analysis

A correlation heatmap is generated to understand the relationships between variables. Fig. 13 shows the correlation between features like meal price, fulfillment center information, and demand.

D. Pre-processing Techniques

- **Numerical Features:** The numerical features in the dataset exhibit varying scales, and many of them display a pronounced right-skew. To address this issue, transformations such as quantile transformation and power transformation were applied to reduce skewness. Both methods were evaluated, with Fig. 12 illustrating an example where the quantile transformation proved to be more effective at reducing skewness compared to the power transformation. However, it's important to note that these transformations primarily aim to normalize the distribution of the data.
- **Categorical Features:** Two widely used methods for transforming categorical features into numerical format are Label Encoding and One-Hot Encoding. Label Encoding assigns a distinct integer value to each category within the feature, based on alphabetical order. On the other hand, One-Hot Encoding creates new binary features for each unique value in the categorical feature. This approach can be resource-intensive, particularly when dealing with a large number of unique categories, as it increases memory and computational requirements. Given the large number of existing features in this dataset, Label Encoding was chosen as the preferred technique for categorical feature transformation.

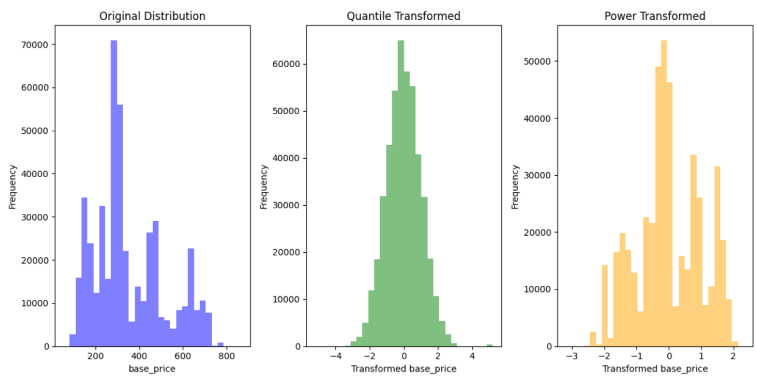

Fig. 12: The comparison between the original distribution, the quantile-transformed distribution, and the power-transformed distribution for one of the numerical features.

E. Model Selection

Ensemble Learning Models: We experiment with various regression models for predicting the number of meal orders. Our selected models include:

- Random Forest Regressor
- Gradient Boosting Regressor
- LightGBM
- XGBoost
- CatBoost

1) ***Random Forest Regressor:*** The Random Forest Regressor is an ensemble technique that constructs several decision trees using different subsets of the data and aggregates their predictions to provide a more robust and generalizable output. In regression tasks, the model averages the output from each tree to predict a continuous value, enhancing performance by reducing overfitting.

Mathematical Formulation Each tree is trained on a bootstrap sample $D_b \subset D$ (where D is the dataset), and at each split, A subset of features which is randomly choosen to identify the best split at each node. Given a collection of trees $T_1, T_2, \ldots, T_B$, the predicted value $\hat{z}$ for an input w in a regression setting is:

$$\hat{z} = \frac{1}{N} \sum_{i=1}^{N} G_i(w),$$

where N is the total trees and $G_i(w)$ is the prediction from the i-th tree. This aggregation helps smooth out high variance, making the prediction more accurate.

*2) **Gradient Boosting Regressor**:* The Gradient Boosting Regressor builds sequentially on weak learners (typically shallow decision trees) by minimizing the residual errors of prior trees. In essence, each tree is added to the model to address the errors of the previous iteration, creating a highly accurate ensemble by sequentially fitting each new tree to the negative gradient of the loss function (the residuals).

Mathematical Formulation The general equation for a gradient boosting regression model is:

$$g(w) = \sum_{k=1}^{K} \alpha \cdot p_k(w),$$

where $p_k(w)$ is the k-th base learner, K is the number of boosting rounds, and η is a learning rate that scales each model to control overfitting. The function $p_k(w)$ at each stage k minimizes the residuals $r_i^{(k)} = y_i - f_{k-1}(w_i)$, where $f_{k-1}(w_i)$ is the current prediction and y_i is the true value.

*3) **LightGBM**:* LightGBM (Light Gradient Boosting Machine) is the best gradient boosting software developed by Microsoft. It uses a histogram-based training technique to speed up and reduce memory usage, making it suitable for processing large datasets. In addition, LightGBM also have techniques like gradient-based one-sided sampling (GOSS) and Exclusive Feature Bundling (EFB) to improve performance and throughput.

Mathematical Formulation LightGBM follows a similar gradient boosting approach but adds optimizations to improve performance. Specifically, it approximates the decision boundaries using a histogram-based method, wherein continuous features are discretized into bins. During each iteration, it selects a subset of gradients (from the largest gradient samples) to grow the tree, simplifying the model's complexity. The model is represented as:

$$r(z) = \sum_{j=1}^{N} \lambda \cdot t_j(z), \quad \text{where } t_j(z) \text{ is derived using GOSS and EFB methodologies.}$$

*4) **XGBoost**:* eXtreme Gradient Boosting-XGBoost is an optimized gradient boosting framework with regularization to prevent overfitting and improve performance. XGBoost uses quadratic Taylor expansion of loss function combining gradient and burlap elements to develop accurate decision tree. It is widely used in competition and business industry due to its high performance and accuracy.

Mathematical Formulation The cost function for XGBoost is defined as:

$$\text{Cost} = \sum_{j=1}^{m} P(z_j, \tilde{z}_j^{(s)}) + \sum_{l=1}^{L} \Omega(g_l),$$

where $P(z_j, \tilde{z}_j^{(s)})$ is the loss function for prediction $\tilde{z}_j^{(s)}$, and $\Omega(g_l)$ is the regularization term that penalizes model complexity, with L trees in the model. The second-order Taylor expansion of the objective is minimized using:

$$\text{Obj}^{(t)} \approx \sum_{i=1}^{n} \left(g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2 \right) + \Omega(f_t),$$

where g_i and h_i are the first and second derivatives of the loss function with respect to the predicted value.

*5) **CatBoost**:* CatBoost (categorical boosting) is designed for the performance of categorical variables by eliminating the need for single-bit encoding. CatBoost uses a new technique called boosting, which reduces the bias of the prediction and improves the prediction by applying changes to the data. It also leverages unique ways to encode categorical features, making it particularly useful in datasets with many categorical variables.

Mathematical Formulation CatBoost optimizes the standard gradient boosting objective, but with an ordered boosting approach that ensures each step's predictions are unbiased by training data leakage. For a dataset D with categorical features C, CatBoost creates a leaf prediction $g(w)$ iteratively:

$$g(w) = \sum_{k=1}^{K} \alpha \cdot p_k(w),$$

where $p_k(w)$ is fitted using permuted categorical encoding and ordered boosting to reduce variance in each stage.

Neural Network Models: We experiment with various Neural Network Models to forecast the number of meal orders. Our selected models include:

- LSTM (Long Short-Term Memory)
- Bi-LSTM (Bidirectional LSTM):

1) **Long Short-Term Memory**
   Long Short-Term Memory is a type of Recurrent Neural Network (RNN) used to remember information over long sequences. It uses **gates** to regulate the flow of information, preventing the vanishing gradient problem that traditional RNNs suffer from. The mathematical formulas for LSTM are:
   - Forget Gate: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$
   - Input Gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$
   - Cell State: $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$
   - Hidden State: $h_t = o_t \cdot \tanh(C_t)$
2) **Bi-LSTM (Bidirectional LSTM)**
   Bi-LSTM is an extension of LSTM that procedures information in both ahead (beyond-to-destiny) and backward (destiny-to-beyond) directions. This allows the model to seize information from each beyond and destiny contexts, that is beneficial in obligations like*machine translation* or *speech recognition*. The mathematical formulas for Bi-LSTM are:
   - Forward LSTM: $h_t^{\text{forward}} = \text{LSTM}(x_t, h_{t-1}^{\text{forward}})$
   - Backward LSTM: $h_t^{\text{backward}} = \text{LSTM}(x_t, h_{t+1}^{\text{backward}})$
   - Final Output: $h_t = [h_t^{\text{forward}}, h_t^{\text{backward}}]$

F. Performance Metrics

The models that are evaluated using the following metrics are as follows:

- **Root Mean Squared Error (RMSE):** Calculates the square root of the mean of the squared differences between discovered and predicted values.

$$\text{Error} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(z_j - \tilde{z}_j)^2}$$

  where z_j stands for the actual value, $\tilde{z}$ is the predicted value which we have calculated, and m is the number of observations.
- **Mean Absolute Error (MAE):** Indicate Averages absolute differences between actual and predicted values.

$$\text{MAD} = \frac{1}{m}\sum_{j=1}^{m}|z_j - \tilde{z}_j|$$

- **Mean Absolute Percentage Error (MAPE):** Calculates the percentage error of predictions.

$$\text{MAPD} = \frac{100}{m}\sum_{j=1}^{m}\left|\frac{z_j - \tilde{z}_j}{z_j}\right|$$

IV. Experimental Results

After Evaluating the performance of multiple regression models using different metrics. The results show that the CatBoost model outperforms other models in terms of root mean square error (RMSE) and root mean square logarithmic error (RMSLE). Table IV summarizes the performance of all the models.

Model	**MSE**	**MSLE**	**RMSE**	**RMSLE**
Random Forest	29009.16	0.3555	170.32	0.5963
Gradient Boosting	40654.48	0.8494	201.63	0.9217
LightGBM	21379.79	0.5236	146.22	0.7236
XGBoost	24244.23	0.6149	155.71	0.7842
CatBoost	20321.37	0.6468	142.55	0.8043

TABLE IV: Performance Comparison of Regression Models

From the table, it is clear that CatBoost achieves the best performance having the small RMSE and RMSLE values, making it the most accurate model for predicting the number of meal orders in this experiment.

For the LSTM and Bi-LSTM models the result of experiment are shown in the table below. The Root Mean Squared Logarithmic Error - RSMLE was used as the evaluation metric.

From the table, it is evident that the LSTM model outperforms the Bi-LSTM model based on the RMSLE metric, indicating better prediction accuracy for the LSTM model in this experiment.

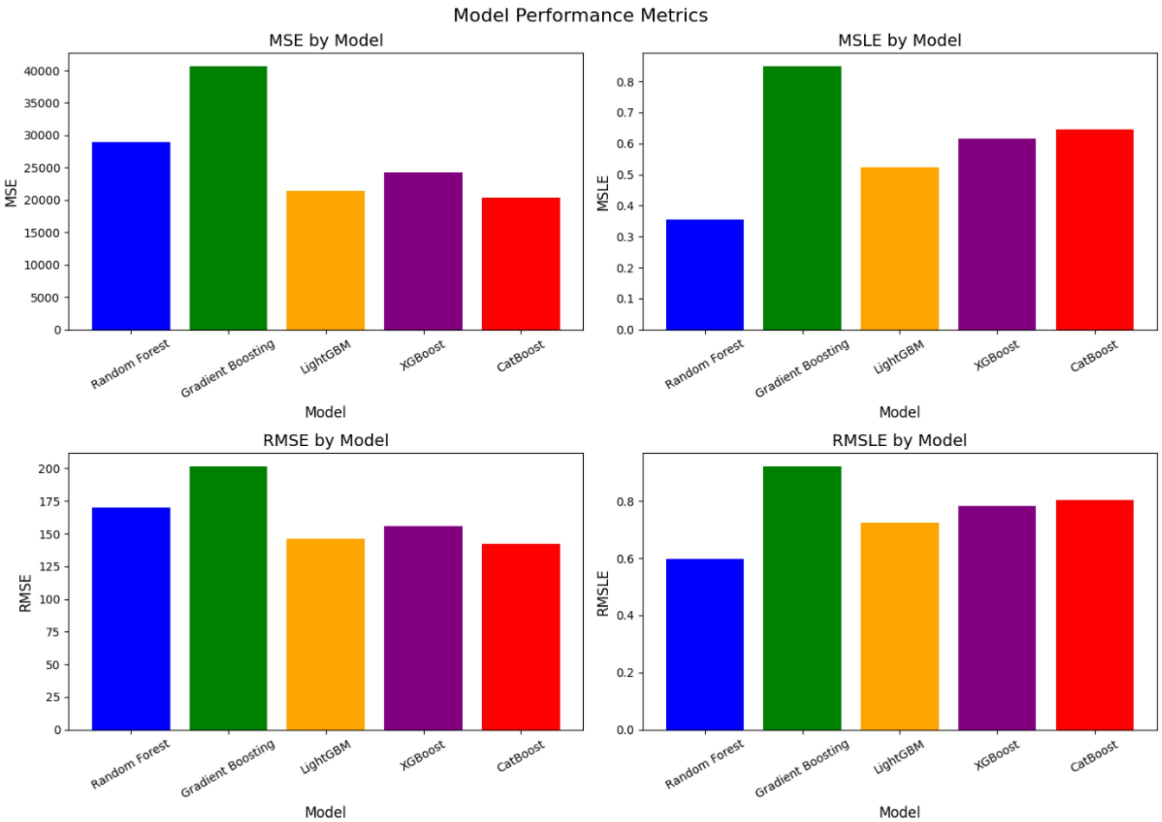

Fig. 13: Performance Comparison of Regression Models

Model	RMSLE
LSTM	1.1509
Bi-LSTM	1.3571

TABLE V: Performance Comparison of LSTM and Bi-LSTM Models

V. Conclusion

Accurate demand forecasting is critical for efficient inventory management in meal delivery services. This study demonstrates the usefulness of deep learning and machine learning models in predicting food volume. Among the models tested, LSTM demonstrated the highest accuracy in forecasting, outperforming other machine learning algorithms. However, the absence of key factors like dates, holidays, and special events in the dataset limited the models' ability to capture seasonal trends and demand spikes. Future work should consider these variables to refine the forecasting models and improve performance, potentially incorporating transfer learning techniques for better results with smaller datasets.

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