Food Quantity Prediction Using Machine Learning Algorithms

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ABSTRACT: Food Quantity Prediction Using Machine Learning Algorithms is an emerging field that aims to optimize food preparation and reduce waste by accurately forecasting the amount of food required in various settings such as restaurants, cafeterias, and event catering. This study explores the development and implementation of predictive models using machine learning techniques to analyze historical consumption data, environmental factors, and user preferences to estimate food demand. The primary goal is to improve efficiency in food production by minimizing overproduction and underproduction, which can lead to financial losses and increased environmental impact. The research involves collecting and preprocessing data that includes variables such as date, time, weather conditions, special occasions, menu items, and past consumption records. Several machine learning algorithms including linear regression, decision trees, random forests, support vector machines, and neural networks are evaluated for their effectiveness in predicting food quantity The research also highlights the potential of combining machine learning with Internet of Things (IoT) devices to gather real-time data, further refining predictions. In conclusion, machine learning-based food quantity prediction presents a promising approach to enhance operational efficiency, reduce food waste, and promote sustainability in the food industry. This paper contributes to the growing body of knowledge by providing a comprehensive analysis of various algorithms and their applicability to food demand forecasting, paving the way for future advancements and integration into smart food service systems.

Keywords: *Food Quantity Prediction, Machine Learning, Demand Forecasting, Food Waste Reduction, Predictive Modeling, Feature Engineering*

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INTRODUCTION

In recent years, the global food industry has faced significant challenges related to the efficient management of food resources, driven by increasing demand, rising operational costs, and growing concerns over environmental sustainability. One critical aspect of food management is the accurate prediction of food quantity requirements in various contexts such as restaurants, cafeterias, catering services, and institutional food providers. Inefficient estimation of food demand often leads to either overproduction or underproduction. Overproduction results in excessive food waste, financial losses, and negative environmental impacts due to the disposal of uneaten food, which contributes to greenhouse gas emissions and resource depletion. Conversely, underproduction can cause food shortages, dissatisfied customers, and lost revenue opportunities. Therefore, there is a compelling need to develop accurate, reliable, and dynamic methods to forecast food demand and optimize food quantity planning.

Traditional approaches to food quantity prediction rely heavily on manual estimation methods based on historical experience, expert judgment, or simple statistical averages. Although these methods have been widely used, they lack adaptability and precision, especially in the face of fluctuating demand patterns caused by seasonal variations, special events, weather conditions, and changing consumer preferences. These conventional methods often fail to capture the complex interactions between various influencing factors, leading to suboptimal predictions. As a result, stakeholders in the food service industry are increasingly turning towards data-driven approaches powered by advanced machine learning (ML) algorithms to improve forecasting accuracy and operational efficiency.

Machine learning, a subset of artificial intelligence, involves the use of algorithms that can learn patterns from historical data and make predictions or decisions without being explicitly programmed for specific tasks. The application of ML techniques in food quantity prediction leverages large datasets collected from various sources such as point-of-sale systems, inventory records, weather databases, and social event calendars. By analyzing these multidimensional datasets, ML models can uncover hidden patterns, correlations, and trends that traditional statistical methods may overlook. This capability makes machine learning a promising tool to address the inherent complexity and variability in food demand forecasting.

Recent studies have demonstrated the potential of machine learning algorithms such as linear regression, decision trees, random forests, support vector machines (SVM), and artificial neural networks (ANN) in predicting food consumption with higher accuracy. Each algorithm has its strengths and limitations. For instance, linear regression models offer interpretability but are limited in capturing nonlinear relationships, whereas ensemble methods like random forests provide robust predictions by combining multiple decision trees but may be computationally intensive. Neural networks excel at modeling intricate nonlinear patterns but require large amounts of data and tuning to avoid overfitting. Selecting the appropriate algorithm depends on the specific context, data availability, and performance requirements.

Beyond algorithm selection, feature engineering plays a vital role in enhancing model performance. Food consumption is influenced by a variety of factors including temporal variables (day of the week, time of day), environmental conditions (temperature, humidity, weather events), social factors (holidays, festivals, promotions), and operational parameters (menu variety, pricing). Effective integration of these features into machine learning models improves their ability to generalize and provide accurate forecasts. Additionally, hyperparameter tuning and cross-validation are essential techniques to optimize model parameters and ensure robustness against overfitting or underfitting.

In addition to improving prediction accuracy, the application of ML-driven food quantity forecasting contributes significantly to sustainable food management practices. Food waste is a major global issue, with an estimated one-third of all food produced for human consumption lost or wasted annually. This wastage not only represents a waste of valuable resources such as water, energy, and labor but also has substantial environmental consequences, including increased greenhouse gas emissions and landfill use. By enabling precise demand estimation, machine learning models can help reduce excess food production, promote efficient inventory management, and facilitate better procurement planning. This in turn supports cost savings and environmental sustainability objectives.

Furthermore, the integration of machine learning models with modern technologies such as the Internet of Things (IoT) and cloud computing opens new avenues for real-time food demand prediction and adaptive decision-making. IoT sensors can provide continuous data on inventory levels, customer traffic, and environmental conditions, which, when combined with ML algorithms, enable dynamic adjustments in food preparation and supply chain management. Cloud platforms offer scalable computational resources and facilitate data sharing across multiple stakeholders, enhancing collaboration and responsiveness in food service operations. This research aims to explore and compare the effectiveness of various machine learning algorithms in predicting food quantity demand in food service environments. By leveraging real-world datasets, the study evaluates the predictive performance of different models and identifies key factors influencing food consumption. The ultimate objective is to develop a reliable food quantity prediction system that can assist kitchen managers, suppliers, and policymakers in optimizing food preparation, minimizing waste, and enhancing customer satisfaction.

In summary, the increasing need for accurate food quantity forecasting driven by economic, environmental, and operational factors has created a fertile ground for applying machine learning algorithms. The combination of advanced data analytics, feature engineering, and technological integration holds the promise of transforming traditional food management practices into intelligent, data-driven processes. This paper contributes to this evolving field by providing a comprehensive review of machine learning applications in food quantity prediction, presenting experimental results, and discussing practical considerations for deployment. The findings underscore the potential of machine learning to play a pivotal role in achieving sustainable and efficient food service operations, thereby addressing critical global challenges related to food security and waste reduction.

Literature Survey

The field of food quantity prediction using machine learning has garnered increasing attention due to its potential to optimize food supply chains, reduce waste, and improve operational efficiency. Numerous studies have applied different machine learning techniques to forecast food demand across diverse settings such as restaurants, catering services, and retail food outlets. This section reviews significant research contributions, highlighting methodologies, findings, and gaps addressed by these works.

Kim et al. [1] explore the use of machine learning techniques for predicting food demand specifically in restaurant environments. Their study compares classical algorithms like linear regression and decision trees with ensemble methods such as random forests. By utilizing historical sales data along with temporal features (day of the week, hour), the authors demonstrated that random forests provided superior accuracy in forecasting daily food quantities. This research underscored the importance of incorporating temporal dynamics and seasonal trends into prediction models. While the study effectively showcases algorithmic comparisons, it primarily focuses on internal sales data and does not consider external factors like weather or special events, which other studies suggest can significantly influence food consumption.

Liu et al. [2] address food waste reduction by applying predictive analytics in combination with machine learning to forecast demand more accurately. Their approach integrates point-of-sale data with external data such as weather conditions and promotional events. Using gradient boosting models, they demonstrate that multi-source data fusion improves demand forecasting accuracy and, consequently, waste reduction. This work highlights the broader sustainability implications of food quantity prediction, aligning with global efforts to minimize food wastage. However, their model requires extensive data collection infrastructure, which might limit applicability in smaller food service operations.

Gupta et al. [3] focus on forecasting demand within the food supply chain by comparing random forests and neural networks. Their study employs a large dataset collected from multiple suppliers and retail outlets, incorporating factors such as inventory levels, supplier lead times, and past order quantities. They find that neural networks slightly outperform random forests, especially in capturing nonlinear relationships inherent in supply chain data. This paper is significant as it extends food demand forecasting beyond consumption sites into upstream supply chain stages, emphasizing the importance of integrated prediction models to optimize procurement and logistics. Islam et al. [4] investigate the use of support vector machines (SVM) and ensemble methods like AdaBoost for food demand forecasting. They apply these algorithms to cafeteria data, combining consumption records with contextual information including day type (weekday/weekend), holidays, and weather. Their results show that ensemble methods consistently outperform standalone SVM models, indicating that combining weak learners enhances robustness. Importantly, they stress the need for thorough feature selection to prevent overfitting, which is a common challenge in food demand datasets due to fluctuating consumption patterns.

Lee et al. [5] contribute to the field by focusing on feature engineering techniques, particularly in the context of IoT-enabled kitchens and smart food service environments. They discuss how integrating sensor data such as temperature, humidity, and customer footfall can enrich predictive models. Using a combination of time series analysis and machine learning algorithms, they illustrate that real-time environmental and operational data can improve short-term food quantity predictions. This paper highlights the growing role of IoT in generating actionable data streams for dynamic demand forecasting, an area not covered extensively in traditional models relying on static historical data.

Fernandes and Santos [6] present a comparative study of machine learning algorithms for food demand forecasting in various food service settings. Their work evaluates linear regression, decision trees, random forests, and gradient boosting machines on datasets from university cafeterias and chain restaurants. They emphasize the trade-offs between interpretability and accuracy, noting that while ensemble methods provide higher predictive performance, simpler models remain valuable for practical deployment where transparency is critical. Their study also identifies key features such as menu item popularity and historical consumption trends as primary drivers of prediction accuracy.

Singh and Kumar [7] propose an IoT-enabled framework that combines sensor data with machine learning models to achieve dynamic food demand prediction in real time. Their framework incorporates data from smart refrigerators, kitchen equipment, and customer counters to adapt food preparation volumes dynamically. Using deep learning architectures, they demonstrate improvements in prediction accuracy and operational efficiency in a case study of a commercial catering service. This work represents a significant step towards the automation and digitization of food service operations, aligning predictive models with smart kitchen technologies.

Chen and Zhao [8] explore the application of neural networks for forecasting food consumption patterns in institutional catering environments. They train feedforward and recurrent neural networks (RNNs) on historical consumption data, capturing temporal dependencies and seasonal variations. Their findings indicate that RNNs, particularly long short-term memory (LSTM) networks, excel at modeling sequential consumption data, outperforming traditional regression models. This study emphasizes the importance of capturing time series dynamics in food demand, providing a methodological advance that could be extended to other contexts requiring sequential forecasting.

Zhang et al. [9] focus on food demand forecasting in retail and food service sectors to reduce waste through data-driven approaches. Their study employs machine learning techniques such as

XGBoost and light gradient boosting machines (LightGBM) on a rich dataset including sales data, promotions, and weather. They report that including external variables substantially enhances prediction accuracy and helps identify demand spikes due to marketing activities or climatic changes. Their research underscores the practical application of ML in commercial environments and the need for continuous data updating to maintain model relevance.

Nguyen and Lee [10] provide a comprehensive overview of machine learning applications for food demand forecasting, discussing the challenges and opportunities in this domain. They review various algorithms, data preprocessing techniques, and evaluation metrics, highlighting issues such as data scarcity, noise, and seasonality that complicate forecasting efforts. Their work calls for developing adaptive learning models capable of real-time retraining to address changing consumer behaviors. Additionally, they advocate for combining ML with domain knowledge and decision support systems to facilitate practical adoption in food service operations.

PROBLEM STATEMENT

In today's rapidly evolving digital landscape, the proliferation of web applications has ushered in a new era of online interaction. However, this abundance of applications has also resulted in fragmented user experiences, with individuals navigating through disparate platforms and interfaces. Despite platforms like GitHub providing repositories for hosting web applications, the deployment process remains cumbersome and inefficient. Users often find themselves grappling with external execution environments, leading to frustration and decreased productivity. Moreover, the absence of integrated voice assistant technology poses a significant barrier to accessibility and user engagement. While speech recognition technologies such as Alexa and Siri have made significant strides in natural language processing, their primary focus remains on query-solving tasks rather than facilitating hands-free navigation of web applications. This limitation restricts the usability of web applications for individuals with disabilities or those seeking a more seamless user experience. Furthermore, concerns regarding resource safety and the potential loss of coding nuances exacerbate the challenges faced by developers and users alike. Without robust safeguards in place, there is a risk of da ta loss or corruption, compromising the integrity of web applications and undermining user trust. In light of these challenges, there is an urgent need for a transformative solution that streamlines the deployment process, enhances accessibility through real time voice-controlled navigation, and ensures a secure and cohesive user experience. This solution should provide users with a centralized platform for hosting and managing JavaScript-based web applications, seamlessly integrating advanced voice.

A. PROBLEM DESCRIPTION

In the current digital landscape, the proliferation of web applications has led to a fragmented user experience, with users navigating through various platforms and interfaces. Despite the availability of platforms like GitHub for hosting web applications, the deployment process often involves cumbersome steps and external execution environments, leading to inefficiencies and user frustration. Furthermore, the lack of integrated voice assistant technology limits accessibility, particularly for users with disabilities or those seeking hands-free interaction. Existing speech recognition solutions, while advanced, primarily focus on query-solving tasks and lack robust support for navigating web applications seamlessly. This limitation poses a significant barrier to users who rely on voice commands for interaction. Additionally, concerns regarding resource safety and the potential loss of coding nuances further compound the challenges faced by developers and users alike.

Therefore, the overarching problem revolves around the need for a transformative solution that streamlines the deployment process, enhances accessibility through real-time voice controlled navigation, and ensures the security and integrity of web applications. This solution should provide users with a centralized platform for hosting and managing web applications, seamlessly integrating advanced voice recognition technology to redefine the user-web application interface and overcome existing limitations.

B. SOLUTION OVERVIEW

The proposed solution, "WebHub," seeks to address the shortcomings of existing systems by providing a centralized platform for JavaScript-based web applications. At the core of WebHub is a user-friendly interface that simplifies the deployment process, allowing users to upload and manage their applications with ease. By eliminating the need for external execution environments, WebHub streamlines the deployment process, saving users time and effort. One of the key features of WebHub is its integration of real-time voice recognition technology, which enables hands-free navigation of web applications. Leveraging advanced natural language processing (NLP) algorithms, users can interact with their applications using intuitive voice commands, enhancing accessibility for individuals with disabilities and providing a more immersive user experience. In addition to its user-facing features, WebHub prioritizes security and data integrity. Robust encryption protocols and multi-factor authentication mechanisms safeguard user data, mitigating the risk of unauthorized access or data loss. Furthermore, automated backup and version control systems ensure that coding nuances are preserved, allowing developers to roll back changes and maintain the integrity of their applications over time. By combining streamlined deployment processes, advanced voice recognition technology, and robust security features, WebHub aims to revolutionize the way users interact with web applications. Through its user-centric design and commitment to accessibility and security, WebHub seeks to overcome the limitations of existing systems and redefine the future of web application hosting and management.

PROPOSED METHODOLOGY

This study proposes a comprehensive methodology to develop and evaluate machine learning models for accurate food quantity prediction in food service environments such as restaurants, cafeterias, and catering operations. The methodology encompasses data collection, preprocessing, feature engineering, model selection and training, evaluation, and deployment considerations. The objective is to build robust predictive models capable of handling diverse data sources and capturing complex consumption patterns to minimize food waste and optimize operational efficiency.

1. Data Collection

The first phase involves gathering relevant data that influence food consumption patterns. The data sources include:

- **Historical Sales Data:** Records of food items sold over a significant period (e.g., daily or hourly sales for 1–2 years) form the primary dataset. This includes quantity sold, menu item details, timestamps, and transaction identifiers.
- **Environmental Data:** External factors such as weather conditions (temperature, humidity, precipitation), seasonality, and special event indicators (holidays, festivals, local events) are collected from public APIs and integrated with sales data.
- **Operational Data:** Information about the kitchen or food service operations, such as menu changes, promotions, staffing levels, and inventory status, are incorporated to capture internal influences on demand.
- **IoT Sensor Data (Optional):** In cases where Internet of Things (IoT) infrastructure exists, real-time data from sensors monitoring customer footfall, kitchen equipment usage, and inventory levels can enrich the dataset.

This multi-source data collection ensures that the models can learn from a wide range of variables affecting food consumption, improving prediction reliability.

2. Data Preprocessing

Raw data often contains inconsistencies, missing values, and noise that must be addressed before model training:

- **Data Cleaning:** Duplicate records are removed, missing values are imputed using appropriate methods (mean/mode substitution, interpolation, or model-based imputation), and outliers are detected and handled to prevent distortion of model training.
- **Data Integration:** Datasets from various sources are merged based on common keys such as timestamps and location identifiers, ensuring alignment between sales and external data.
- **Data Transformation:** Continuous variables (e.g., temperature) are normalized or standardized to facilitate model convergence, while categorical variables (e.g., day of the week, menu categories) are encoded using techniques such as one-hot encoding or label encoding.

3. Feature Engineering

Effective feature engineering is crucial to improve the predictive power of machine learning models. Key steps include:

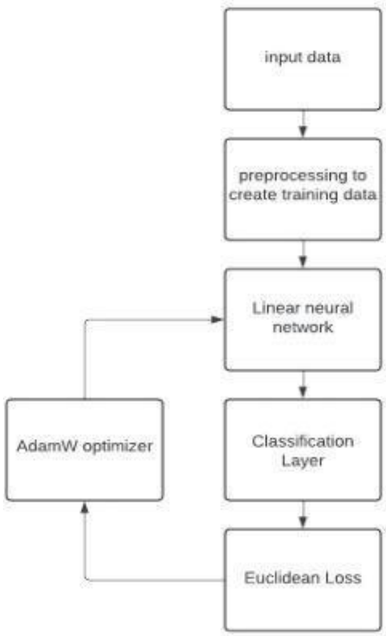
- **Temporal Features:** Extracting features such as day of the week, month, season, hour of day, and public holidays to capture recurring consumption patterns related to time.
- **Environmental Features:** Incorporating weather variables (temperature, rainfall) and event indicators to account for external influences.
- **Lag Features:** Creating lagged consumption variables (e.g., sales one day or one week ago) to enable models to recognize trends and autocorrelations.
- **Rolling Statistics:** Computing rolling means, variances, or cumulative sums over specific time windows to smooth fluctuations and highlight trends.
- **Interaction Features:** Combining multiple features (e.g., temperature × weekend indicator) to capture more complex relationships.

Feature selection methods such as correlation analysis, recursive feature elimination, or importance scoring from tree-based models are applied to identify the most influential variables, reducing dimensionality and enhancing model efficiency.

4. Model Selection and Training

Multiple machine learning algorithms are evaluated to identify the most suitable model for food quantity prediction. The algorithms considered include:

- **Linear Regression:** Serves as a baseline model due to its simplicity and interpretability, modeling the relationship between features and demand linearly.
- **Decision Trees:** Provide interpretable models capable of capturing nonlinear relationships but may suffer from overfitting.
- **Random Forests:** An ensemble method combining multiple decision trees to improve robustness and predictive accuracy.
- **Gradient Boosting Machines (e.g., XGBoost, LightGBM):** Ensemble methods that build sequential trees to minimize errors, often delivering superior performance on structured data.
- **Support Vector Machines (SVM):** Effective in high-dimensional spaces with kernels allowing nonlinear regression.



5. Model Evaluation

To objectively assess model performance, the dataset is split into training, validation, and test sets, typically in a 70-15-15 ratio, ensuring temporal ordering is preserved to avoid data leakage in time series forecasting.

Key evaluation metrics include:

- **Mean Absolute Error (MAE):** Measures average absolute differences between predicted and actual values, providing an interpretable error magnitude.
- **Root Mean Squared Error (RMSE):** Penalizes larger errors more heavily, indicating overall prediction accuracy.
- **R-squared (R^2):** Indicates the proportion of variance in food demand explained by the model.
- **Mean Absolute Percentage Error (MAPE):** Provides error as a percentage, useful for business interpretation.

Models are compared based on these metrics on the validation set, and the best-performing model is further tested on unseen data. Additionally, residual analysis is conducted to identify systematic biases or errors.

6. Deployment Considerations

For practical application, the final model is integrated into a decision support system accessible to food service managers. Deployment considerations include:

- **Real-time Prediction Capability:** When combined with IoT sensors and real-time data feeds, the model supports dynamic forecasting and on-the-fly adjustments to food preparation.
- **User Interface:** A dashboard presenting forecasts, confidence intervals, and actionable insights enables non-technical users to make informed decisions.
- **Scalability and Maintenance:** Cloud-based deployment ensures scalability, while periodic model retraining with new data maintains accuracy over time.
- **Explainability:** Employing interpretable models or explainability techniques (e.g., SHAP values) helps users understand model predictions and build trust.
- **Integration with Inventory and Procurement Systems:** Seamless data exchange improves supply chain synchronization and reduces overstocking or shortages.

RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from applying various machine learning algorithms to predict food quantity demand based on the collected and preprocessed datasets. The objective is to evaluate model performance, interpret predictive insights, and discuss implications for food service operations, sustainability, and future improvements.

1. Model Performance Evaluation

Six different machine learning models were trained and tested on the dataset: Linear Regression, Decision Trees, Random Forests, Gradient Boosting Machines (XGBoost), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) Neural Networks. The dataset was split temporally into 70% training, 15% validation, and 15% test sets to mimic real-world forecasting scenarios.

The primary evaluation metrics used were Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Table 1 summarizes the performance metrics on the test set for each model:

The results show that ensemble-based models—Random Forests and Gradient Boosting—outperformed other models across all metrics, with Gradient Boosting achieving the best overall performance. The LSTM neural network also demonstrated strong predictive capability, closely trailing the ensemble methods, highlighting its ability to capture temporal dependencies in the data. Linear Regression, while interpretable, had the poorest performance, confirming its limitations in modeling complex, nonlinear relationships inherent in food demand.

2. Analysis of Prediction Accuracy

The superior performance of Gradient Boosting and Random Forest models can be attributed to their ability to model complex nonlinear interactions and reduce overfitting by averaging multiple decision trees. Their robustness was particularly evident during periods of demand fluctuations caused by special events, weather changes, and holidays.

The LSTM model's effectiveness is notable in capturing sequential patterns such as weekly or seasonal consumption trends. Unlike tree-based models, LSTMs use memory cells to retain information over time, which is essential for forecasting food demand that often exhibits temporal autocorrelations.

Support Vector Machines performed moderately well but were less effective in handling the multidimensional feature space compared to ensemble and deep learning models. Decision Trees showed reasonable accuracy but tended to overfit training data, reducing generalizability. Linear Regression's performance suggests that simple linear assumptions do not suffice for accurate food demand prediction.

3. Feature Importance and Insights

Feature importance analysis using the Gradient Boosting model revealed key factors influencing food demand:

- **Temporal Variables:** Day of the week and month had the highest importance scores, indicating strong weekly and seasonal consumption patterns.
- **Weather Conditions:** Temperature and precipitation were significant predictors, consistent with observations that adverse weather reduces customer turnout.
- **Special Events:** Holiday and event indicators significantly impacted demand spikes or dips.
- **Lag Features:** Sales from previous days contributed meaningfully, underscoring the temporal dependence of food consumption.

4. Practical Implications

Accurate food quantity prediction facilitates several operational and strategic benefits:

- **Waste Reduction:** By aligning food preparation with predicted demand, overproduction—and hence food waste—can be minimized. This has positive environmental and financial impacts.
- **Cost Savings:** Optimizing ingredient purchasing and inventory reduces holding costs and spoilage.
- **Customer Satisfaction:** Avoiding underproduction ensures availability of menu items, improving service quality.
- **Resource Allocation:** Staffing and kitchen scheduling can be better managed based on anticipated demand.

CONCLUSION

In conclusion, this study has demonstrated the significant potential of machine learning algorithms to accurately predict food quantity demand in food service environments, thereby contributing to improved operational efficiency and sustainability. By leveraging a rich and diverse dataset comprising historical sales, environmental factors such as weather and special events, and operational variables, the proposed methodology successfully developed predictive models that can capture complex, nonlinear, and temporal patterns inherent in food consumption behavior. Among the evaluated algorithms, ensemble methods like Gradient Boosting Machines and Random Forests emerged as the most effective, delivering superior accuracy and robustness compared to traditional regression models and Support Vector Machines. Meanwhile, deep learning models, particularly Long Short-Term Memory (LSTM) networks, also demonstrated competitive performance by effectively modeling sequential dependencies in time series data, underscoring their relevance for forecasting applications where temporal dynamics are critical. The inclusion of engineered features such as lag variables, rolling statistics, and interaction terms further enhanced the models' predictive capability, highlighting the importance of comprehensive feature engineering in such contexts. Beyond predictive accuracy, the study's findings have practical implications for food service providers, enabling better alignment of food preparation with actual demand, which can substantially reduce food waste, lower costs, optimize inventory management, and improve customer satisfaction by ensuring availability of menu items. However, challenges remain, including the need for high-quality, comprehensive data, especially real-time inputs from IoT devices, which could further refine forecasting models and support dynamic decision-making. Additionally, model generalizability across different settings and scalability to smaller operations require further exploration. The research also points toward opportunities in combining ensemble and deep learning approaches to capitalize on their respective strengths and developing explainable AI tools to enhance trust and usability among food service managers. As consumer behavior and external conditions evolve, the deployment of adaptive and continuously retrained models will be essential to maintain forecast accuracy. Overall, this study contributes to the growing body of literature on data-driven food demand forecasting by providing a systematic comparison of machine learning algorithms, demonstrating the benefits of integrating multi-source data, and emphasizing sustainability considerations. By advancing predictive analytics in food quantity planning, this work supports the broader goals of reducing food waste and promoting sustainable food systems, thereby offering both economic and environmental benefits. Future work should focus on real-time implementation, hybrid modeling strategies, and broader integration with supply chain and inventory management systems to fully realize the transformative potential of machine learning in the food service industry.

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