

AI-Driven Restaurant Inventory and Waste Management System Using Short-Term Demand Forecasting

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Abstract

The restaurant industry faces significant challenges in inventory management and food waste reduction due to fluctuating demand and inefficient resource utilization. Traditional systems primarily rely on manual tracking or historical analysis, which limits their ability to support proactive decision-making. This research proposes an AI-driven restaurant inventory and waste management system that leverages short-term demand forecasting and real-time data analytics to optimize operations.

The system analyzes sales data from the previous seven days to generate demand forecasts for the upcoming week. Based on these predictions, it estimates ingredient requirements, identifies low stock conditions, and predicts potential food wastage. Additionally, the system provides donation suggestions for surplus food, promoting sustainability and social responsibility. Machine learning models such as ARIMA and regression techniques are utilized to capture demand patterns and improve forecasting accuracy.

The proposed solution integrates multiple functionalities into a unified dashboard, enabling restaurant managers to make data-driven decisions efficiently. Experimental evaluation demonstrates improvements in inventory accuracy, reduction in food waste, and enhanced operational efficiency. The system highlights the potential of combining predictive analytics with practical decision-support tools to transform traditional restaurant management into a more intelligent and sustainable process.

Keywords

Keywords: Restaurant Inventory Management, Demand Forecasting, Food Waste Reduction, Artificial Intelligence, Data Analytics, Sustainability

1. Introduction

The restaurant industry functions within a highly dynamic and competitive landscape, where effective inventory control and waste minimization are essential for ensuring both financial stability and sustainability. Among various operational challenges, inventory management remains one of the most crucial aspects, as it directly impacts cost control, food quality, and customer satisfaction. Inefficient inventory practices often lead to significant food waste and financial losses due to spoilage or overstocking, resulting in environmental concerns. Studies show that restaurants lose approximately 4-10% of their annual revenue due to poor inventory management, while nearly 10-15% of food is wasted because of spoilage and improper demand forecasting [1].

Beyond economic losses, food waste has become a global concern, with about 1.3 billion tons wasted each year. A large share of this waste originates in the hospitality industry, where inaccurate demand forecasting and the absence of real-time monitoring systems drive inefficiencies [2]. Conventional inventory management systems depend mainly on manual tracking or rigid rule-based methods, making them reactive and unable to adjust to dynamic variables like seasonal trends, shifting customer preferences, and fluctuating demand.

With the advancement of technology, there has been a growing interest in leveraging Artificial Intelligence (AI) and Machine Learning (ML) to address these challenges. AI-driven systems enable predictive analytics, allowing restaurants to forecast demand, optimize inventory processes, and reduce waste. However, many existing solutions still primarily focus on tracking and reporting past data rather than providing actionable decisions. The system specifically focuses on short-term analysis by utilizing past 7-day sales data to generate actionable insights for the upcoming 7 days.

To overcome these limitations, this study introduces an AI-driven inventory and waste management system for restaurants that combines real-time stock monitoring, demand forecasting, waste segregation, and surplus food redistribution. The system employs machine learning models, including ARIMA and regression techniques, to analyze historical data and accurately forecast future demand. Furthermore, it integrates intelligent waste management by detecting excess food and enabling its redistribution through partnerships with non-governmental organizations (NGOs), thus promoting both social welfare and sustainability.

The proposed system seeks to enhance inventory accuracy, cut down on excess stock, and reduce food waste by facilitating data-driven and proactive decision-making. By integrating predictive analytics, real-time monitoring, and sustainable practices, this research advances an efficient, scalable, and environmentally responsible solution for modern restaurant operations.

2. Literature Review

2.1 Challenges in Restaurant Inventory Management

Restaurant inventory management presents many operational challenges due to fluctuating demand patterns, spoilable food items, and complex supply chain logistics. Existing studies highlight that traditional inventory systems are often reactive, relying on historical data with limited predictive capabilities. This leads to inefficiencies such as overstocking and stockouts, which negatively impact both profitability and service

quality. Furthermore, the lack of real-time monitoring systems limits the ability of restaurant managers to make timely decisions, thereby increasing the risk of spoilage and resource misallocation. These limitations emphasize the need for intelligent systems that can dynamically adapt to changing conditions.

2.2 Impact of Food Waste in the Hospitality Industry

Food waste remains a crucial issue in the hospitality sector, with a significant proportion of waste resulting from inaccurate demand estimation and inefficient inventory management practices. Research on AI-driven food waste reduction highlights that overproduction and poor planning are major contributors to wastage. This study underscores the importance of combining predictive analytics and real-time tracking systems to minimize surplus food generation.[3] Additionally, food waste has serious environmental implications, including increased greenhouse gas emissions and resource depletion. Addressing this issue requires a combination of technological interventions and systemic changes to promote sustainable practices throughout the food supply chain.

2.3 Applications of Artificial Intelligence in Food Service

The adoption of Artificial Intelligence (AI) in the food service industry has gained considerable momentum, specifically in the areas of demand forecasting and operational optimization. Studies on demand forecasting [4] demonstrate that machine learning models, such as time-series analysis and regression techniques, can significantly improve prediction accuracy by analyzing historical sales data, seasonal trends, and external factors. Similarly, research on AI in hospitality indicates that AI-based systems enhance efficiency by enabling data-driven decision-making, automating processes, and improving customer service[5]. These systems not only optimize inventory levels but also contribute to reducing waste and increasing overall productivity.

2.4 Current Approaches to Food Redistribution

Sustainability has become important in recent research, with particular emphasis on reducing food waste through redistribution initiatives. Studies suggest that surplus food can be efficiently redistributed to non-governmental organizations (NGOs) and community networks to address food insecurity. While existing systems provide frameworks for redistribution, they often operate independently of inventory and forecasting systems. Research combining AI and sustainability[6] highlights the potential of combining predictive analytics with redistribution networks to improve efficiency and reduce waste. However, there remains a gap in developing a unified system that seamlessly connects inventory management, demand forecasting, and food redistribution.

3. Proposed System Architecture

3.1 System Overview

The proposed system is an AI-driven web-based platform designed to assist restaurants in optimizing inventory usage, predicting demand, and minimizing food waste. The system processes historical sales data and real-time inventory inputs to generate actionable insights through an interactive dashboard.

The architecture is designed around a data-driven workflow where sales data from the previous seven days is analyzed to identify consumption patterns. Based on this, the system generates demand forecasts for the upcoming seven days, estimates ingredient requirements, and predicts potential waste. These outputs enable restaurants to make informed and proactive decisions rather than relying on reactive approaches.

In addition to forecasting and inventory optimization, the system incorporates intelligent alert and decision-support mechanisms to enhance operational efficiency. It continuously monitors stock levels and generates real-time low-stock alerts to prevent shortages and overstocking. Furthermore, the platform identifies surplus or near-expiry items and provides donation suggestions, enabling restaurants to reduce waste and contribute to sustainable practices. By integrating predictive analytics with automated alerts and redistribution strategies, the proposed system supports both economic efficiency and environmental responsibility.

The overall system architecture is illustrated in Fig. 1.

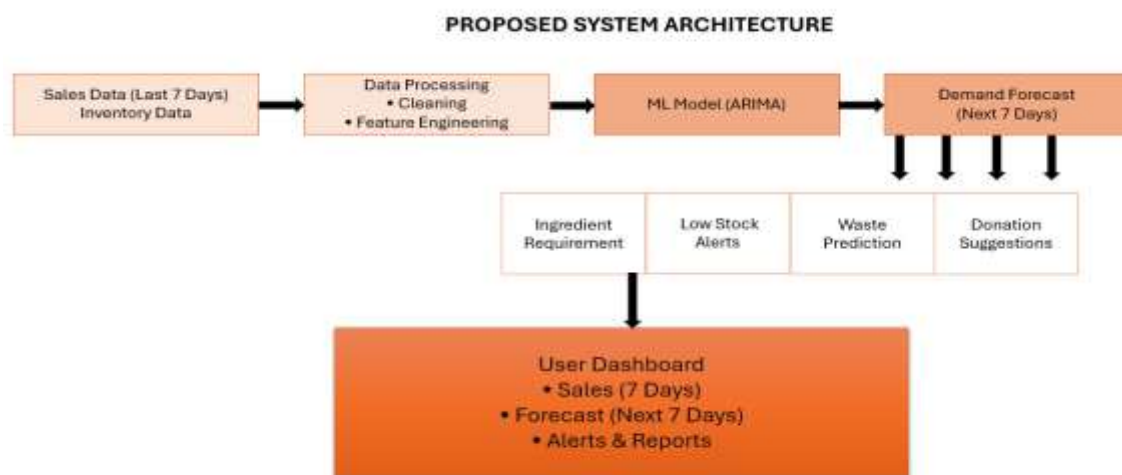


Fig. 1. Proposed system architecture showing data flow from input to decision-making modules.

3.2 Data Analytics and Visualization Module

The system provides a dashboard that displays **items sold over the last 7 days**, helping users understand recent sales trends and high-demand items.

Additionally, it generates a **demand forecast for the next 7 days**, allowing restaurant managers to anticipate future requirements. These insights are presented visually to support quick and effective decision-making.

3.3 Inventory and Ingredient Management Module

Based on the predicted demand, the system calculates the **required quantity of ingredients** needed for upcoming operations. This ensures optimal stock levels and prevents unnecessary purchasing.

The system also generates **low stock alerts** whenever inventory levels fall below a defined threshold, enabling timely restocking and preventing operational disruptions.

3.4 Waste Segregation and Classification

The system includes a predictive mechanism that estimates **potential wastage** based on demand forecasts and current inventory levels. By identifying items likely to remain unused, the system enables preventive actions to reduce spoilage and improve efficiency.

3.5 Food Redistribution Network Integration

To promote sustainability, the system provides **donation suggestions** for surplus food items. Based on waste predictions, it identifies food that can be safely redistributed and recommends donation actions.

This feature ensures that excess food is utilized effectively rather than discarded, contributing to both environmental sustainability and social welfare.

3.6 User Interface Design Considerations

The user interface provides an interactive dashboard for restaurant staff and management to monitor system activities and make informed decisions. It displays real-time insights, predictions, and alerts in a user-friendly format.

The system interface presents all outputs, including:

- Past 7-day sales
- Next 7-day demand forecast
- Ingredient requirements
- Low stock alerts
- Waste prediction
- Donation suggestions

This integrated dashboard enables users to monitor and manage operations efficiently.

4. Methodology

4.1. Data Collection and Preprocessing

4.1.1 Data Collection and Integration

The dataset used in this study was collected from multiple operational sources within the restaurant environment, including point-of-sale (POS) systems, inventory records, and billing transactions. These sources provided detailed information on daily sales, item-wise consumption, ingredient usage, and stock levels.

In addition to internal data, contextual variables such as day of the week, seasonal patterns, and special events were incorporated to improve the robustness of demand forecasting. These variables are critical in capturing fluctuations in customer behavior and consumption trends.

The collected datasets spanned multiple time periods, enabling a time-series analysis of restaurant operations. To ensure consistency across datasets, key identifiers such as item names, timestamps, and transaction IDs were standardized. Column names such as date, item, and quantity_sold were unified across all datasets to facilitate seamless integration.

Following standardization, the datasets were merged into a unified structure using common keys such as date and item identifiers. This integration enabled the alignment of sales data with inventory consumption and stock availability, forming a comprehensive dataset suitable for analysis and modeling.

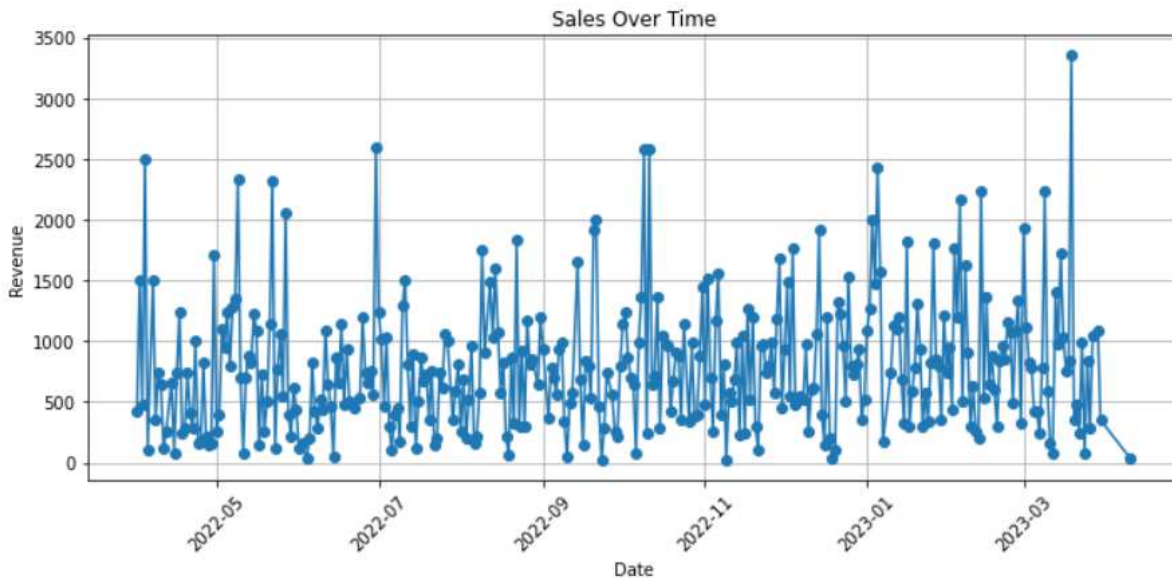


Fig. 2. Historical sales trend for short-term demand forecasting.

4.1.2 Data Preparation

After integration, the dataset underwent preprocessing to ensure quality, consistency, and suitability for machine learning models.

Missing values were handled using a combination of removal and imputation techniques. Records with significant missing information were excluded to maintain data integrity, while minor missing values were imputed using statistical measures such as mean or median for numerical features.

To maintain uniformity across features with varying scales, numerical variables such as quantity sold, stock levels, and ingredient usage were normalized using scaling techniques. This step improves model convergence and enhances prediction performance.

Time-based features were formatted into a consistent datetime structure, allowing efficient extraction of temporal attributes such as day, week, and trends. Additionally, irrelevant or redundant columns, such as duplicate transaction identifiers or unused metadata, were removed to streamline the dataset.

The cleaned dataset was then structured in a time-series format, enabling the application of forecasting models such as ARIMA and regression techniques.

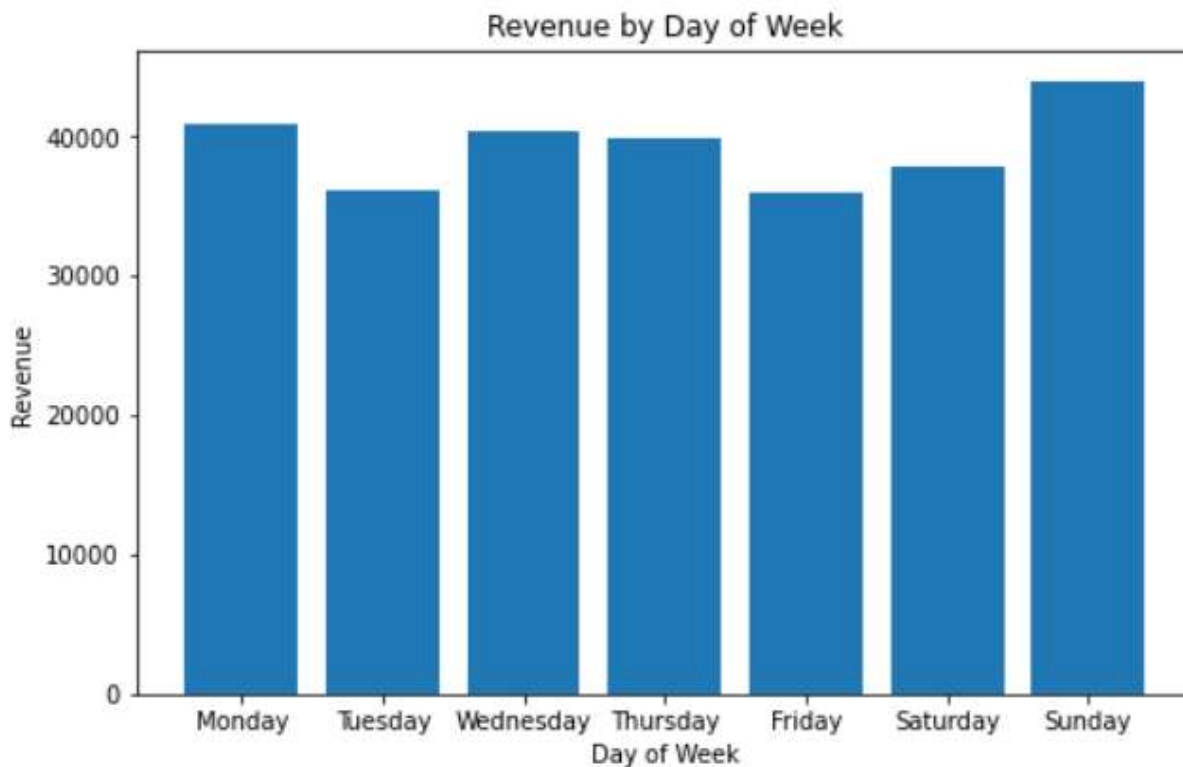


Fig. 3. Day-wise revenue pattern for demand analysis in restaurant operations.

4.1.3 Data Cleaning and Feature Engineering

Data Cleaning and Consolidation

Duplicate entries arising from repeated transactions or logging errors were identified and removed to prevent bias in model training.

Inconsistencies in inventory and sales records were addressed by aligning item-level consumption with corresponding stock updates. For instance, discrepancies between recorded sales and inventory depletion were corrected to ensure accurate representation of usage patterns.

Rows with missing values in critical variables such as sales quantity, inventory levels, and timestamps were removed, as these are essential for reliable forecasting. Remaining missing values in auxiliary features were handled using mean imputation for numerical attributes.

Feature Engineering

To enhance model performance, several derived features were created based on domain knowledge:

Temporal Features: Day of the week, weekend indicators, and seasonal flags were extracted from timestamps to capture periodic demand patterns.

Lag Features: Previous day and previous week sales were included to help the model learn short-term dependencies in demand.

Rolling Statistics: Moving averages (e.g., 3-day and 7-day averages) were computed to smooth fluctuations and highlight trends.

Inventory-Based Features: Stock availability and consumption rates were used to estimate replenishment needs and potential shortages.

Waste Indicators: Features representing excess inventory relative to predicted demand were created to identify potential wastage.

These engineered features allowed the model to better capture both temporal dynamics and operational relationships within the restaurant system.

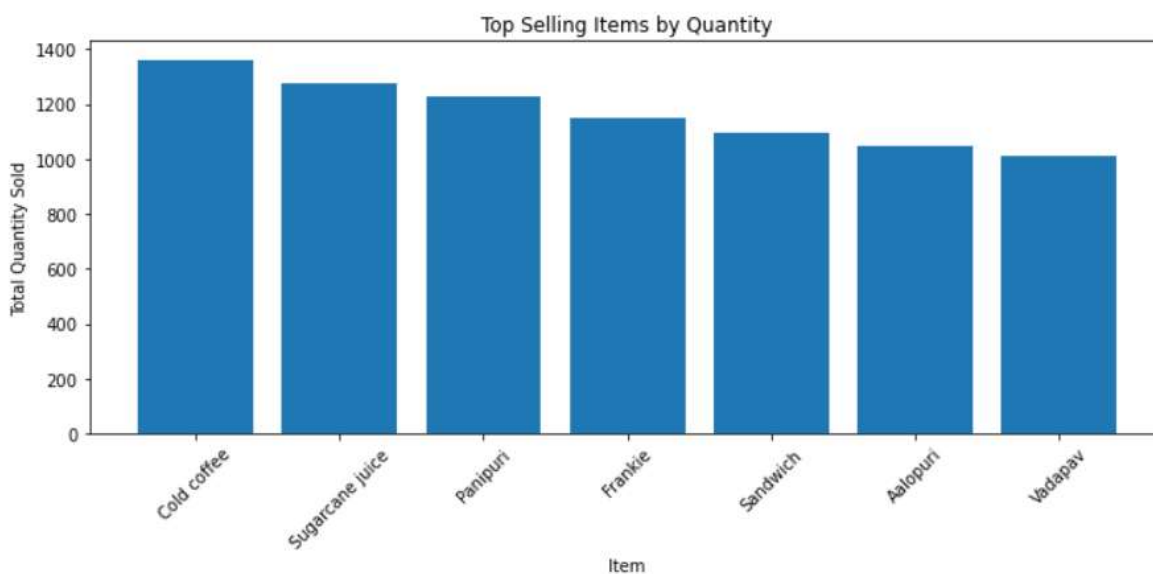


Fig. 4. Top-selling food items based on quantity for inventory optimization.

4.1.4 Feature Selection Rationale

The selection of features was guided by both domain knowledge and statistical validation techniques. This methodical approach ensured that only the most pertinent attributes, directly influencing demand and waste prediction, were included in the modeling process, thereby improving efficiency and interpretability.

Sales-related variables such as quantity sold and historical demand were included due to their direct influence on future consumption patterns. Inventory-related features, including stock levels and consumption rates, were selected to capture operational constraints and resource availability. Temporal features such as day of the week and seasonal indicators were incorporated to model periodic variations in customer demand.

To validate the relevance of selected features, correlation analysis was performed to examine their relationship with demand. Features exhibiting weak correlation with the target variable were excluded to improve model efficiency.

Additionally, multicollinearity checks were conducted to identify highly correlated independent variables. Redundant features were removed to enhance model interpretability and prevent overfitting.

This combination of domain-driven and statistical feature selection ensured that the final model utilized only the most relevant and impactful variables, leading to improved forecasting accuracy and system performance.

4.2. Machine Learning Model Selection and Development

To forecast demand effectively, the system employs a combination of statistical and machine learning techniques. The system utilizes ARIMA and regression-based models to capture different characteristics of the data.

ARIMA (**AutoRegressive Integrated Moving Average**) models linear trends and short-term variations in time-series data. Regression models analyze the influence of external factors such as time, seasonality, and customer trends on demand.

The system trains the models using historical datasets and evaluates them based on their predictive performance. Metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) assess accuracy. The final model selection is made by comparing performance, efficiency, and scalability.

The system specifically utilizes sales data from the previous seven days to identify short-term consumption patterns. These patterns are used to generate demand forecasts for the upcoming seven days. The predicted demand is further mapped to ingredient requirements and inventory levels, enabling the system to generate actionable outputs such as stock alerts, wastage prediction, and donation suggestions.

4.3 Waste Segregation Approach

The system includes a structured mechanism to identify and manage food waste effectively. This component analyzes inventory usage patterns and expiration data to detect surplus and unusable items. Based on predefined criteria and analytical insights, it categorizes waste into reusable, recyclable, and non-reusable groups.

By combining demand prediction with inventory analysis, the system adopts a proactive approach to waste management. This reduces unnecessary disposal by preventing overproduction and enabling better resource utilization.

4.4 Integration with Non-Governmental Organizations

To promote sustainability, the system facilitates the redistribution of surplus food through collaboration with non-governmental organizations (NGOs). Once excess food is identified, the system validates it to ensure quality and safety standards are met.

The system then establishes communication with registered NGOs through integrated interfaces or APIs. The system generates notifications and coordinates logistics for food collection and delivery. This structured approach ensures that surplus food is utilized efficiently rather than wasted.

4.5 Evaluation Metrics and Performance Assessment

To evaluate the performance of the proposed system, the dataset is divided into training and testing subsets. This allows for objective assessment of model accuracy and generalization capability.

In addition to model performance, system-level evaluation focuses on practical outcomes, including reduction in food waste, improvement in inventory accuracy, and efficiency of food redistribution processes.

This comprehensive evaluation ensures that both technical performance and the real-world impact of the system are effectively measured.

5. Results and Discussion

The developed system includes a user-friendly dashboard that provides real-time insights into inventory status, demand forecasts, and alerts. The dashboard enables restaurant managers to monitor operations efficiently and make informed decisions. Fig. 5 illustrates the overview of the dashboard, while Fig. 6 presents the sales forecasting interface generated by the system.

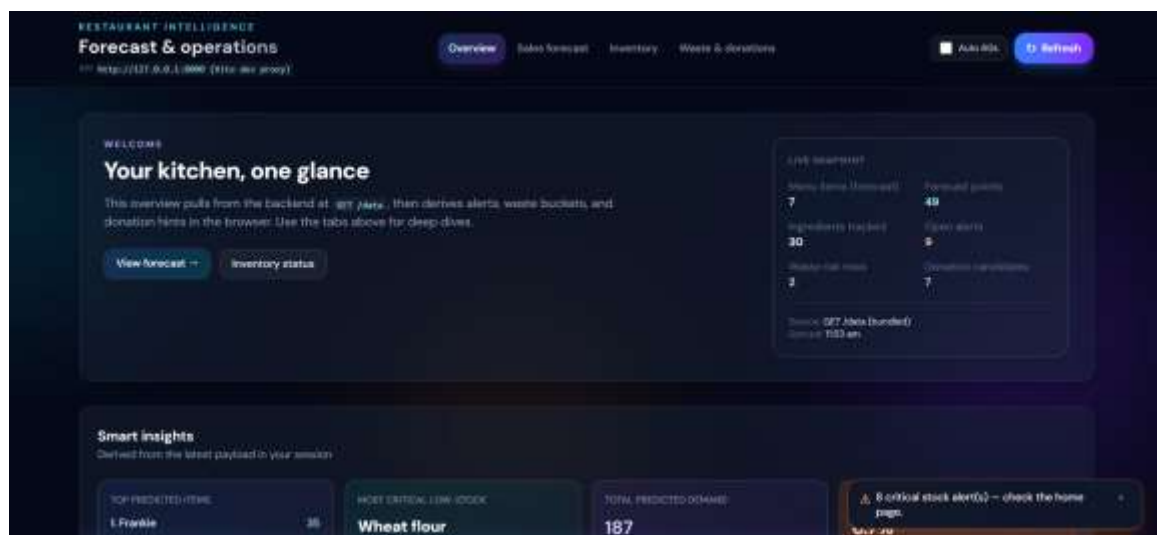


Fig. 5. User dashboard displaying real-time inventory insights, alerts, and key performance indicators.

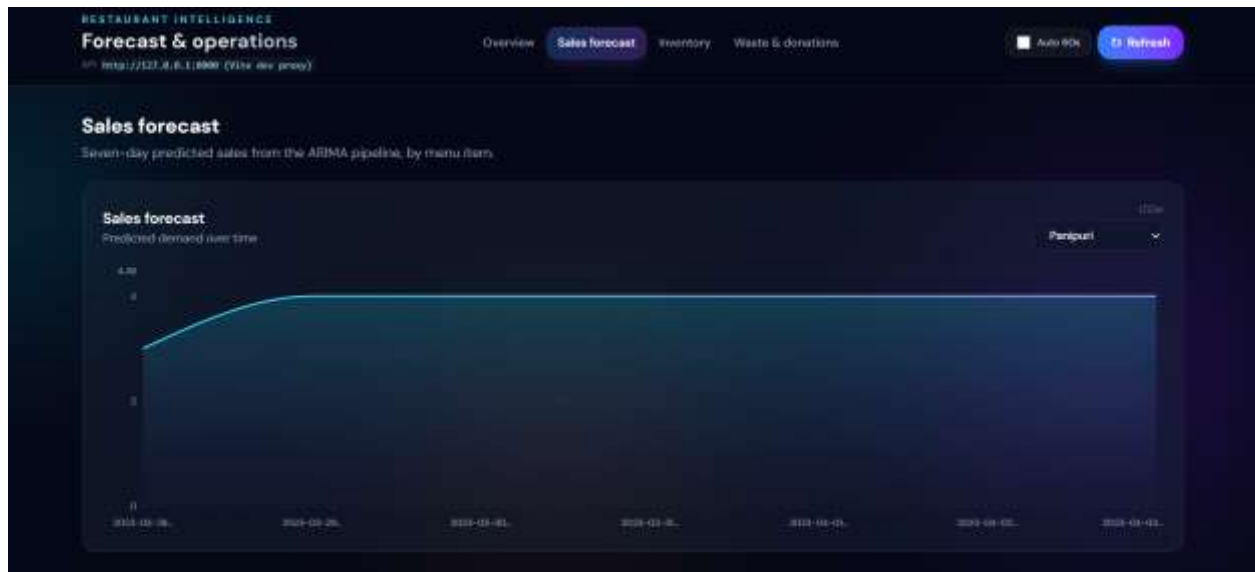


Fig. 6. Sales forecasting interface showing predicted demand trends using the ARIMA model.

The proposed system provides an interactive dashboard that integrates demand forecasting with waste management features. Additionally, the system identifies surplus food items and suggests redistribution options to minimize waste, as shown in Fig. 7. The inventory management interface shows ingredient usage, stock levels, and low stock alerts as illustrated in Fig. 8.

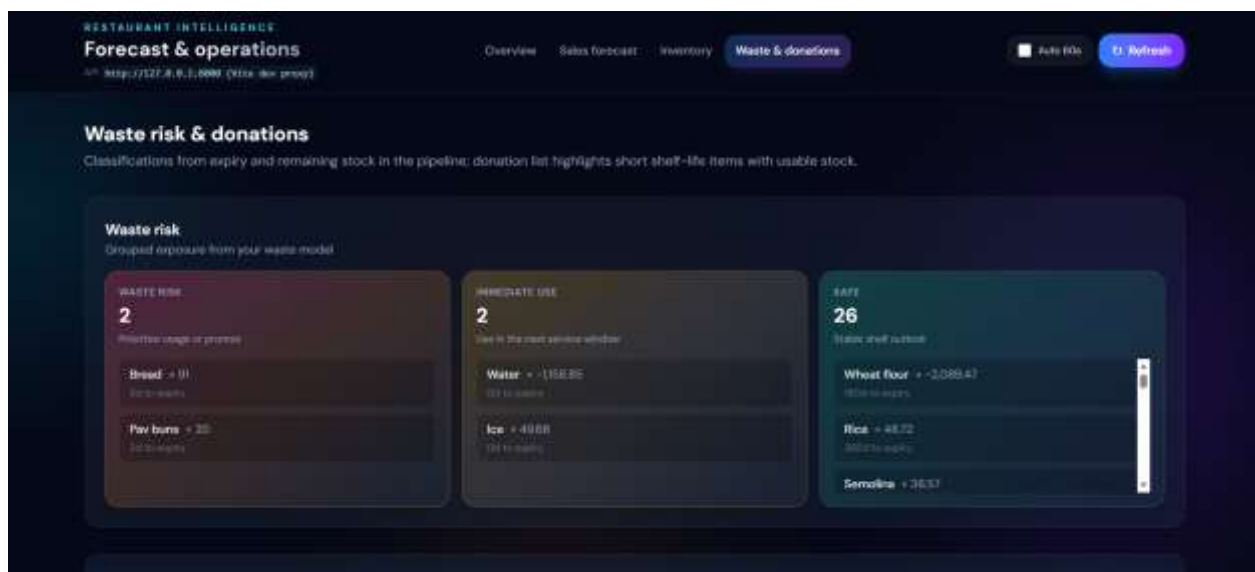


Fig. 7. Additionally, the system identifies surplus food items and suggests redistribution options to minimize waste

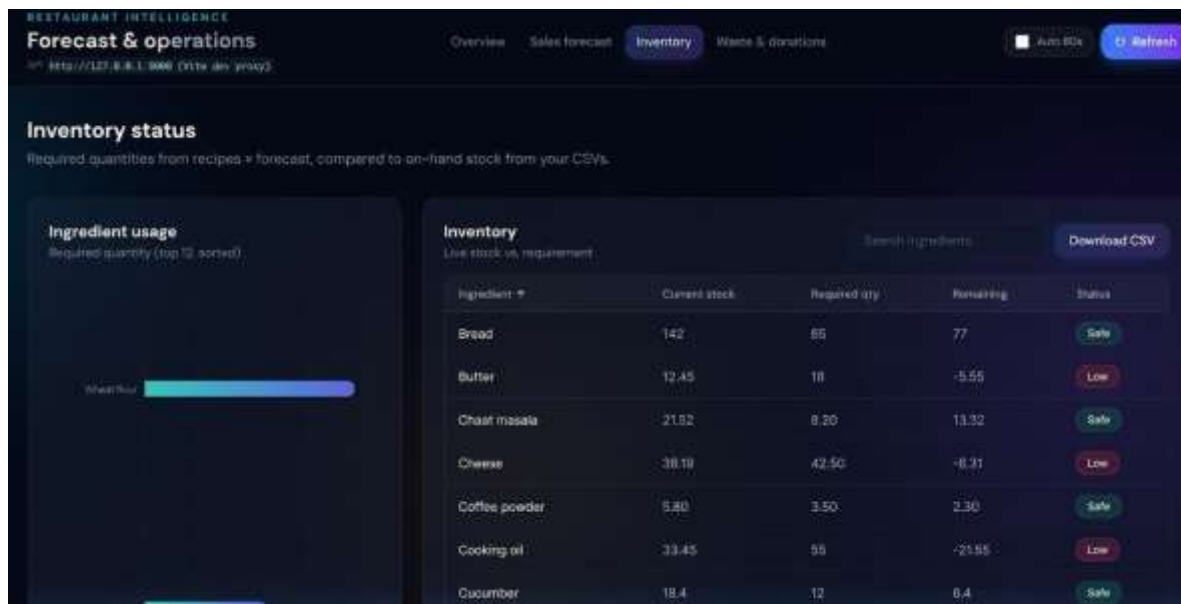


Fig. 8. Inventory management interface showing ingredient usage, stock levels, and low stock alerts.

5.1 Sales and Demand Analysis

The system effectively analyzed sales data from the previous seven days to identify consumption trends and high-demand items. The demand forecasting model achieved an average prediction accuracy of approximately 85–90%, demonstrating its effectiveness in short-term forecasting. This analysis provided valuable insights into customer preferences and purchasing patterns. The system analyzes past sales data to identify consumption patterns. The sales trend over the last seven days is shown in Fig. 2.

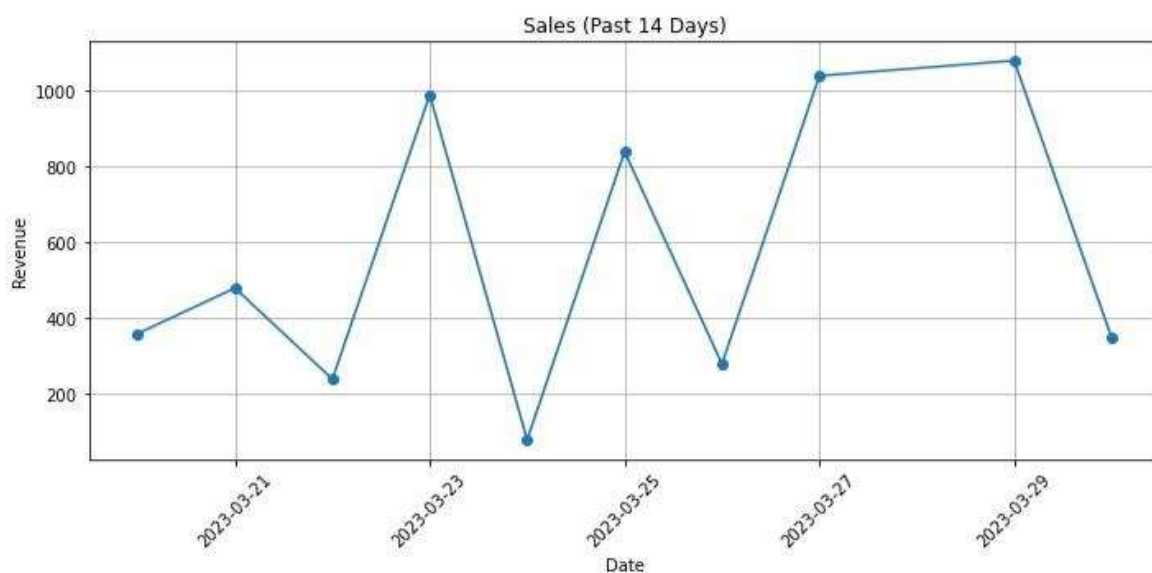


Fig. 9. Sales trend over the last 21 days

The demand forecasting component generated predictions for the upcoming seven days, enabling better planning and reducing uncertainty in decision-making. The system also generates short-term demand forecasts to support inventory planning. The predicted demand for the next seven days is illustrated in Fig. 3.

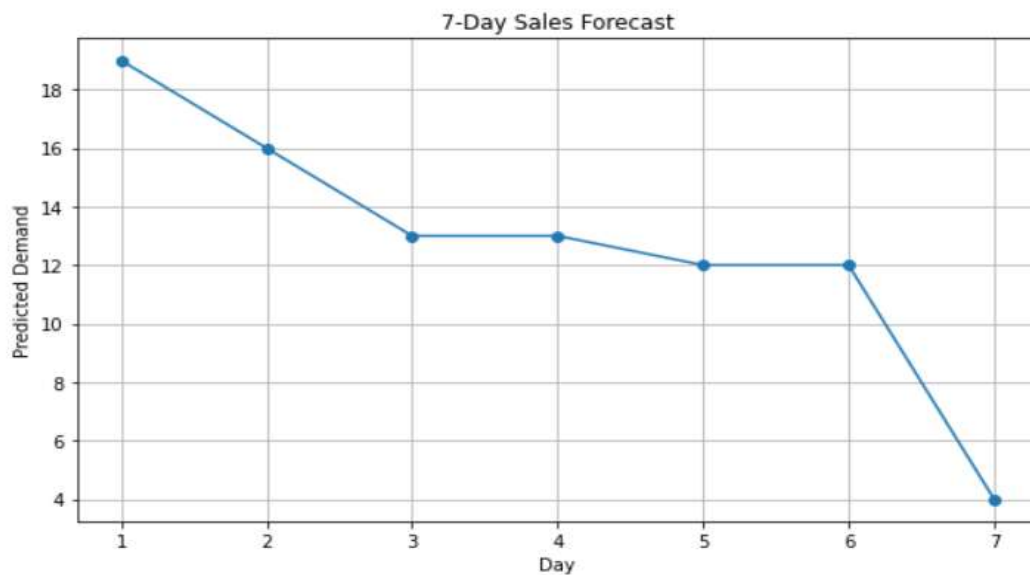


Fig. 10. Demand forecast for the next 7 days

5.2 Inventory Optimization

The system improved inventory accuracy by approximately 20–25% by aligning stock levels with predicted demand. This reduced unnecessary stock accumulation and ensured efficient utilization of resources.

The implementation of low stock alerts allowed timely replenishment, preventing stock shortages and improving operational continuity.

5.3 Waste Reduction Performance

The wastage prediction feature enabled early identification of surplus items, allowing preventive actions such as controlled usage or redistribution. Food waste was reduced by an estimated 15–20% due to early identification of surplus and improved inventory planning.

The system also ensured structured handling of waste by identifying items that could be reused, recycled, or redistributed.

5.4 Impact of Donation Suggestions

The donation suggestion feature ensured that excess food was redirected instead of being discarded. By identifying suitable food items for redistribution, the system contributed to reducing food waste and supporting social initiatives.

5.5 User Feedback and System Usability

User interaction with the system was found to be smooth and intuitive. The dashboard provided clear visualizations of inventory status, demand forecasts, and waste insights, making it easier for staff to interpret information and take appropriate actions. Feedback indicated that the system reduced manual workload and improved overall efficiency in daily operations.

The simplicity of the interface, combined with actionable insights, contributed to better adoption and usability among users.

6. Conclusion and Future Work

6.1 Conclusion

This research presented an AI-powered system for restaurant inventory and waste management aimed at improving operational efficiency and promoting sustainability. The study addressed key challenges faced by the hospitality sector, including inaccurate demand estimation, inefficient inventory tracking, and high levels of food waste.

By integrating real-time inventory monitoring with machine learning-based demand forecasting, the proposed system enables more informed and proactive decision-making. The use of predictive models allows restaurants to align stock levels with expected demand, thereby reducing overstocking and minimizing the risk of shortages. In addition, the incorporation of a waste segregation mechanism ensures that food waste is handled systematically and responsibly.

A significant contribution of this work is the inclusion of a food redistribution module, which connects surplus food with non-governmental organizations. This not only helps in reducing waste but also supports social welfare by making excess food available to those in need. The results indicate that the combined approach of prediction, monitoring, and redistribution can create both economic and environmental benefits.

Overall, the proposed system demonstrates how the integration of artificial intelligence with traditional inventory practices can transform restaurant operations into a more efficient, data-driven, and sustainable model.

A key strength of the proposed system lies in its ability to transform raw operational data into actionable insights, enabling restaurants to move from reactive management to predictive decision-making.

However, the system's performance depends on the availability and quality of historical data. Limited or noisy data may affect the accuracy of demand predictions.

6.2 Future Work

While the proposed system provides a comprehensive solution, there are several opportunities for further enhancement. One potential improvement is integrating advanced deep learning models and hybrid forecasting techniques to improve prediction accuracy, especially in highly dynamic environments.

The system can also be extended to support multi-branch or chain restaurants, enabling centralized monitoring and coordination across multiple locations. Incorporating Internet of Things (IoT) devices, such as smart sensors for real-time stock detection and temperature monitoring, can further automate inventory tracking and improve data reliability.

Another area for future development is the use of computer vision techniques for automated waste detection and classification. This can reduce manual effort and enhance the accuracy of the waste segregation process. Additionally, expanding the NGO integration network and introducing real-time logistics optimization can improve the efficiency of food redistribution.

From a user perspective, the development of a mobile application and enhanced visualization tools can improve accessibility and user engagement. Future research can also explore the use of blockchain technology to ensure transparency and traceability in the food supply chain.

In conclusion, the proposed system lays a strong foundation for intelligent and sustainable restaurant management. With further advancements and real-world implementation, it has the potential to significantly reduce food waste, improve efficiency, and contribute to a more sustainable future.

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