AI-Enabled Food Demand Forecasting and Waste Reduction System for Sri Lankan Restaurants

1st Anuradha Jayathunga
Department of Information Technology (Faculty of Computing) Sri Lanka Institute of Information Technology (SLIIT)
Malabe, Sri Lanka
it22642950@my.sliit.lk

2nd Nethum Thilakarathna
Department of Information Technology (Faculty of Computing) Sri Lanka Institute of Information Technology (SLIIT)
Malabe, Sri Lanka
it22073846@my.sliit.lk

Mr. Ravi Supunya
Department of Information Technology (Faculty of Computing) Sri Lanka Institute of Information Technology (Project Supervisor)
Matara, Sri Lanka
supunya.s@sliit.lk

Mrs. Chathurya Kumarapperuma
Department of Information Technology (Faculty of Computing) Sri Lanka Institute of Information Technology (Co-Supervisor)
Malabe, Sri Lanka
chathurya.k@sliit.lk

Abstract*— Small-to medium-sized restaurants in Sri Lanka encounter ambiguity in their demand owing to climate and cultural activities. They utilize manual estimation to plan their inventory, which leads to stock-outs and waste generation. In this study, an artificial intelligence-based system for forecasting and controlling inventory was developed. It predicts demand, transforms forecasts into ingredient purchases, and optimizes buffers using waste data. The proposed system has a hybrid forecasting mechanism using the Light Gradient Boosting Machine and Prophet algorithms, with temporal information supplemented by weighted fuzzy logic-based contextual mechanisms using NASA's Power API data and a local cultural calendar of Sri Lanka. The forecasted information is converted to ingredient demands via a recipe mapping mechanism with an adaptive buffer strategy that updates the safety stock based on wastage data and exponential smoothing. The proposed system is implemented with a Next.js/React front-end and Django back-end and evaluated based on MAE/RMSE/MAPE over 30 days. The findings show that the hybrid machine learning method provided better results than static buffers by providing accurate predictions and reducing waste.

Keywords: Food service demand variability, Context-aware inventory optimization, Hybrid machine learning forecasting, Adaptive safety stock management, Waste reduction strategies in restaurants

I. INTRODUCTION

For small- and medium-sized restaurants in Sri Lanka, the biggest operational hurdle is the unpredictable demand in the food service sector. This issue manifests as substantial fluctuations in customer numbers and demand for specific menu items, which are influenced by external factors such as climate change, cultural event schedules, and public holidays. These variations complicate the inventory management. Consequently, restaurant owners struggle to maintain optimal stock levels in their kitchens. Currently, inventory planning relies predominantly on manual estimation and record-keeping, which are often time-consuming and prone to errors. The absence of data-driven strategies frequently results in either shortages, leading to negative customer experiences and lost sales, or overproduction of food, culminating in waste and increased operational costs [1] [2].

Although inventory systems are available to facilitate the digitalization of processes, they are ineffective for small restaurants in developing countries because of their limitations [3]. Most traditional methods involve isolated forecasting efforts that attempt to predict future sales but fail to translate these predictions into accurate production plans. This disconnect between forecasting and inventory control leads to stock management inefficiencies. Furthermore, these systems function as standalone tools that do not receive essential feedback on their operations. As they do not account for actual food wastage in the kitchen or real-time consumption patterns, inventory buffer policies become ineffective over time, resulting in persistent mismatches between supply and demand [4]. Additionally, the lack of integration with local contextual factors further reduces the applicability of these systems in dynamic environments such as the food service sector in Sri Lanka.

Consequently, the proposed framework facilitates the development of forecasted demand and inventory for all specified scenarios within the local restaurant industry. Enhancements in the forecasting procedure were achieved by designing a robust data processing pipeline and implementing a highly effective hybrid machine-learning approach for demand forecasting. This approach uniquely incorporates temporal, cultural, climatic, and ingredient-related factors, thereby enabling more accurate and context-aware predictions than those of previous models. Furthermore, this study developed a novel adaptive buffering approach that dynamically adjusts inventory levels based on real-time feedback, thereby minimizing the shortages and waste. The integration of forecasting and inventory management creates a closed-loop system that continuously improves accuracy and efficiency. By leveraging local data and contextual factors, For Sri Lanka's small- and medium-sized restaurant sector, the framework delivers a scalable solution that handles its unique operational hurdles [5].

It is important to acknowledge that the innovation introduced in this study is substantially significant for the sustainable development of the industry. It facilitates the transition from prolonged manual calculations to automated forecast generation within the local restaurant domain, thereby improving operational efficiency and reducing food waste. The framework's adaptability to local conditions and feedback-driven inventory adjustments presents a practical pathway for small restaurants to embrace digital transformation without incurring prohibitive costs or complexities. This advancement not only addresses immediate operational challenges but also contributes to the broader goals of sustainability and resource optimization in the Sri Lankan food service sector [6].

Section II reviews the existing research on restaurant demand prediction and identifies key gaps. Section III explains the system design, method, mixed forecasting model and buffer algorithm. Section IV discusses the tests, results, and effectiveness. Finally, Section V presents the conclusions and future research ideas.

II. LITERATURE REVIEW

A. Machine Learning Approaches to Restaurant Demand Prediction

The evolution of demand forecasting in food services is well documented in the literature, from basic statistical methods to machine learning. Initially, ARIMA and exponential smoothing were used for sales time-series forecasting; however, these linear techniques often failed to predict accurately because the real-time demand was nonlinear [7] [8]. Recent studies show machine learning models like decision trees, Random Forest, LightGBM, and Facebook Prophet [9], [10] are effective with multivariate datasets, capturing complex patterns and improving accuracy over traditional methods. However, they rely on vast amounts of data, making them impractical for small-scale organizations that lack extensive historical data sets. Moreover, although some studies consider calendar factors, none have included intricate cultural calendar variables specific to Sri Lanka [11]. Incorporating such localized events could enhance forecasting models' ability to predict demand fluctuations unique to regional consumer behavior. This highlights the need for context-aware forecasting approaches that integrate data-driven techniques and culturally relevant information.

B. Inventory and Reorder Management

Early research on food sector inventory management emphasized two classic approaches: minimizing costs via the Economic Order Quantity (EOQ) and maintaining fixed safety stock levels [12]. By trading off holding expenses against ordering expenses, the EOQ calculations identify the ideal purchase quantity. Meanwhile, unchanging safety stock inventories absorb fluctuations in customer demand and supplier reliability. However, these approaches assume stable demand patterns and do not fully address the challenges of perishable goods, which require dynamic strategies.

In the digital era, inventory management systems have digitized these elements, enabling sophisticated monitoring and control. Modern systems use automated alerts to notify managers when stock levels drop, facilitating timely replenishment and reducing stockout or overstock risks [13]. This digitization enhances efficiency by providing real-time inventory visibility, streamlining procurement, and enabling data-driven decision-making.

Despite these advancements, many systems still use fixed rules and static parameters that are derived from traditional models. Research shows that static safety stocks inadequately manage perishable restaurant supplies, which spoil quickly and have a limited shelf life [14]. The fluctuating nature of daily food service demands complicates inventory management. Static safety stocks cannot adapt, leading to waste or lost sales.

Thus, there is a growing recognition of the need for adaptive and dynamic inventory management that responds to real-time data on demand variability, supply disruptions, and perishability issues. These approaches may use predictive analytics, machine learning, and dynamic safety stock calculations to continuously optimize inventory, balance cost efficiency with service quality, reduce waste and ensure availability.

C. Identified Research Gaps

A thorough critical review of the existing literature indicates two main research gaps. First, there is a conspicuous absence of synergy between demand prediction and ingredient inventory optimization. Most extant models consider forecasting as an independent module without dynamically translating forecasted menu sales into recipe-derived ingredient demands [15]. This separation limits the practical applicability of demand forecasts, as it fails to capture the complexity of the ingredient usage patterns associated with diverse menu items [16]. Second, the existing literature lacks operational feedback. In most instances, the inventory buffer is not adjusted based on the actual amount of waste produced during kitchen operations, resulting in static safety stocks that do not reflect the real-time performance or changing conditions of the kitchen environment. This study addresses these research gaps using a novel integrated model. Unlike the separate prediction methods adopted in previous studies, this model uses a simplified hybrid method that directly converts context-based forecasts into actionable plans, thereby bridging the gap between demand forecasting and inventory management. Moreover, it presents an innovative adaptive inventory buffer algorithm that continuously readjusts the target inventory based on actual waste, enabling a responsive and data-driven approach to inventory management that evolves with operational realities. This integration fosters improved resource utilization, cost savings, and sustainability in the kitchen.

III. METHODOLOGY

The architectural plan for deploying the new solution is organized into a carefully structured sequence of steps that integrates two primary components: a forecasting/predictive engine and an inventory management system. This design ensures a seamless interaction between predictive analytics and operational execution, allowing continuous data exchange and system adaptation. Central to this architectural strategy is the implementation of a continuous feedback loop, which distinguishes it from traditional isolated predictive algorithms by enabling ongoing refinement and real-time responsiveness throughout the inventory lifecycle.

A. System Architecture & Data Flow

This process chain starts with the storage of daily transactions. All of these details, together with time and weather variables, were used as inputs for the forecasting function to predict future demand on the restaurant menu. The predicted demand was then parsed by the kitchen production planning module, which maps menu item quantities to specific ingredient requirements using defined recipes. The inventory module calculates the required purchases based on these ingredient projections and dynamic buffer levels, passing actionable orders to the suppliers [17]. Finally, real unsold waste is captured and fed back into the system to automatically update the safety buffer policy [18].

B. Hybrid Forecasting Model

The first core component is a hybrid forecasting model tailored for small datasets typical of localized restaurants [19]. It adopts a dual approach to make these forecasts.

- Machine Learning Base Forecast: A straightforward machine learning model, LightGBM will be utilized to analyze historical sales data in conjunction with the day of the week and month [20].
- Rule Based Adjustment Engine: The second part of the system acts as a" human-logic" layer that refines the ML baseline by accounting for high-variance local events. This engine has been modernized to address the rigidity of standard rule-based systems.

  1. Fuzzy Logic Scaling: Instead of binary “if-then” triggers, this component employs Fuzzy Logic to process

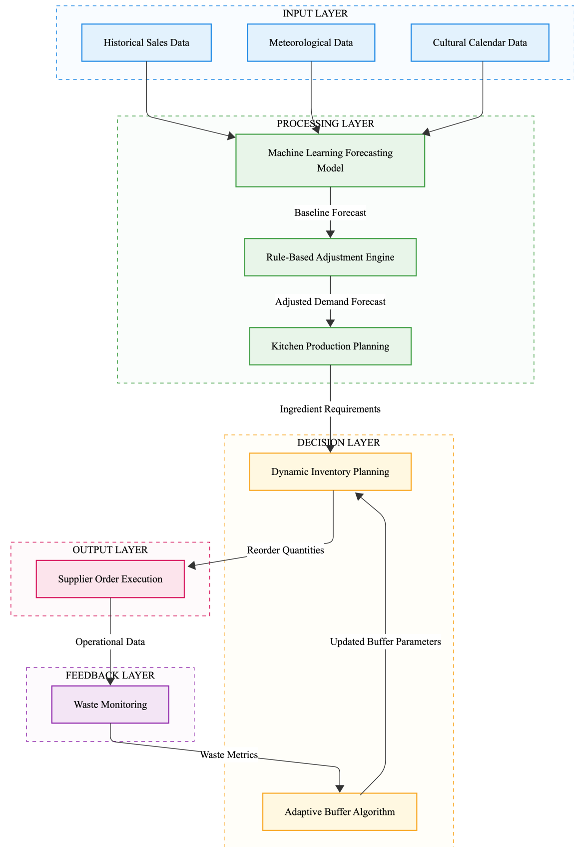

Fig. 1. Architecture of the forecasting and inventory management system.

environmental data. It incorporates real-time meteorological features (temperature and rainfall intensity obtained via NASA’s Power API) and a Sri Lankan cultural calendar. The system computes a continuous adjustment factor (δ), which scales demand proportionally to the intensity of events; for example, the forecast is gradually reduced as rainfall increases, rather than applying a single “on/off” multiplier [21].

  2. Weighted Integration and Conflict Resolution: To handle scenarios in which multiple factors overlap (for example, a major cultural festival occurring during a storm), the engine employs a Weighted Priority Hierarchy. Overlapping modifiers are balanced through a weighted average, preventing the” Final Forecast” from exceeding the restaurant’s actual physical capacity or inventory limits. [22] [23]. The final adjusted demand forecast was calculated as follows:

$$\hat{Y}_{final} = \hat{Y}_{base} \times \frac{\sum_{i=1}^{Z} w_i \delta_i}{\sum w_i}$$

In this equation, $\hat{Y}_{\text{final}}$ represents the calibrated baseline prediction generated by the ML core, which incorporates lagged and rolling features. The term δ_i denotes the fuzzy adjustment factor corresponding to each contextual event, whereas w_i represents the assigned weight that reflects the historical reliability of the respective rule. This formulation ensures a mathematically grounded forecasting approach tailored to the Sri Lankan context.

C. Adaptive Buffer Algorithm

The second fundamental component converts the optimized forecasts into tangible inventory actions. The system is constructed on a robust and scalable architecture, featuring a Next.js and React frontend that employs TypeScript for the user interface, in conjunction with a Django REST Framework (DRF) backend. The underlying data are managed within a PostgreSQL database, and Python-based machine learning models are serialized and loaded into the backend service using joblib.

- Dynamic Inventory Planning: The system computes the total required ingredient quantity from the menu forecasts. The target stock level is calculated dynamically as follows:

$$S_{target} = L_{reorder} + B_{size}$$

  Where S_{target} is the target stock level, $L_{reorder}$ is the baseline reorder level, and B_{size} is the active buffer size. The system then evaluates the projected remaining stock to categorize the risk status and automatically suggests purchase quantities.
- Adaptive Buffer Algorithm: To prevent static overpurchasing, the system features a waste-driven feedback mechanism. Menu waste is converted into ingredient-equivalent waste through recipe mapping. The algorithm calculates the target buffer based on the average daily waste (W_{avg}) over a configurable lookback window and the desired buffer days (D_{buffer}) as follows:

$$B_{target} = W_{avg} \times D_{buffer}$$

  To ensure operational stability and prevent volatile swings in purchasing, the system applies an exponential smoothing mechanism to update the final buffer policy as follows:

$$B_{new} = B_{old}(1-\alpha) + B_{target}\alpha$$

  where α is the smoothing factor that governs the update rate of the model. This allows the system to automatically adjust the safety buffers based on actual operational inefficiencies rather than rigid assumptions.

D. Implementation Technology Stack

This section describes the practical implementation of the system, including the processes involved in data preparation, the technical setup used for deployment, and the metrics designed to assess the predictive accuracy and operational viability of the system.

E. Dataset Collection and Preprocessing

The development of the hybrid forecasting module and assessment of the adaptive inventory buffer used a dataset from the historical data of small- and medium-sized Sri Lankan restaurants. This dataset includes daily sales, menu item transactions, and supplier invoices over 24 months. A standardized Sri Lankan cultural calendar was embedded to monitor public holidays, and daily temperature and precipitation data were collected using the OpenWeatherMap API. Preprocessing aligned data for time-series analysis and cleaning discrepancies in manually entered sales data in CSV files. The dates were standardized, and the sales per item were aggregated daily. Feature engineering-derived temporal features (e.g., day of the week, month) and computed rolling statistics (lag 1 and lag 7) [24].

F. Hardware and Software Environment

The system was created and assessed using a strongly decoupled software architecture built for scalability and minimization of operational costs.

- The backend development utilized the Django REST Framework (DRF) in conjunction with a PostgreSQL Database. The machine learning component was constructed within a Pythonic environment, employing the Pandas, NumPy, and Scikit-learn libraries to facilitate the management of LightGBM as the core predictive model. Facebook Prophet was employed exclusively during the research phase to validate seasonal assumptions but was not deployed in the final production system. The resulting LightGBM model was serialized as a .pkl file and integrated into the backend. The user interface was developed using Next.js, React, and TypeScript, with Tailwind CSS for styling.
- The computational models and backend testing were conducted on a system equipped with an AMD Ryzen 7 processor, 16GB of RAM, and an NVIDIA RTX 3060 graphics card.

G. Evaluation Metrics

A dual-metric evaluation strategy was used to ensure that the system achieved both the predictive and operational goals.

- Predictive accuracy was assessed for both the LightGBM baseline and hybrid models using the metrics of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) and MAPE (Mean Absolute Percentage Error). These metrics quantify the average magnitude of the errors, facilitating direct comparisons with the moving average baseline models.The system incorporates a Bias Correction layer and a Rule Engine to dynamically calibrate forecasts based on 32 unique Sri Lankan cultural events and real-time weather data from the NASA POWER API.
- Operational performance was assessed through two primary metrics. First, the latency time metric was employed to evaluate API performance, ensuring prompt updates to the Next.js dashboard regarding complex

inventory statuses, such as OK, low, and stock out. Second, the algorithm's performance was assessed by examining the percentage reduction of physical food waste per day in relation to the stock-out frequency over a 30-day simulation period [25].

IV. RESULTS AND DISCUSSION

This section provides a comprehensive evaluation of the effectiveness of the proposed AI-assisted system for demand forecasting and inventory management in restaurant settings. This study focuses on assessing the predictive accuracy of the hybrid model by analyzing key performance indicators across multiple datasets and highlighting its ability to outperform conventional forecasting methods. Furthermore, this section explores the operational impact of the adaptive inventory buffer, detailing how it dynamically calibrates stock levels in response to fluctuations in the predicted demand, thereby optimizing inventory turnover and minimizing the costs associated with overstocking and stock outs. The analysis also includes comparative insights across diverse restaurant environments to demonstrate the robustness and scalability of the system.

A. Evaluation Setup and Datasets

To assess the efficiency of the proposed system, comprehensive data on past sales, inventory levels, and waste generation were collected from 50 small- and medium-sized restaurants in Sri Lanka. This dataset spanned 24–48 months and provided a robust temporal scope for analysis. The data were systematically divided into two subsets: a training set constituting 80% of the total data, used to develop and calibrate the model, and a testing set comprising the remaining 20%, reserved for validating the system's predictive performance. To simulate real-world operations, a 30-day operational period was modeled, during which the responsiveness of the dynamic inventory buffer to the actual kitchen waste patterns was monitored and evaluated.

B. Forecasting Accuracy Results

The accuracy of the proposed hybrid model, which combines a LightGBM baseline with a Rule-Based Adjustment Engine, was rigorously evaluated against standalone models and traditional moving average baselines. The hybrid approach proved particularly effective during "rare events" such as religious holidays, where standard models lack sufficient historical data to learn complex interactions, such as the 60% drop in meat sales during Vesak.

As shown in Table II, the hybrid model achieved a significant improvement over the standalone LightGBM model, which recorded a MAPE of 9.93% on the same test set. In terms of predictive reliability, the hybrid system demonstrated a superior accuracy of 90.07%, outperforming the 87.60% accuracy achieved by the standalone LightGBM model.The integration of the Sri Lankan cultural calendar and localized weather data through the rule-based engine enabled the model to accurately capture demand surges. Furthermore, the hybrid approach offers enhanced interpretability, allowing stakeholders to see exactly which rules (e.g., weather adjustments or pre-holiday effects) influenced a specific forecast.

Furthermore, the hybrid approach offers enhanced interpretability by explicitly modeling the influence of known demand drivers, thereby providing actionable insights beyond mere predictive accuracy. This interpretability is crucial for stakeholders who require transparent and explainable forecasting models to make informed operational decisions. The results underscore the potential benefits of combining data-driven machine learning techniques with expert knowledge encoded in rule-based systems to improve the accuracy and usability of demand forecasting models in culturally sensitive contexts.

TABLE I
PERFORMANCE COMPARISON OF BASELINE MODELS

Model Name	MAE	MAPE(%)
LightGBM (Standalone)	7.21	12.4
Facebook Prophet	8.42	14.2
Moving Average (Baseline)	9.49	16.8

TABLE II
COMPARATIVE PERFORMANCE: STANDALONE LIGHTGBM VS. HYBRID MODEL

Model Architecture	MAE	RMSE	MAPE (%)
LightGBM (Standalone)	7.21	9.87	12.40
Proposed Hybrid Model	**6.04**	**8.14**	**9.93**

C. Inventory Performance and Waste Reduction

The primary strength of the system lies in its ability to translate accurate forecasts into substantial waste reduction, thereby enhancing economic and environmental results. During the 30-day simulation, the adaptive buffer algorithm consistently adjusted the overall reorder levels in response to simulated daily kitchen waste, demonstrating a dynamic, data-driven approach to inventory control. As illustrated in Figure 2, this waste-responsive feedback mechanism resulted in a significant reduction in the total food waste of 25% to 35% compared with the traditional static buffer methods commonly employed by restaurants. Notably, this decrease in overproduction did not compromise service quality, as the stockout rate remained below 5%, ensuring that customer demand was met reliably. To elucidate the detailed functioning of this algorithm, Figure 3 highlights the performance of a single high-volatility ingredient, fresh seafood. When a simulated cultural event triggered a sudden increase in demand, the ingredient-specific buffer was recalibrated within 48 h, demonstrating the system's ability to respond rapidly to unexpected market fluctuations. This demonstrates the system's capability to autonomously detect and rectify anomalies while maintaining cost-effectiveness and ensuring customer satisfaction. Collectively, these features underscore the potential of adaptive buffering to transform inventory management practices by balancing waste minimization and service excellence in the food industry.

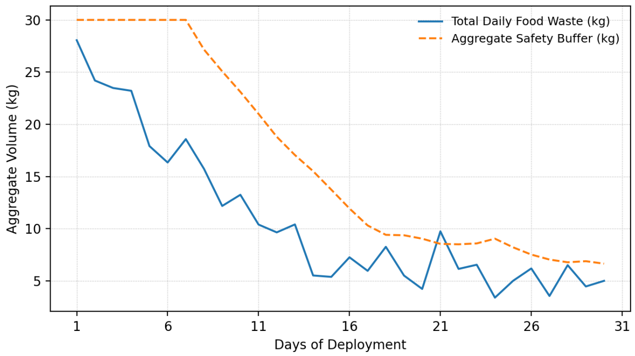

Fig. 2. Daily food waste vs. adaptive safety stock buffer over 30 days.

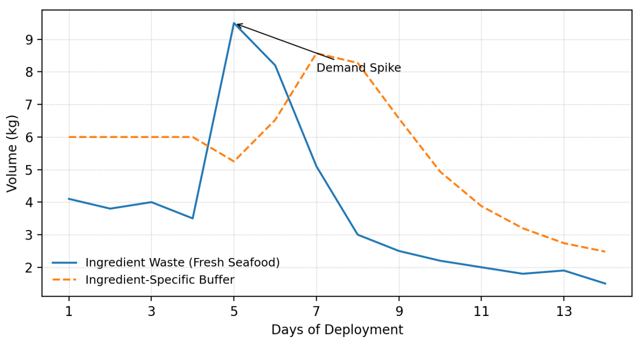

Fig. 3. Adaptive buffer recovery for seafood during demand spike.

D. Discussion and Operational Feasibility

The results validate the practical use of this system in Sri Lankan food service operations, thereby demonstrating its effectiveness in real-world scenarios. Leveraging cost-effective scalability technologies, such as PostgreSQL and open-source Python libraries, the system offers a feasible alternative to costly enterprise ERP solutions, which are often inaccessible to small- and medium-sized healthcare service providers. The Next.js frontend, which translates complex metrics into simple "OK/Low/Out" indicators, addresses low digital literacy, ensuring that users can interpret and act on recommendations without advanced knowledge.

Several challenges arose during implementation that need to be addressed to optimize performance. The primary issue was the inconsistent data quality in historical logbooks, which are critical for accurate predictions. Common problems included manual entry errors, missing invoices, and incomplete records, which necessitated extensive preprocessing. This underscores the need for active user involvement and stringent data management to maintain integrity and ensure long-term success. Training users on proper data recording and integrating automated validation can help mitigate these issues.

This study highlights end-to-end integration, distinguishing it from research on standalone models. An unexpected finding was the hybrid forecaster's enhanced accuracy and ability to correct minor errors via an adaptive waste-driven feedback loop. By treating kitchen waste as active data input, the system demonstrates sustainable inventory management as a continuous process, allowing dynamic adjustments based on real-time feedback, reducing waste, and improving resource allocation efficiency of the system. Such feedback mechanisms represent a significant advancement toward resilient and responsive operations.

V. Conclusion

This study introduced an AI-assisted framework for demand forecasting and inventory management, specifically designed for small-to medium-sized restaurants in Sri Lanka. The system managed demand fluctuations from local cultural events and weather changes by combining a machine-learning model with a weighted fuzzy-logic engine. This study goes beyond traditional analytics by proposing an adaptive inventory buffer algorithm. This algorithm adjusts the safety stock levels by tracking daily kitchen waste and using exponential smoothing. The results showed that this hybrid method enhanced forecasting accuracy compared to static models, decreased food waste, and improved procurement efficiency without increasing food shortage risk. This architecture offers a sustainable and cost-efficient digital solution by integrating AI forecasting into kitchen operations.

Although the findings are encouraging, this study has some limitations. First, the accuracy of the machine learning module is limited by the quality of historical data, which is often obtained from manually maintained logbooks that are prone to errors. Second, the cultural calendar is deterministic; it manages major holidays but does not adapt to unexpected micro-events. Finally, the inventory planning module uses generalized buffer logic and does not fully consider shelf life degradation rates for perishable items, thereby affecting waste metrics.

Future investigations should focus on enhancing data independence and prediction precision. Integrating the architecture with POS systems and supplier APIs would automate data collection and eradicate manual input error. Embedding shelf-life decay models into the buffer algorithm would enable ingredient-specific safety-stock optimization. Examining localized IoT devices in kitchens can automate waste tracking, relieve staff from manual logging, and establish a sustainable inventory system. Leveraging machine learning on real-time data streams improves system adaptability to unforeseen demand patterns, enhancing responsiveness to market shifts. The development of a feedback loop could facilitate continuous self-optimization, allowing the framework to evolve with changing restaurant environments. These advancements would contribute to a more resilient and intelligent inventory management solution tailored to dynamic restaurant operations.

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