Optimization of Food Inputs in Restaurants in Metropolitan Lima Through Prediction and Monitoring Based on Machine Learning

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Abstract: This work presents the development of a web-based monitoring and prediction system designed to optimize food supply in restaurants in Metropolitan Lima, addressing challenges such as efficient inventory management and food waste reduction. The solution employs six Machine Learning models (Random Forest, Gradient Boosting, Ridge Regression, Lasso Regression, Linear SVR, and Neural Network), evaluated using accuracy metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Among the models, Gradient Boosting demonstrated the best performance, with an MSE of 0.0032, RMSE of 0.057, and MAE of 0.027, outperforming the others in terms of accuracy, including Neural Network and Random Forest, which also offered competitive results. While the approach was developed in the specific context of Metropolitan Lima, the applied methods and obtained results can be adapted to other urban markets with similar dynamics, demonstrating broader applicability. This system not only promotes more efficient and sustainable inventory planning, but also contributes to the economic growth of restaurants by optimizing resources and improving their profitability in a highly competitive environment.

1 INTRODUCTION

This article addresses inefficient inventory management in restaurants in Metropolitan Lima, a problem that generates food waste and affects the economic and environmental sustainability of these establishments. According to the United Nations (2019; as cited in Wu & Teng, 2022), approximately one third of the food produced globally is wasted each year, which equates to large-scale economic and environmental losses, so improving accuracy in purchasing planning is crucial.

Existing solutions to improve inventory management in restaurants have explored various Machine Learning techniques, showing their potential in resource optimization. In the study carried out by Wu and Teng (2023), a machine learning system was implemented in a restaurant chain in Peru, managing to reduce food waste from 200-400 kg per day to just 115 g per customer in a standard buffet. However, despite the advances made in the implementation of Machine Learning solutions for inventory management, the adaptation of these tools to specific contexts such as that of Metropolitan Lima remains a challenge, mainly due to the variability in consumption patterns and the quality of the available data. In addition, most current models lack mechanisms to automatically adjust and are not designed to adapt to fluctuations in demand, which can lead to situations of oversupply or shortage of inputs, limiting their effectiveness in dynamic environments.

This work proposes a web-based prediction system adapted to local needs, which integrates not only a single algorithm, but several Machine Learning models. These models will be dynamically adjusted based on consumption statistics and patterns, allowing the system to optimally adapt to the specific conditions of each restaurant, thus optimizing the supply of inputs and reducing waste.

The following sections of the paper will address the state of the art, system design, results, discussions, conclusions, and future projections.

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2 RELATED WORKS

Several studies highlight the importance of advanced technologies in optimizing supply chains in the food sector. Dadi et al. (2021) highlights the use of machine learning and other digital tools to reduce human intervention and improve accuracy in data management, resulting in a significant reduction in waste and optimization of response times. Along these lines, Islam et al. (2021) present a demand forecasting approach along with an optimization model that increases supply chain efficiency by 15% and reduces costs by 10%, by minimizing uncertainty in supplier selection and order allocation. In addition, Birkmaier et al. (2022) propose an advanced forecasting system that reduces historical data bias by 75%, allowing for better synchronization between supply and demand for perishable products, which increases in-store quality and optimizes inventory freshness. Finally, the study by Beheshti et al. (2022) introduces a closed supply chain model in peri-urban areas, which increases the waste collector's expected profits by 30% and improves the profitability of the chain through the application of recycling techniques and flexibility contracts.

On the other hand, reducing waste in the food supply chain has been a key objective in several recent studies. Birkmaier et al. (2022) show that an advanced forecasting system can prevent waste generation by optimizing the synchronization between supply and demand, which considerably reduces the volume of discarded food. Sharma et al. (2022) integrates smart devices such as the e-nose, e-eye, and e-tongue to monitor food quality in real time, achieving a 30% decrease in food waste thanks to the implementation of this technology. Meanwhile, Herron et al. (2022) implement a "First Expire, First Out" (FEFO) management model to reduce losses in the retail trade of perishable products, showing that after 8 hours at more than 4°C, the risk of loss of product shelf life increases by 43.8%. Similarly, Kumar (2023) implements machine learning to improve the accuracy of demand prediction, which allows reducing food waste, with a decrease in prediction error, achieving an RMSE of 18.83 and an MAE of 14.18 in his predictions.

Furthermore, advances in demand prediction techniques have proven to be essential for effective inventory management in the food sector, allowing companies to anticipate supply needs and adjust their strategies. Posch et al. (2022) employ Bayesian modeling methods and generalized additive models (GAMs), achieving a mean absolute error (MAD) of 2.681 and a root mean square error (MSE) of 14.133 in predicting food and beverage sales in restaurants, which is significantly higher than traditional approaches. Likewise, Migueis et al. (2022) use long-term memory neural networks (LSTM) to forecast demand for fresh fish, achieving an RMSE of 27.82 and a MAE of 20.63, which reduces inventory buildup and improves accuracy in stock levels. Finally, the study by Makridis et al. (2023) implements a prediction system for food safety using time series and NLP, achieving a mean square error (MSE) of 0.922 in predicting food recalls, thus optimizing food safety and inventory management.

By synthesizing these findings, this work underscores the importance of integrating advanced forecasting systems, waste reduction strategies, and demand prediction techniques to develop a comprehensive and adaptive solution for inventory management. Unlike previous approaches, which often focus on isolated elements or specific contexts, this research combines multiple machine learning models into a unified framework that allows for dynamic adjustments to varying conditions.

3 SYSTEM DESIGN

3.1 Architecture

The logical architecture of the web system has been designed to optimize the prediction and monitoring of the supply of inputs in restaurants in Metropolitan Lima.

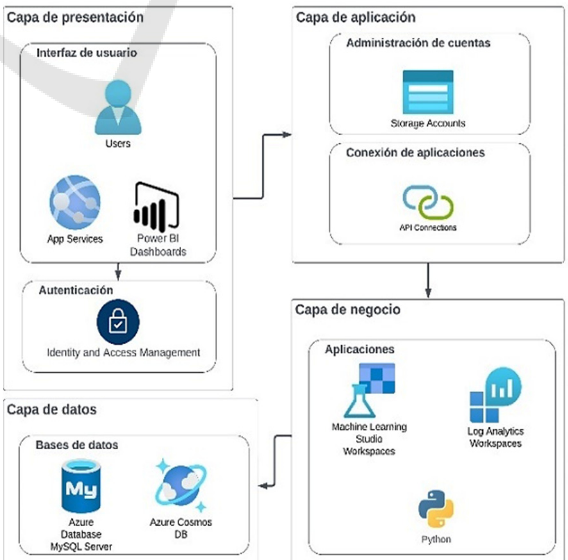

Figure 1: Logical architecture of the web system.

Figure 1 explains that the solution effectively integrates advanced technologies such as Machine Learning, Python, and Azure cloud platforms, strategically distributed across four layers: Presentation, Application, Business, and Data. On the other hand, with the implemented machine learning algorithms, the system allows an accurate prediction of demand, which contributes to improving inventory planning and reducing the loss of inputs. In addition, the platform offers an interface accessible from web and mobile devices, supported by Power BI for the visualization of data in real time, which facilitates continuous and detailed monitoring. In the backend, processes are automated, and alerts are implemented that simplify data-driven decision making. Finally, the infrastructure has been designed to be scalable and adaptable to the changing needs of the restaurant sector, ensuring efficient and sustainable management of food inputs.

3.1.1 Presentation Layer

The presentation layer is designed to offer an accessible and dynamic user experience through Azure App Services. Users interact with the application from this interface, which can be either a web app or a mobile app. In addition, dashboards generated by Power BI are integrated into this layer, providing interactive visualizations and detailed reports on system performance, based on information stored in databases. This layer allows users to manage the system and visualize data efficiently and securely.

3.1.2 Application Layer

The application layer acts as an intermediary between the presentation and business/data layers. It ensures that user requests are handled correctly. In this layer, APIs are controlled to handle requests to the database and other external services. Storage Accounts provide secure storage of files and documents that may be required for the application, while API Connections allow integration with other external services, such as payment gateways or authentication services.

3.1.3 Business Layer

In this layer, data is processed and business rules that define the application logic are executed. Data processing is done using Python, which also handles predictions and advanced calculations using machine learning algorithms. To ensure robust processing, platforms such as Machine Learning Studio Workspaces are integrated, which allows prediction models to be trained and deployed. In addition, the application status is continuously monitored using Log Analytics Workspaces to ensure performance and detect any possible anomalies or errors.

3.1.4 Data Layer

The data layer stores all the information necessary for system operation, including user configurations, roles, transactions, and historical records. Azure Cosmos DB provides a highly scalable system for managing non-relational data and real-time data, while Azure Database MySQL Server manages structured relational data. Data is synchronized and analyzed to generate reports in Power BI, which connects to dashboards and provides key visualizations for administrators.

3.2 Methodology

3.2.1 Dataset

The dataset initially consisted of synthetic data created to simulate typical restaurant sales patterns, sourced from publicly available information, industry reports, and general sales trends. This synthetic data included daily sales figures, types of dishes sold, preparation times, and inventory management details, providing a foundation for testing and refining the initial machine learning models. Once the initial model was developed, it was validated with real data extracted from the sales and inventory systems of a restaurant. The real dataset spans a full year and incorporates both seasonal trends and variations in demand, offering a more accurate representation of the restaurant's operations. This combination of synthetic and real data allowed for a thorough evaluation of the system's ability to adapt to actual conditions, enhancing the reliability of the results and ensuring that the model could effectively optimize inventory management and reduce food waste in a real-world setting.

3.2.2 Model

The model implemented for the prediction and monitoring of food supply in restaurants in Metropolitan Lima is based on a machine learning approach that integrates various algorithms to maximize the accuracy of the predictions. This framework follows a data flow that ranges from the initial collection of information to the visualization of results in real time.

In this context, data preprocessing plays a crucial role, as it ensures the quality of the information used for model training. This process involves data cleaning, which removes duplicate entries and corrects errors, as well as normalizing values and transforming categorical variables into numerical ones.

3.2.3 Indicators

The success indicators used in evaluating model accuracy are based on common prediction error metrics, each with its own particular characteristics.

Table 1 below describes the indicators that will be used to evaluate the system's performance and its effectiveness in predicting and monitoring the supply of inputs in restaurants. These metrics are essential to ensure that the system meets the established objectives and can make adjustments in real time based on the results obtained.

Table 1: List of indicators to assess the accuracy of the prediction.

Metrics	Description	Equation
Mean Squared Error (MSE)	Calculates the average of the squared errors between the predicted values and the actual values. It penalizes large errors, useful for normal distributions. (IBM, 2024)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$
Root Mean Squared Error (RMSE)	It is the square root of the MSE, representing the errors in the same units as the predicted values. It facilitates interpretation by users. (IBM, 2024)	$RMSE = \sqrt{\frac{\sum(y_i - \tilde{y}_i)^2}{N - P}}$
Mean Absolute Error (MAE)	Calculates the average of the absolute differences between predicted and actual values, without giving extra weight to large errors. (IBM Cognos, 2024)	$MAE = \frac{1}{n}\sum_{i=1}^{n}(\lvert Y_i - \hat{Y}_i\rvert)^2$

3.2.4 Training

To begin training the model, extensive data preprocessing was performed, including cleaning, normalization, and transforming categorical variables into numerical ones, ensuring that the model could optimally learn from the information provided. In addition, several machine learning algorithms were implemented, including Random Forest, Gradient Boosting, Ridge Regression, Lasso Regression, Linear SVR, and neural networks (MLP).

Finally, the performance of each model was evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), which allowed comparing and selecting the most efficient model for predicting food input demand. This comprehensive approach not only optimizes the Machine Learning model, but also contributes to more effective supply management in the restaurant.

3.2.5 Interfaces

The web-based prediction and monitoring system interface, developed in Azure, offers an intuitive and dynamic environment designed to optimize workflow and usability. Users can interact with dashboards displaying key data such as supply levels, consumption trends, and demand forecasts. These visualizations provide a clear overview, helping users make informed decisions about inventory and procurement. A key feature is the Machine Learning algorithm module, which shows performance metrics and enables users to assess prediction accuracy. As new data is added, the system automatically compares the updated predictions, allowing users to adjust parameters and improve future forecasts.

The interface also includes an alert system that notifies users if discrepancies are detected between the model's predictions and the incoming data, signaling when adjustments may be needed. This allows for timely intervention and ensures more accurate predictions. Additionally, the system is flexible and customizable, adapting to specific restaurant needs and evolving demand patterns. Accessible across a range of devices, the interface provides a scalable solution for efficient inventory management and waste reduction.

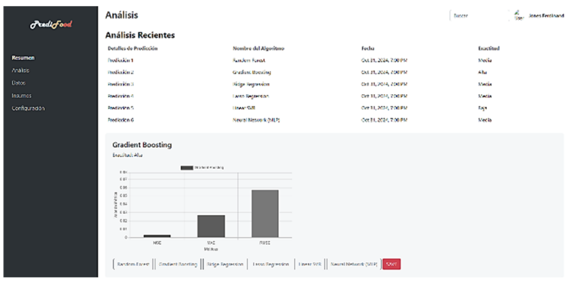

Figure 2: Summary of prediction percentages with machine learning.

4 RESULTS

This section shows the results obtained by evaluating six selected Machine Learning models: Random Forest, Gradient Boosting, Ridge Regression, Lasso Regression, Linear SVR, and Neural Network (MLP). These models were trained and evaluated to predict inventory demand in restaurants, seeking to reduce food waste and optimize purchase planning. The evaluation metrics used include the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), which measure the performance of each model in terms of accuracy and adaptive capacity.

4.1 Results Table

Table 2 presents the results of the metrics for each of the evaluated models. This table highlights the MSE, RMSE and MAE values, which allow the error in the predictions of each model to be quantified. These results directly inform the prediction of ingredient quantities needed for optimal restaurant inventory management.

Table 2: List of results according to indicators.

Models	MSE	RMSE	MAE
Random Forest	0.0035	0.059	0.028
Gradient Boosting	0.0032	0.057	0.027
Ridge Regression	0.0045	0.067	0.031
Lasso Regression	0.0043	0.065	0.030
Linear SVR	0.0050	0.071	0.034
Neural Network (MLP)	0.0037	0.061	0.029

The values obtained in MSE, RMSE, and MAE reveal that the Gradient Boosting model obtained the lowest values in all the metrics, indicating a minimum error in the inventory demand predictions. These percentages are instrumental in calculating the necessary ingredients for various dishes, enabling a more precise weekly forecast of their required quantities. The Random Forest and Neural Network (MLP) models also show competitive performance, albeit with slight increases in the error metrics compared to Gradient Boosting.

4.2 Metric Comparison Charts

To visually illustrate the performance of the models, several graphs were generated that allow a detailed comparison of the MSE, RMSE and MAE metrics between the evaluated models.

4.2.1 Bar Chart for MSE

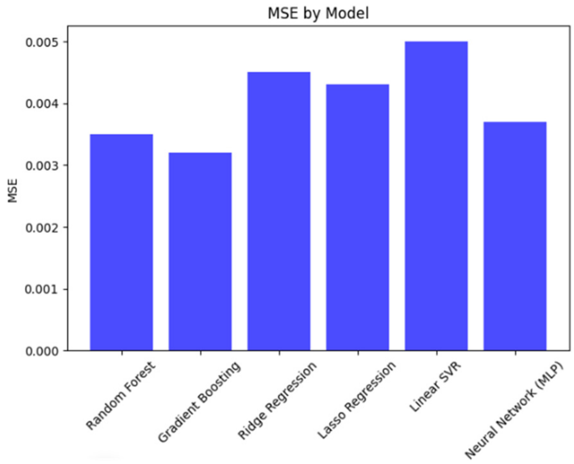

Figure 3: Comparison of Mean Squared Error (MSE) between Models.

Figure 3 shows the mean squared error (MSE) values for each model. This graph shows that Gradient Boosting and Random Forest have the lowest MSE values, suggesting a greater ability of these models to minimize squared errors in their predictions. This implies that compared to other models, Gradient Boosting and Random Forest are more effective in the accuracy of their estimates, which is crucial for informed decision making in the context of data analysis.

4.2.2 Bar Chart for RMSE

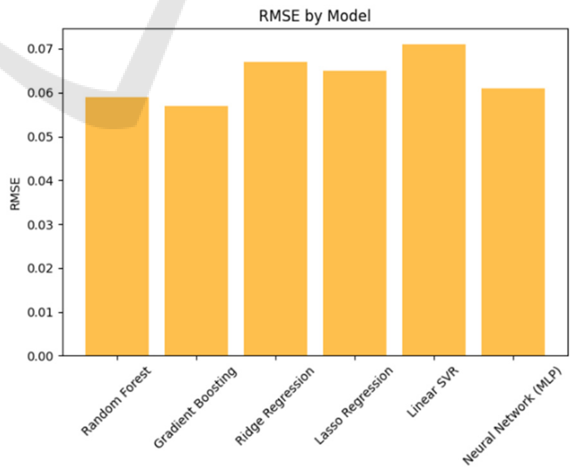

Figure 4: Root Mean Squared Error (RMSE) Analysis for Prediction Accuracy.

Figure 4 presents the root mean square error (RMSE) values, which reflect the average of the squared errors on the same scale as the data. Gradient boosting keeps the RMSE lowest, making it the model with the most accurate prediction, closely followed by random forest and neural network (MLP).

4.2.3 Line Chart for MAE

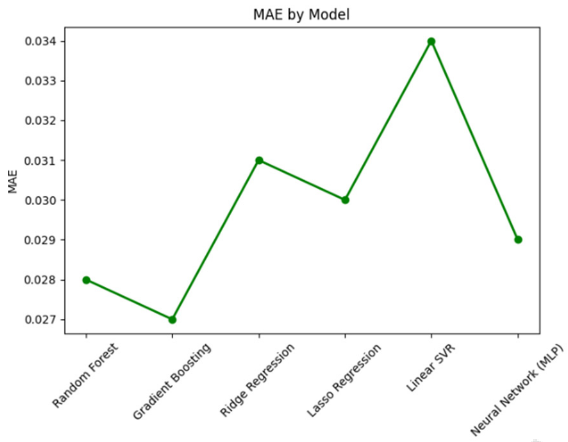

Figure 5: Mean Absolute Error (MAE) Evaluation in Inventory Forecasting.

In Figure 5, the Mean Absolute Error (MAE) values for each model are shown, providing a clear view of the average absolute errors. Gradient Boosting and Random Forest stand out again with low values, suggesting their effectiveness in minimizing absolute errors in inventory demand predictions. This level of precision supports better planning for weekly ingredient needs, helping estaurants avoid overstocking and reducing waste.

4.2.4 Scatter Plot for Comparison of MSE and RMSE

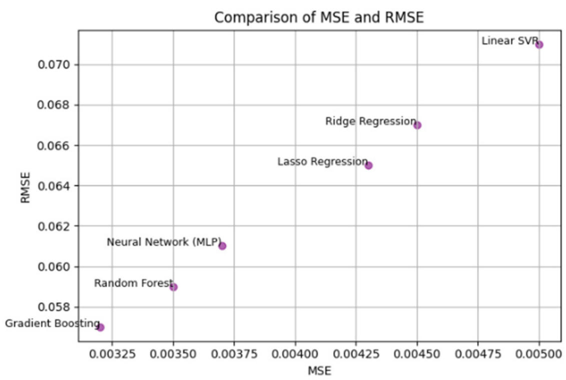

Figure 6: Scatter Plot: Relationship between MSE and RMSE in Models.

Figure 6 presents a scatterplot comparing the Root Mean Square Error (MSE) and Root Mean Square Error (RMSE) for each model, highlighting the relationship between these two error metrics. Gradient Boosting and Random Forest exhibit consistency by maintaining low values across both metrics. This reliability in prediction accuracy further enhances the ability to forecast ingredient requirements efficiently, ensuring smoother inventory management.

4.2.5 Grouped Bar Chart for MAE and RMSE

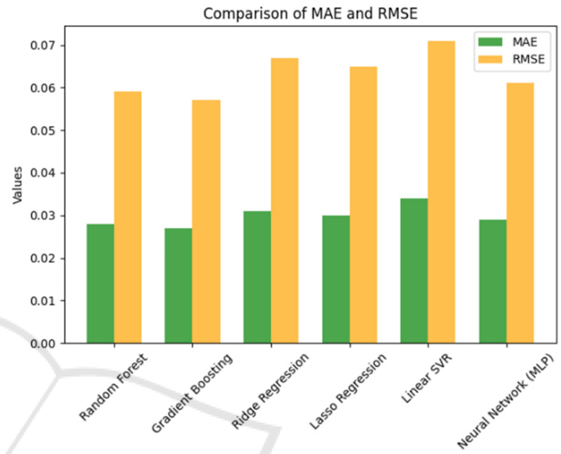

Figure 7: Comparison of MAE and RMSE Metrics in Evaluated Models.

Figure 7 presents a scatterplot comparing the Root Mean Square Error (MSE) and Root Mean Square Error (RMSE) for each model, highlighting the relationship between these two error metrics. It is observed that Gradient Boosting and Random Forest maintain low values in both metrics, demonstrating consistency in the accuracy of the predictions.

5 DISCUSSIONS

The results of this work demonstrate significant improvements in demand prediction and inventory management in restaurants in Metropolitan Lima, surpassing in accuracy studies such as Kumar et al. (2023), which achieved an RMSE of 18.83 and an MAE of 14.18. Our system employs models such as Gradient Boosting and Random Forest, which automatically adjust to daily variations, optimizing supply and reducing waste of inputs, which distinguishes it from previous approaches, such as the Bayesian model of Posch et al. (2022) with an MSE of 14.133, or the system of Birkmaier et al. (2022), which reduces historical biases in perishable data by 75% but lacks local adaptability. This solution not only contributes to existing knowledge in inventory prediction but could also be implemented in other food sector environments, such as hotels, where input optimization is key to reducing costs and increasing sustainability.

6 CONCLUSIONS

This work demonstrates the effectiveness of a prediction and monitoring system for optimizing the supply of inputs in restaurants in Metropolitan Lima, achieving a significant reduction in food waste and an improvement in inventory management. The implementation of Machine Learning provides an accurate estimate of demand, adapting to consumption variations and the particularities of the restaurant sector. The advantages of this system include more efficient resource planning and a positive impact on the operational and economic sustainability of establishments. However, the limitations of the system lie in its dependence on data quality and its adjustment to specific patterns, which could require further improvements to increase its adaptability. The results can be applied to inventory optimization in other food sectors, and future research could integrate new data sources and improve the automation of the system, thus increasing its impact on the sustainability of the sector.

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