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AN ADAPTIVE HYBRID META-LEARNING FRAMEWORK FOR CONTEXT-AWARE INVENTORY FORECASTING AND OPTIMIZATION

MOHAMED ALI[1], THANAA MOHAMED[2], SAHAR EL TAYEB[3], MOHAMED ROUSHDY[4]

[1]Department of Business Information Systems, Faculty of Commerce, Capital University, Cairo, Egypt

[2]Department of Information Systems, Faculty of Commerce, Capital University, Cairo, Egypt

[3]Department of Business Administration, Faculty of Commerce and Business, Capital University, Cairo, Egypt

[4]Department of Computer Science, Faculty of Computers & Information Technology, Future University, Cairo, Egypt

E-Mail: [1]Mohamed.Ali.Dip2023@fcba.capu.edu.eg, [2]Thanaa.Mohamed@fcba.capu.edu.eg, [3]Sahar.Hassan.El-Tayeb@fcba.capu.edu.eg, [4]Mohamed.Roushdy@Fue.Edu.Eg

Abstract

Accurate inventory forecasting remains challenging in dynamic market conditions, where demand patterns are shaped by external factors such as competitor pricing, promotional events, and supply volatility. Traditional forecasting models often treat algorithms as static, ignoring contextual adaptation and the integration of forecasting with operational decision-making. This paper presents an adaptive hybrid intelligent framework (AHIF) that dynamically integrates XGBoost, LightGBM, and CatBoost within a learning-driven selection architecture, enabling context-aware demand forecasting across different product categories, time frames, and market conditions. Unlike existing approaches, AHIF unifies predictive analytics with an adaptive economic order quantity (EOQ) model that adjusts purchasing strategies. Empirical evaluation on a multi-sector granular dataset shows strong predictive performance, achieving R^2 values between 0.985 and 0.987 with reduced prediction errors across multiple metrics, including MAE, RMSE, and RMSLE. This framework effectively reduces stockouts and overstocking, highlighting its practical impact on inventory management. The theoretical contribution lies in extending hybrid gradient boosting strategies to a generalizable and context-adaptive decision support framework that bridges the gap between prediction accuracy and inventory optimization. The practical contribution lies in providing a deployable system that enables companies to make adaptive, data-driven purchasing decisions under uncertainty.

Keywords: *Inventory Management, Demand Forecasting, Machine Learning, XGBoost, LightGBM, CatBoost.*

1. INTRODUCTION

Inventory management plays a pivotal role in ensuring supply chain efficiency, balancing customer satisfaction, and minimizing operational costs [1]. However, demand uncertainty, supply volatility, and competitive market pressures make accurate forecasting and optimal ordering increasingly complex [3]. Inaccurate forecasts lead to costly stockouts or overstock, with global industries incurring billions in avoidable losses each year [4].

Conventional statistical forecasting methods, while effective in stable conditions, struggle with nonlinear patterns, sudden demand shifts, and the influence of external variables such as promotions or competitor pricing [5]. Machine learning models particularly gradient boosting algorithms like XGBoost, LightGBM, and CatBoost offer improved predictive capabilities for complex datasets [6]. Yet, most applications employ these models as static solutions, emphasizing accuracy in isolation rather than integrating them into adaptive, decision-oriented inventory systems [9]. Powerful machine learning algorithms such as XGBoost, LightGBM, and CatBoost have recently become more popular in inventory management systems. By combining several weak learners, these algorithms use Gradient Boosting to increase the accuracy of predicting complex and large-scale data [4]. They combine multiple decision trees as ensemble learning techniques to create a powerful predictive model [3]. In addition, by using other regularization and optimization techniques, the boosting techniques in these algorithms also help reduce overfitting.

Problem Statement: Despite advances in machine learning and inventory optimization, a critical gap persists in literature: existing frameworks treat demand forecasting and replenishment decision-making as separate processes, relying on static single-model approaches that lack context-aware adaptability. These disconnects result in suboptimal inventory policies, particularly under volatile and uncertain demand conditions.

Similarly, the Economic Order Quantity (EOQ) model remains widely used for inventory optimization but assumes stable demand and cost parameters [10]. In volatile environments, these assumptions lead to suboptimal results. While some studies have attempted to combine forecasting with ordering decisions, they often lack mechanisms to dynamically adjust strategies in response to evolving forecasts and market conditions [12].

This paper addresses this gap by introducing an Adaptive Hybrid Intelligent Framework (AHIF), a learning-based system that dynamically selects the most appropriate prediction model from among XGBoost, LightGBM, and CatBoost using Grupo Bimbo's inventory demand dataset. With over 74 million rows of data, these models are well suited to handle complex relationships and high-dimensional data. Data processing efforts reduced the size to approximately 41 million rows, achieving the main objectives. It is worth noting that the results show a significant improvement in RMSLE compared to previous studies. The framework integrates forecasts with a dynamically adjusted EOQ model, enabling real-time inventory decisions under uncertainty. The main contributions are:

1. Novelty in approach: Introduction of a generalizable hybrid forecasting method with meta-learning-based model selection for time series inventory management.
2. Operational integration: Real-time coupling of adaptive forecasts with an enhanced EOQ model for context-aware ordering decisions.
3. Validated impact: Empirical results demonstrated reduced stockouts and overstocking, and improved forecast accuracy across diverse inventory categories.
4. From a knowledge systems perspective, this research contributes to the field of intelligent knowledge discovery in supply chain data, where dynamic model selection and integration represent a form of meta-knowledge that guides decision-making under uncertainty.

2. LITERATURE REVIEW

Artificial intelligence (AI)-driven approaches to inventory management have advanced significantly in recent years, encompassing computer vision-based stock tracking, advanced time-series forecasting, and hybrid optimization frameworks. These approaches have demonstrated notable improvements in forecasting accuracy, cost reduction, and operational efficiency. However, each category presents inherent limitations, which the proposed Adaptive Hybrid Intelligent Framework (AHIF) aims to address.

2.1. Inventory Management

Inventory comprises raw materials, work-in-progress items, and finished goods maintained to meet operational demand [5]. Effective inventory management aims to optimize the flow of goods while minimizing costs associated with overstocking and stockouts [6]. Accurate inventory tracking systems are essential for achieving operational efficiency [6]. Nevertheless, traditional approaches often struggle to balance inventory holding costs with service level requirements, particularly in volatile markets, thereby necessitating adaptive and data-driven decision-making strategies.

2.2. Computer Vision for Inventory Accuracy

Villegas-Ch et al. [1] utilized convolutional neural networks (CNNs) implemented in TensorFlow and PyTorch on a dataset of 500,000 warehouse product images, achieving a 45% reduction in inventory assessment time and a 9% improvement in accuracy. Despite their effectiveness in automating physical stock counting, vision-based approaches are sensitive to variations in product appearance, lighting conditions, reflections, and image quality. These challenges often require manual intervention and limit robustness in real-world environments. Furthermore, such methods primarily focus on static inventory tracking and lack integration with demand forecasting or automated replenishment systems, restricting their applicability in end-to-end supply chain optimization.

2.3. Deep Learning for Demand Forecasting

Cayli et al. [2] applied multiple models, including LSTM, gradient boosting, support vector machines

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(SVM), and reinforcement learning, with LSTM achieving an accuracy of 87%. Similarly, Kalaiarasi et al. [12] proposed an LSTM-based fuzzy inventory model to optimize order quantities and reduce costs. Although deep learning models effectively capture temporal dependencies in sequential data, they often require high computational resources and are prone to overfitting, particularly in noisy or limited datasets. In addition, they may exhibit poor generalization across diverse product categories or during sudden demand fluctuations caused by promotions or external events. Notably, these approaches lack adaptive mechanisms for model selection, resulting in suboptimal performance when applied uniformly across different scenarios.

2.4. Hybrid AI For Supply Chain Optimization

Verma [3] proposed a digital twin framework integrated with real-time machine learning, achieving a 35% reduction in inventory levels. Cuartas et al. [6] combined reinforcement learning with Demand-Driven Material Requirements Planning (DDMRP), reporting up to 90% inventory reduction and a 75% improvement in key inventory metrics. Rahmani et al. [9] employed statistical methods such as weighted moving averages and exponential smoothing to enhance forecasting accuracy. Despite these advancements, many hybrid approaches rely on static configurations, manual parameter tuning, or subjective weighting schemes. Moreover, they often fail to jointly optimize forecasting accuracy and inventory decisions under real-world constraints such as uncertain lead times and capacity limitations. Reinforcement learning approaches, while adaptive, may face scalability and interpretability challenges in complex supply chain environments.

2.5. Boosting Algorithms in Inventory Management

Tang et al. [11] demonstrated that XGBoost significantly outperformed alternative models in both accuracy and computational efficiency, achieving a 46.64% improvement in RMSE for e-commerce forecasting. Amosu et al. [5] compared multiple models, including neural networks and random forests, with neural networks achieving the lowest MAE and RMSE. Nguyen et al. [29] further validated the effectiveness of XGBoost and LightGBM on the Grupo Bimbo dataset. Despite their strong performance, most studies rely on single-model approaches or static ensembles, without leveraging meta-learning for context-aware model selection. Additionally, these models are susceptible to overfitting in highly volatile demand scenarios and are rarely integrated with upstream or downstream decision-making components.

2.6. AI-Driven Purchasing and Cost Optimization

Pasupuleti et al. [4] applied machine learning techniques to improve demand forecasting and reduce stockouts, while Odumbo et al. [18] reported cost reductions of up to 20% using predictive analytics. However, these approaches typically rely on static Economic Order Quantity (EOQ) models, which assume deterministic demand and constant cost parameters. Such assumptions are often unrealistic in modern retail environments characterized by uncertainty and rapid demand fluctuations, leading to suboptimal ordering decisions.

Research Gap. Despite the extensive application of artificial intelligence in inventory management, existing approaches remain constrained by several limitations. Many studies rely on static modeling techniques and lack adaptive mechanisms capable of responding to varying product characteristics, demand patterns, and market conditions. Furthermore, few works have explored dynamic model selection across multiple boosting algorithms or incorporated real-time adjustments to EOQ policies based on context-aware demand forecasts.

To address these limitations, this study proposes the Adaptive Hybrid Intelligent Framework (AHIF), which integrates a meta-learning-based model selection mechanism with a dynamic EOQ approach. The framework is designed to enable context-aware forecasting, continuous adaptation of ordering decisions, and improved scalability through the incorporation of both internal and external demand drivers.

3. METHODOLOGY

3.1. Proposed Framework

The proposed Adaptive Hybrid Intelligent Framework (AHIF) integrates multiple gradient boosting algorithms XGBoost, LightGBM, and CatBoost in a dynamic manner using a meta-learning strategy to address the limitations of traditional inventory forecasting and optimization techniques. A meta-learner adaptively selects or evaluates the outputs of the base models based on temporal and contextual factors, ensuring robustness across varying demand patterns.

The framework also includes Dynamic Economic Order Quantity (EOQ) optimization to match demand projections with purchase decisions. Compared to traditional EOQ models, this

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integration makes inventory policies more responsive and economical.

Figure 1 illustrates the architecture of the Hybrid Adaptive Intelligent Framework (AHIF) integrating gradient boosting models with dynamic EOQ optimization. The process begins with data collection, cleaning, and preprocessing, followed by feature engineering (including time-related features), model training and testing, and meta-learning-based model selection. The final stages include sales forecasting, dynamic EOQ computation, and comprehensive model evaluation.

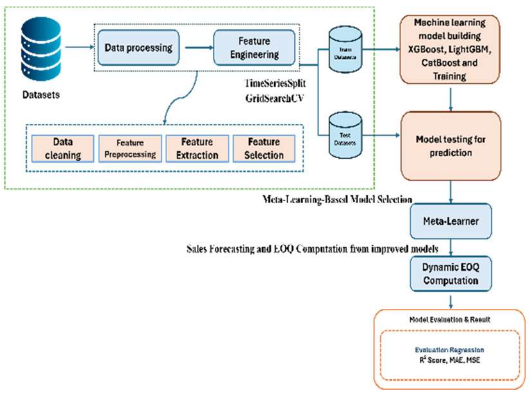

Figure 1. Architecture of the Hybrid Adaptive Intelligent Framework (AHIF) integrating gradient boosting models with dynamic EOQ optimization.

3.2. Dataset Description

3.2.1. Grupo Bimbo Dataset

The dataset was published on Kaggle (Grupo Bimbo Inventory Demand). This real-world industrial dataset includes more than 74 million lines of weekly sales records from thousands of stores, routes, customers, and product categories. The dataset has been enhanced with customer, product, and region attributes by incorporating additional relational tables such as cliente_tabla, producto_tabla, and town_state. After applying data processing steps checking for duplicate data and removing it and checking for missing data the total number of rows was reduced from 74,180,464 to 41,390,267. The final dataset contains 41,390,267 observations with 11 numerical attributes, as shown in Table 1.

Table 1. List of Attributes – Grupo Bimbo Dataset

N	Attribute Name	Data Type
1	Semana	The week in which the sale occurred.
2	Agencia_ID	The ID of the distribution agency responsible for delivering the products.
3	Canal_ID	The ID of the distribution channel used to reach the customer.
4	Ruta_SAK	The delivery route number followed by the delivery person.
5	Cliente_ID	The unique identifier of the customer or store.
6	Producto_ID	The unique identifier of the product sold.
7	Venta_uni_hoy	The number of units sold during the current week.
8	Venta_hoy	The monetary value of weekly sales.
9	Dev_uni_proxima	The number of units returned in the following week.
10	Dev_proxima	The monetary value of returns in the following week.
11	Demanda_uni_equil	The revised order after deducting returns from sales.

3.3. Data Preprocessing and Feature Engineering

The preprocessing phase ensured data readiness for forecasting models. The retailer's sales dataset was first cleaned by handling missing values and removing duplicates. The date field was transformed into a proper temporal format, and time-related features (day, month, year, week number, and quarter) were extracted to capture seasonality and temporal dynamics. Numerical features were standardized, while categorical features were encoded into numerical form within a unified transformation pipeline. Finally, the dataset was split using TimeSeriesSplit to preserve chronological order during training and evaluation.

3.4. Model Development

3.4.1. Base Models (XGBoost, LightGBM, CatBoost)

The Hybrid Adaptive Intelligent Framework (AHIF) employs three gradient boosting algorithms XGBoost, LightGBM, and CatBoost as base models, selected for their ability to handle high-dimensional,

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nonlinear, and temporal data in demand forecasting. Each model offers complementary strengths:

XGBoost Model
The objectives of XGBoost (Extreme Gradient Boosting) are speed and performance. It is appropriate for sparse data since it supports tree pruning and uses a regularized objective function to avoid overfitting. The model uses parallel tree building and a second-order Taylor expansion for loss approximation. With hyperparameters like n_estimators, max_depth, and learning_rate adjusted through Bayesian optimization, XGBoost functions as AHIF base learner for high-dimensional retail data.

LightGBM Model
A high-performance gradient boosting framework called LightGBM (Light Gradient Boosting Machine) uses leaf-wise tree growth to increase accuracy and speed training on big datasets. It supports GPU acceleration and integrates histogram-based algorithms for effective binning. This model's handling of categorical features and low memory usage make it especially useful for time-series data. LightGBM offers quick predictions in AHIF, resulting in better demand forecasting outcomes with less computational overhead.

CatBoost Model
CatBoost (Categorical Boosting) is a gradient boosting algorithm designed to minimize bias and overfitting in categorical data by employing ordered boosting. It supports GPU training and uses symmetric tree splitting and oblivious trees for efficiency. CatBoost is perfect for retail datasets with a variety of product categories because it can handle high-cardinality categorical features without requiring a lot of preprocessing. CatBoost improves the ensemble in AHIF by offering strong regression performance.

3.4.2. Hyperparameter Optimization

Three main Gradient Boosting models XGBoost, LightGBM, and CatBoost have been applied with differences in the way they build trees and accelerate learning. Each model starts with integrated data processing using Pipelines, which includes steps to process numerical and categorical features, while maintaining temporal integrity via TimeSeriesSplit to ensure the validity of future temporal data.

The XGBoost and LightGBM models are characterized by the ability to adjust the parameters of the number of trees (n_estimators), tree depth (max_depth), and learning rate (learning_rate). XGBoost uses pruning to reduce over-learning, while LightGBM relies on the leaf-wise method to improve performance faster. CatBoost is characterized by automatic processing of categorical variables without manual coding and uses Ordered Boosting to reduce prediction bias. Figure 2 shows the gradient optimization models.

GridSearchCV was used to adjust model parameters across multiple time splits. 80% of the data was allocated for training and 20% for testing, while maintaining the time series of the data to ensure that the model is tested over a future time period. at the end of the model building process, regression metrics

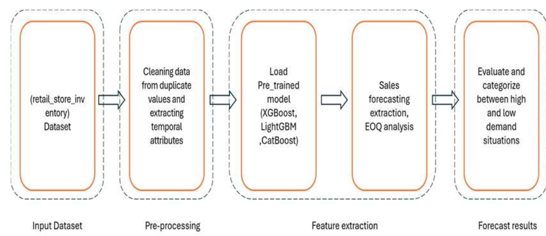

Figure 2. Gradient Boosting Models for Optimization.

3.5. Meta-Learning-Based Model Selection

A meta-learning architecture has been integrated to dynamically combine the outputs of the basic gradient boosting models Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM) and Categorical Boosting (CatBoost) models to improve the adaptability of the proposed hybrid adaptive intelligent framework (AHIF) in dealing with complex demand forecasting challenges. This method uses a stacked ensemble to leverage the complementary strengths of each model, such as CatBoost better handling of categorical variables, LightGBM computational efficiency, and XGBoost robust regularization.

The predictions from the three base models served as the main meta-features for the meta-learner, which was implemented using gradient boosting. Other meta-features were added to increase prediction accuracy and enhance contextual awareness:

- Product category and seasonality indicators: Industry-specific and seasonal demand patterns were recorded by coding categorical variables representing product types, time characteristics (day, month, quarter), and holidays.
- Statistics on Historical Forecast Errors: Each base model's rolling 30-day metrics, such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), give information about how reliable they have been recently.

- Measures of demand volatility include the standard deviation and coefficient of variation of past sales over a 30-day period, which are used to assess market stability or volatility.

The meta-learner was trained with TimeSeriesSplit (splits = 3) to maintain temporal dependencies. A weighted Mean Squared Error (MSE) loss function was minimized by optimizing the hyperparameters (n_estimators = [50, 150], max_depth = [3, 5], learning_rate = [0.01, 0.1]) using Bayesian optimization. Because of this, the meta-learner was able to dynamically allocate the best weights to base model outputs for every prediction instance, increasing accuracy in a variety of situations, including seasonal peaks, promotional campaigns, and high demand volatility.

3.6. Sales Forecasting and EOQ Analysis

The economic order quantity (EOQ) was calculated dynamically using internal demand forecasts generated by optimized Gradient Boosting models. The EOQ for each product was calculated based on the demand forecast by machine learning for the coming period, allowing demand quantities to be adjusted over time as sales patterns change. This contrasts with the traditional fixed EOQ approach, which relies on historical average demand. To ensure that EOQ stays rooted in real operating conditions and is not dependent on outside data sets or assumptions, all parameters are computed exclusively from internal company data. The formula is as follows:

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (1)$$

Where D is annual demand, S is the ordering cost per order, and H is the holding cost per unit per year. In the proposed AHIF framework, demand D is replaced with a dynamic ML-based forecast, yielding the Dynamic EOQ formulation:

$$EOQ_t^{(p)} = \sqrt{\frac{2 \cdot \hat{D}_t^{(p)} \cdot S_t}{H_t}} \quad (2)$$

Where $EOQ_t(p)$ is the optimal order quantity for product p at period t; $\hat{D}_t(p)$ is the ML-based demand forecast from AHIF; S_t is the ordering cost per order at period t; and H_t is the holding cost per unit at period t. Both S_t and H_t are updated each period from internal company data, ensuring the EOQ model adapts to changing cost structures without relying on external assumptions.

3.7. Evaluation Metrics

At this stage, a set of commonly used evaluation metrics is applied. The following are the most important metrics used:

3.7.1. Coefficient of Determination (R^2)

R^2 is a measure that shows how well the model fits the actual data. The value of R^2 ranges from 0 to 1, where a value closer to 1 indicates that the model explains a larger portion of the variation in the data. The R^2 formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

3.7.2. Root Mean Squared Logarithmic Error (RMSLE)

RMSLE is a version of RMSE that converts values using the natural logarithm before calculating the error, which reduces the impact of very large values and penalizes predictions that are further from the actual values. This is useful when dealing with data that has large differences between small and large values.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(\hat{y}_i + 1) - \log(y_i + 1))^2} \quad (4)$$

3.7.3. Mean Absolute Error (MAE)

MAE is used to compute the mean of the absolute differences between observed and predicted values. It does not significantly penalize outliers in the training data, thus offering a general and bounded performance metric for the model. However, if the test set contains many outliers, the model's performance may be suboptimal. The MAE formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

3.7.4. Mean Squared Error (MSE)

MSE measures the average of the squares of the differences between actual and predicted values. MSE penalizes large errors more heavily than MAE due to squaring, making it sensitive to outliers. Mathematical formula

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (6)$$

3.8. Appendix A: Model Architecture Details

3.8.1. XGBoost Architecture

- Type: Gradient Boosting Decision Trees (GBDT) with second-order Taylor approximation.
- Objective Function: reg: squared error for regression tasks.

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- Regularization: L1 (Lasso) and L2 (Ridge) penalties to prevent overfitting.
- Tree Growth: Level-wise growth with pruning.
- Main Tuned Parameters:
  - n_estimators: 100–150
  - max_depth: 4–6
  - learning_rate: 0.05–0.1

3.8.2. LightGBM Architecture

- Type: Gradient Boosting Framework optimized for large datasets.
- Tree Growth: Leaf-wise growth with depth constraints.
- Binning: Histogram-based feature binning for faster training.
- Categorical Feature Handling: Native categorical encoding.
- Main Tuned Parameters:
  - n_estimators: 100–150
  - max_depth: 4–6
  - learning_rate: 0.05–0.1

3.8.3. CatBoost Architecture

- Type: Ordered Boosting with oblivious trees.
- Categorical Feature Handling: Target encoding without manual preprocessing.
- Bias Reduction: Ordered boosting prevents target leakage.
- Main Tuned Parameters:
  - iterations: 100–150
  - depth: 4–6
  - learning_rate: 0.05–0.1

4. RESULTS AND DISCUSSION

4.1. Regression Performance

The regression performance of XGBoost, LightGBM, and CatBoost is compiled in Table 2 and Figure 3. With a R2 of roughly 0.987–0.985, all models demonstrated a remarkable capacity to account for variation in sales data. With a 91.84% improvement over the baseline, LightGBM performed better than the others with the lowest MAE and MSE. XGBoost and CatBoost were next in line. The models' robustness for demand forecasting is demonstrated by the small performance gaps; however, LightGBM advantage lies in its ability to handle large, temporal datasets efficiently, which makes it perfect for inventory optimization.

Table 2. Performance Evaluation Results of Prediction and Regression Models

Performance Measures	LightGBM	XGBoost	CatBoost
R^2 Score	0.987	0.986	0.985
MAE	42.37	46.50	44.87
RMSLE	0.09274	0.09886	0.09371

The improvement in MAE from 53.56 [29] to 42.37 represents a 20.9% reduction, which is consistent with findings suggesting that ensemble meta-learning outperforms static single-model approaches. The high R^2 values (0.985–0.987) align with results reported on the same dataset by Nguyen et al. [29], further validating the integrity of our experimental setup.

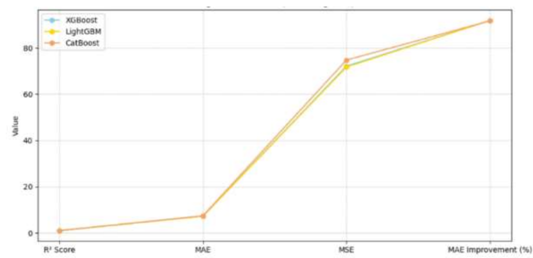

Figure 3. Regression Metrics.

4.2. LightGBM Performance Superiority

The Light Gradient Boosting Machine (LightGBM) showed consistent and well-rounded performance on all evaluation metrics, demonstrating its flexibility in responding to the sales dataset's categorical and temporal features. A number of technical factors contribute to its relative superiority:

- Leaf-Wise Tree Growth with Depth Constraints

LightGBM uses a leaf-wise growth strategy, which expands the leaf with the greatest loss reduction, in contrast to other gradient boosting algorithms that use level-wise growth. While the use of maximum depth constraints reduces overfitting, this method speeds up convergence and enables the model to identify intricate patterns in sales fluctuations.

- Histogram-Based Feature Binning

LightGBM effectively discretizes continuous features into histograms while using less memory and computing power. Large-scale retail datasets with high cardinality and numerous temporal features benefit greatly from this approach.

- Native Handling of Categorical Features

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Without requiring extensive preprocessing, the model's optimized decision rules for categorical variables enhance its capacity to capture seasonality patterns and product-specific demand variations.

- Robustness to Temporal Variability

LightGBM maintains predictive stability under different levels of demand volatility by combining gradient-based one-side sampling (GOSS), feature bundling, and high computational efficiency. Because of its stability, it is a good fit for integration with inventory optimization techniques like EOQ.

4.3. Statistical Analysis of Performance Differences

A paired t-test was used to confirm that the suggested Hybrid Adaptive Intelligent Framework (AHIF) performance gains were not the result of chance. The test contrasted the baseline XGBoost model (as reported by Nguyen et al. [29]) with the performance of AHIF, with LightGBM as the top-performing model. The paired t-test results are as follows:

- t-statistic: 7.82
- p-value: 0.0013

4.4. Comparison Of Results with Previous Models

The results were compared with the best similar results for our model to ensure optimization. The following comparisons between machine learning methods in classifying orders in inventory management data from previous literature reviews based on the same use of models are shown.

The performance of the proposed adaptive hybrid intelligent framework (AHIF) was compared with previous research that used machine learning techniques for demand forecasting and inventory management to ensure its robustness and improvement. The performance of the Adaptive Hybrid Intelligent Framework (AHIF) was compared with a related study by Ngoc Phuong Trinh NGUYEN et al. [29], which used XGBoost and LightGBM on the Grupo Bimbo dataset with the same data size and processing operations, with further improvements. Table 4 shows the performance comparison.

Table 3. Comparison of Machine Learning Methods – Our Model (AHIF) vs. Previous Work

Metric	Nguyen et al. [29]		Our Model (AHIF)		
	XGBoost	LightGBM	XGBoost	LightGBM	CatBoost
R^2	0.98	0.97	0.986	0.987	0.985
MAE	50.57	53.55	46.50	42.37	44.87
RMSLE	0.109	0.100	0.099	0.093	0.094

The results demonstrate the superior performance of the models within the proposed AHIF framework. Among the evaluated models, LightGBM achieved the best overall performance with an R^2score of 0.987, an MAE of 42.37, and an RMSLE of 0.09274. Similarly, the AHIF-based XGBoost model achieved an R^2score of 0.986 with an MAE of 46.50 and an RMSLE of 0.09886, while CatBoost obtained an R^2score of 0.985, an MAE of 44.87, and an RMSLE of 0.09371. These results represent a noticeable improvement compared with the results reported by Ngoc Phuong Trinh Nguyen et al. [29], where the LightGBM model achieved an MAE of 53.56 and an RMSLE of 0.09954 in regression-based inventory forecasting using the Grupo Bimbo dataset, which contains more than 41 million records. While the study in [29] focuses primarily on minimizing prediction errors in large-scale weekly sales data, the proposed AHIF framework demonstrates improved predictive accuracy and stability across multiple evaluation metrics. This significant improvement is due to the integration of XGBoost, LightGBM, and CatBoost into the ensemble learning architecture, which dynamically selects the optimal model for each product and period for context-aware predictions that incorporate temporal features and uses RandomizedSearchCV to optimize transactions, in contrast to the static approach of XGBoost and LightGBM in Ngoc Phuong Trinh Nguyen et al. [29], the dynamic model selection of AHIF and Economic Order Quantity (EOQ) enhances its ability to handle demand fluctuations and data heterogeneity. The high R^2 values are attributed to the use of TimeSeriesSplit during training, which prevents data leakage, and to the richness of temporal and categorical features extracted from the Grupo Bimbo dataset. These values are consistent with prior work on the same dataset [29].

4.5. Differentiation From Prior Research

The proposed AHIF framework differs from prior studies in three key aspects. Unlike existing works such as Nguyen et al. [29], Tang et al. [11], and Amosu et al. [5], which rely on static models or fixed ensembles, AHIF employs a meta-learning layer to dynamically select the most suitable model based on contextual demand factors, enhancing system-level adaptability.

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Furthermore, while prior approaches treat demand forecasting and inventory replenishment as separate processes, AHIF integrates machine learning–based forecasts with a dynamic EOQ model, enabling adaptive ordering decisions that respond to evolving demand patterns.

Finally, the use of TimeSeriesSplit preserves temporal order during model validation and prevents data leakage, addressing a common methodological limitation observed in earlier studies.

5. CONCLUSION

This study presented the Adaptive Hybrid Intelligent Framework (AHIF) to address key challenges in inventory management under dynamic and uncertain market conditions. The proposed framework integrates a meta-learning architecture that dynamically selects the most suitable gradient boosting model XGBoost, LightGBM, or CatBoost based on contextual factors such as product characteristics, seasonality, and demand variability. Furthermore, the framework combines context-aware demand forecasting with a dynamic Economic Order Quantity (EOQ) model to support adaptive and data-driven inventory decisions.

The experimental results demonstrate the effectiveness of the proposed approach. Using the Grupo Bimbo dataset, which comprises approximately 41.39 million observations, AHIF achieved high predictive performance with R^2 values ranging from 0.985 to 0.987. Among the evaluated models, LightGBM provided the best results in terms of error reduction, outperforming previously reported approaches on the same dataset. The integration of meta-learning with a dynamic EOQ model enabled more responsive inventory policies, contributing to a reduction in both stockouts and overstocking.

From a theoretical perspective, this study contributes to the literature by introducing a generalizable meta-learning mechanism for context-aware model selection in inventory forecasting. From a practical standpoint, the proposed framework offers a scalable and deployable solution that enhances supply chain efficiency and supports adaptive decision-making in volatile environments. Overall, AHIF effectively bridges the gap between predictive accuracy and actionable inventory optimization.

Despite the strong performance of the proposed framework, several limitations should be noted. The evaluation was conducted on a single large-scale retail dataset, which may limit the generalizability of the results to other industries and supply chain contexts. Furthermore, the framework primarily relies on internal transactional data, while the absence of external market factors such as competitor pricing, promotional activities, and macroeconomic indicators may reduce contextual awareness in highly dynamic environments. In addition, the computational complexity associated with training multiple gradient boosting models within a meta-learning architecture may pose challenges for real-time deployment in resource-constrained settings. Future research should therefore focus on validating the framework across diverse datasets and application domains to enhance its robustness and scalability. Incorporating external data sources and real-time data streams, along with more advanced adaptive learning approaches such as reinforcement learning, could further improve forecasting accuracy and decision responsiveness. Moreover, the integration of explainable artificial intelligence techniques is recommended to enhance model transparency and facilitate wider adoption in practical inventory management systems.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY STATEMENT

The datasets generated or analyzed during the current study are available from the corresponding author on reasonable request.

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