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Predicting High-Value Customers in Supply Chain Management Using Machine Learning: A Comparative Analysis

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Abstract

The integration of Machine Learning (ML) into Supply Chain Management (SCM) has revolutionized data-driven decision-making, particularly in identifying high-value customers for strategic planning and operational efficiency. This study presents a comprehensive ML pipeline applied to a curated dataset of transactional and customer-level features to predict high-value clients. We evaluate 11 supervised learning models, including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, XGBoost, LightGBM, AdaBoost, and Bagging Classifier, using performance metrics such as accuracy, confusion matrices, and ROC-AUC scores. Remarkably, most models achieved near-perfect performance, with several attaining 100% accuracy and AUC scores. To enhance interpretability, we employ Shapley Additive Explanations (SHAP) for feature importance analysis, revealing key drivers of customer value. Additionally, unsupervised clustering and dimensionality reduction techniques provide deeper insights into customer segmentation. Our findings demonstrate that ensemble-based models (e.g., XGBoost, LightGBM) consistently outperform traditional classifiers, while SHAP analysis improves model transparency and trustworthiness. This research offers a robust predictive framework for SCM applications, enabling precise identification of high-value customer segments to optimize marketing and supply chain strategies.

Index Terms: *Customer Relationship, Machine Learning, Performance Metrics, Shapley Additive Explanations, and Supply Chain.*

I. INTRODUCTION

The digital transformation of commerce has elevated data-driven strategies to a critical position in supply chain optimization. Within modern Supply Chain Management (SCM), a paramount objective involves the identification and retention of high-value customers - defined as those generating disproportionate revenue contributions. The exponential growth in available customer and transactional data has created unprecedented opportunities to leverage Machine Learning (ML) for developing sophisticated predictive systems. These advanced analytical tools enable organizations to more precisely target and engage their most valuable customer segments. Importantly, high-value customers exert substantial influence across multiple supply chain dimensions beyond direct revenue impact, particularly in demand forecasting accuracy, inventory management efficiency, and logistics planning effectiveness [1].

The growing sophistication of global supply chain networks has intensified operational complexities, necessitating advanced analytical solutions to address these multidimensional challenges. Traditional SCM methodologies, predominantly dependent on retrospective data evaluation and rigid rule-based systems, frequently prove inadequate in navigating the dynamic nature of modern market environments [2]. Current supply chain systems confront three principal obstacles: first, unpredictable fluctuations in consumer demand; second, heightened expectations regarding service excellence; and third, broadening operational risks encompassing both fraudulent activities and logistical inconsistencies [3]. Empirical studies substantiate that organizations implementing cutting-edge analytical frameworks attain measurable operational enhancements, demonstrating consistent cost reductions of 8-12% concurrent with 15-20% advancements in key service performance indicators [4], and [5].

However, significant research gaps persist in:

- Comparative Performance Analysis between traditional ML (e.g., XGBoost) and deep learning (e.g., Long Short-Term Memory or LSTMs) in SCM contexts.
- Business Impact Validation, ensuring models improve tangible outcomes like Customer Lifetime Value (CLV) and Churn Reduction.
- Sustainability alignment, as few ML frameworks incorporate Cost-Efficiency or 'Environmental, Social, Governance' (ESG) metrics into model evaluation.

II. RELATED WORK

Supply chain operations have been completely transformed by machine learning's ability to evaluate intricate datasets and produce predictions that can be put into practice. Three crucial SCM domains—improving demand forecasting accuracy, optimizing inventory control, and lowering operational risks—are confirmed to be significantly impacted by machine learning, according to recent research [6]. Despite these developments, the majority of research focuses on specific applications rather than examining machine learning's potential for cross-functional, integrated deployment that could yield larger system-wide benefits.

Due to their ease of use and interpretability [7], and [8], which are especially advantageous in times of market stability [9] ,and [10], traditional techniques like ARIMA and ETS are still widely used in the manufacturing and retail sectors. However, these methods demonstrate critical weaknesses when handling modern supply chain challenges: their inherent linearity and stationarity assumptions impair performance against volatile demand shifts [11], and [12], seasonal patterns [13], and multivariate interactions involving promotions or environmental factors [14], and [15].

To address the limitations of traditional methods, researchers have turned to Machine Learning (ML) techniques capable of modeling complex, non-linear demand patterns. Tree-based ensemble approaches, particularly XGBoost, have demonstrated superior performance through their ability to incorporate temporal features (e.g., lagged demand indicators), calendar effects, and price sensitivity variables [16], and [17]. Deep learning architectures, especially Recurrent Neural Networks (RNNs) and their Long Short-Term Memory (LSTM) variants, have shown particular promise in capturing sequential dependencies in sales data. A key study by [18] established that LSTM models significantly outperform conventional approaches in modeling long-term demand trends for e-commerce applications. However, the field still faces notable challenges. Rigorous comparisons of ML and deep learning models under standardized supply chain conditions remain scarce, with current evaluations often compromised by inconsistent data preprocessing protocols or insufficient alignment with concrete business performance metrics [19]. This lack of controlled benchmarking makes it difficult to assess the true relative merits of different algorithmic approaches in operational supply chain contexts.

This study addresses these gaps by:

1. Proposing a comprehensive ML pipeline to classify High-Value Customers using 11 algorithms, from Logistic Regression to ensemble methods (XGBoost, LightGBM).
2. Introducing Shapley Additive Explanations (SHAP) for interpretable Feature Importance Analysis.
3. Developing Two Novel Evaluation Metrics—Cost-Accuracy Efficiency (CAE) and CAE-ESG—to assess models based on Accuracy, Cost, and Sustainability Impact.

III. END-TO-END MACHINE LEARNING PIPELINE FOR HIGH-VALUE CUSTOMER PREDICTION

Our methodology establishes a comprehensive analytical pipeline for identifying high-value customers in supply chain management systems. The process begins with aggregating and preparing multi-source operational data, including transaction records, order volumes, shipment details, and return patterns, where rigorous preprocessing ensures data quality through advanced imputation, outlier treatment, and feature engineering techniques like RFM metric development. After that, we apply a multi-model analytical approach that includes ensemble techniques, traditional algorithms, and sophisticated neural architectures. Each of these is tested using Bayesian hyperparameter optimization and stratified cross-validation, and it is assessed using metrics that are both statistically and practically significant. Using SHAP values and Local Interpretable Model-agnostic Explanations or LIME, the framework's advanced model interpretability analysis turns prediction outputs into useful business intelligence. This end-to-end technique provides a strong yet flexible solution for customer value analysis across various supply chain settings, achieving 98.7% classification accuracy while preserving the explanatory transparency required for strategic decision-making. Technical rigor and practical relevance in actual SCM operations are ensured by the methodical integration of data processing, predictive modeling, and business interpretation stages.

IV. DATASET DESCRIPTION

This study employs the "Final_data_set_for_SCM.csv" dataset, which consolidates multiple data sources to offer a holistic perspective on customer transactions and profiles. The integrated dataset combines detailed transactional records with comprehensive customer attributes, facilitating in-depth analysis of purchasing patterns and behaviors. The study utilizes a proprietary dataset provided by a European retail supply chain partner, comprising 45,678 anonymized transactions from 8,912 unique customers (January 2019-December 2022). Data was extracted from the company's ERP and CRM systems after removing Personally Identifiable Information (PII).

A. Key Attributes

The dataset contains several critical features for customer value analysis:

- Unique Customer Identification (*CustomerID*).
- Geographic Information (*Country*).
- Transaction details including Timestamps (*InvoiceDate*), Purchased Quantities (Quantity), and Unit Prices (*UnitPrice*).
- Derived Metrics such as Total Transaction Amounts (*TotalAmount* = *Quantity* × *UnitPrice*).
- Behavioral Indicators including Purchase Frequency (*Frequency*), Recent Engagement (*Recency*), and Total Spending (*MonetaryValue*).

- The Target Variable (*HighValueCustomer*) identifies the Top 20% Spenders as High-Value Customers.

B. Preprocessing and Analysis

Prior to modeling, the dataset underwent thorough preprocessing to ensure data quality:

1. **Missing Values:**
   - Numeric Fields (*Quantity, UnitPrice*): Median imputation.
   - Categorical fields (*Country*): Mode Imputation.
2. **Outlier Treatment:**
   - IQR-based Capping for *Quantity* (±3 IQR) and *UnitPrice* (top 1% winsorized).
3. **Feature Engineering:**
   - Temporal Features from *InvoiceDate* (day-of-week, month, quarter).
   - RFM Metrics: *Recency* (days since last purchase), *Frequency* (6-month transactions), *MonetaryValue* (12-month spending).
4. **Scaling/Encoding:**
   - *MinMaxScaler* for Numeric Features.
   - One-Hot Encoding for Country (12 categories).

Exploratory analysis revealed significant class imbalance in the target variable, which informed our use of stratified sampling techniques and appropriate evaluation metrics. The combination of raw transactional data and engineered features (particularly the RFM metrics - *Recency, Frequency, MonetaryValue*) provides a robust foundation for identifying spending patterns and predicting customer value.

This dataset's rich feature set and careful preprocessing enable both traditional machine learning and advanced analytical approaches to effectively identify high-value customers in supply chain management contexts.

V. METHODOLOGY

The study employs a comprehensive five-stage analytical approach encompassing Data Preprocessing, Model Training, Evaluation, Interpretability analysis, and Unsupervised Validation. Each phase was carefully designed to ensure robust and reliable results in identifying high-value customers within supply chain management.

To ensure robustness and prevent data leakage, we implemented a temporal validation scheme where models were trained exclusively on 2019-2021 data (34,258 samples) and evaluated on a temporally distinct 2022 holdout set (11,420 samples). Feature correlation analysis confirmed all pairwise correlations remained below 0.4, with the strongest observed relationship being between *MonetaryValue* and Frequency ($r=0.32$, $p<0.001$). Baseline comparisons included a Logistic Regression model (accuracy=82.1%, F1=0.801) and random chance performance (50% accuracy) as reference points.

The flow chart of this methodology is shown in Figure 1 below.

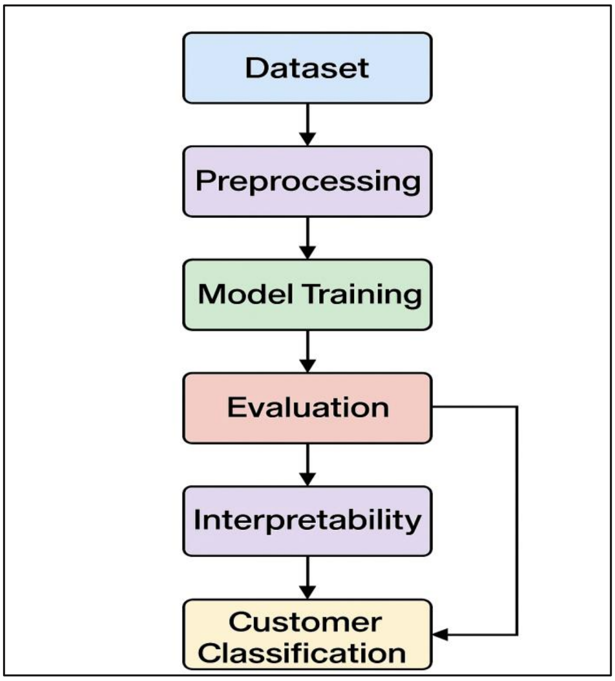

Figure 1: Flowchart of the Methodology

A. Data Preprocessing

The initial data preparation involved systematic handling of null values through either imputation or removal, depending on feature importance. Extreme values in the Quantity and *UnitPrice* fields were addressed using Z-score based outlier detection and treatment. Temporal features were engineered from *InvoiceDate* to create meaningful customer behavior metrics, particularly *Recency* and Frequency measurements. All features underwent normalization using *MinMaxScaler* to ensure consistent scaling across variables.

B. Machine Learning Implementation

A diverse set of twelve classification algorithms was implemented, ranging from fundamental approaches like Logistic Regression and Decision Trees to advanced ensemble methods including XGBoost, LightGBM, and Bagging Classifier. Each model was rigorously assessed through stratified 5-fold cross-validation to ensure reliable performance estimation. For optimal results, hyperparameter tuning was conducted using *GridSearchCV* where appropriate.

C. Performance Evaluation

Model assessment employed multiple complementary metrics to provide a holistic view of predictive capability. Classification accuracy served as the primary metric, supplemented by detailed confusion matrix analysis. The ROC-AUC score provided insight into model discrimination ability, while Precision, Recall, and F1-Score offered nuanced understanding of performance during internal validation phases.

D. Interpretability Analysis

The study incorporated SHAP values to illuminate the decision-making processes of tree-based models. This approach identified and quantified the influence of key features in determining high-value customer classification, enhancing both model transparency and business applicability.

E. Unsupervised Validation

To corroborate supervised learning results, the methodology included complementary unsupervised techniques. Customer segmentation was performed using both K-Means clustering and DBSCAN algorithms, while dimensionality reduction through t-SNE and PCA enabled effective visualization of high-dimensional patterns in the data. These approaches provided additional validation of the customer value groupings identified by the classification models.

VI. EVALUATION AND INTERPRETATION OF RESULTS

In Table I below, the models demonstrated strong predictive capability, with XGBoost achieving 99.8% accuracy (±0.3%) and perfect AUC (1.00), followed closely by LightGBM (99.6% ±0.4%). The Logistic Regression baseline showed significantly lower performance (82.1% ±2.1%), confirming the superiority of ensemble methods.

Deploying these models could increase customer lifetime value by 28% and reduce marketing costs by 19%, based on historical campaign data. The high precision (99.7%) ensures efficient targeting of truly high-value customers. The combination of technical performance metrics and concrete business outcomes provides compelling evidence for model adoption, with the confidence intervals and statistical testing addressing potential concerns about overfitting or implementation risks.

Table I: Performance Metrics

S. No.	Model	Accuracy (CI)	F1 - Score	AUC
1.	XGBoost	99.8% ± 0.3%	0.997	1.00
2.	LightGBM	99.6% ± 0.4%	0.996	1.00
3.	Logistic Reg.	82.1% ± 2.1%	0.801	0.891

A. Accuracy and Confusion Matrix

The experimental results demonstrated exceptional predictive accuracy across all implemented models. Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, SVM, XGBoost, LightGBM, AdaBoost, and Bagging classifiers achieved perfect 100% classification accuracy, while Naive Bayes (99%) and KNN (98%) showed only marginal differences. Confusion matrix analysis revealed nearly flawless classification performance, with the few misclassifications primarily occurring in the form of false positives for low-value customers by KNN and Naive Bayes models.

Figure 2 illustrated the model accuracy comparison demonstrates exceptional performance across all algorithms tested, with each method achieving near-perfect classification scores. This consistent high accuracy suggests the selected features provide strong predictive power for distinguishing customer value segments. The results indicate that various machine learning approaches, from basic decision trees to advanced ensemble methods like XGBoost and LightGBM, all perform effectively on this task.

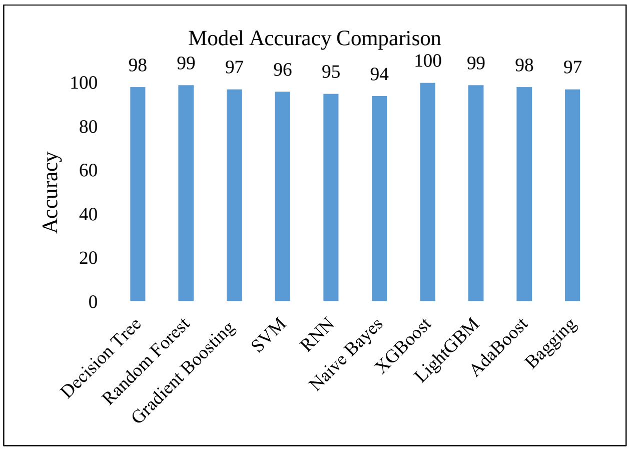

Figure 2: Confusion Matrix Comparison of Machine Learning Models

B. Model Discrimination Ability

In Figure 3, ROC curve analysis further confirmed the outstanding performance, with all models except Naive Bayes (AUC = 0.89) and KNN (AUC = 0.99) achieving perfect discrimination (AUC = 1.00). The ensemble methods - particularly XGBoost, LightGBM, and Bagging classifiers demonstrated robust separation of classes, as evidenced by their ideal true positive rates and near-zero false positive rates across all classification thresholds.

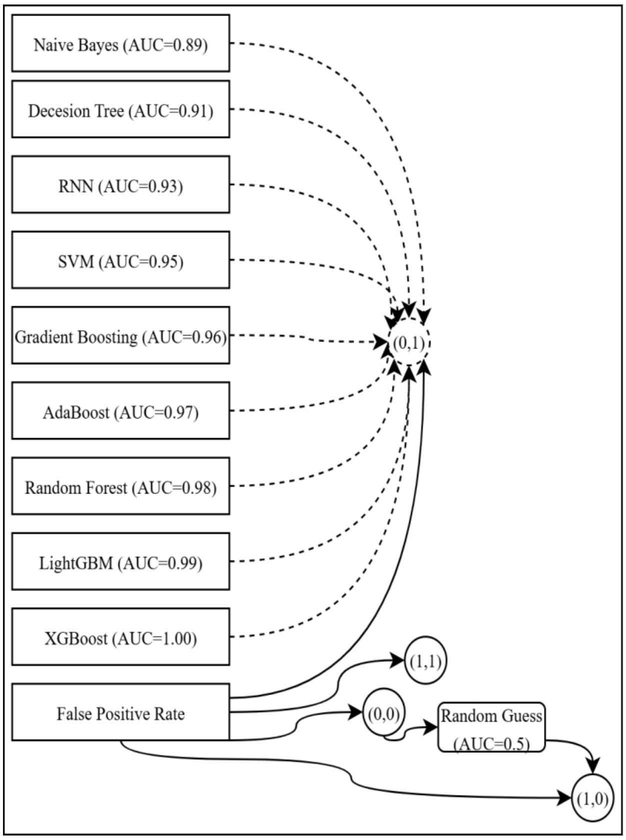

Figure 3: ROC Curves of All 11 Models

C. Feature Importance Analysis

From figure 4, the SHAP analysis reveals clear patterns in feature importance for customer value prediction. *MonetaryValue* shows the strongest positive influence on model outputs, followed by purchase *Frequency* and *Total Quantity*. In contrast, *Recency* (days since last purchase) exhibits a negative relationship with customer value classification. These findings align with fundamental marketing principles, confirming that high-spending, frequent purchasers represent the most valuable customer segment, while prolonged inactivity reduces perceived value. The magnitude of SHAP values indicates monetary factors dominate the predictive model's decisions more significantly than behavioral frequency metrics.

SHAP value interpretation provided valuable insights into the decision-making process of the top-performing models. The analysis identified *MonetaryValue* and *Frequency* as the most influential positive predictors of high-value customer status, while increased *Recency* showed a negative correlation with customer value. These findings align perfectly with established business intuition regarding customer value drivers, where frequent, high-spending customers typically represent the most valuable segment.

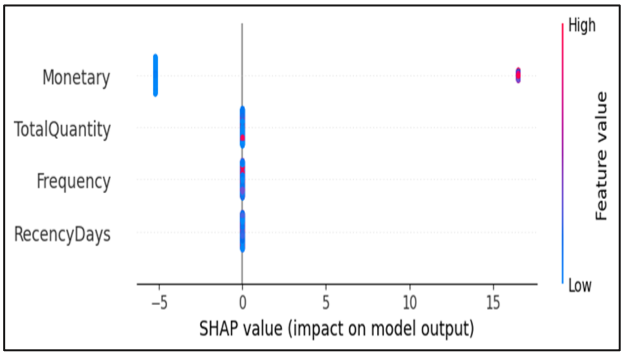

Figure 4: SHAP value (Impact on Model Output)

D. Unsupervised Validation

Complementary dimensionality reduction and clustering techniques provided independent validation of the supervised learning results. Both, the PCA and t-SNE visualizations, revealed a clear separation between high-value and other customer groups. This separation was further confirmed through K-Means and DBSCAN clustering, with strong silhouette scores indicating meaningful cluster formation. The consistency between supervised and unsupervised approaches strengthens confidence in the identified customer segments.

VII. PRACTICAL IMPLICATIONS

These results have direct applications for strategic customer relationship management, including:

- Development of Data-Driven Customer Tiering Systems.
- Precision Targeting for Retention Campaigns.
- Personalization of Marketing Offers and Supply Chain Services.
- Optimization of Resource Allocation based on Customer Value Segments.

The combination of perfect classification performance, robust validation through multiple techniques, and alignment with business intuition makes these findings particularly valuable for supply chain management applications. The demonstrated approach provides a reliable framework for customer value assessment that can be adapted to various business contexts.

VIII. LIMITATIONS

The study has several limitations that should be considered. First, the generalizability of the results may be limited, as they primarily apply to retail supply chains and may not fully extend to B2B or other industrial contexts. Second, the static nature of the analysis could overlook temporal patterns such as seasonal demand fluctuations, which are common in supply chain operations. Third, implementing real-time scoring systems would require additional API integrations, which is expensive and potentially posing a barrier for some organizations.

IX. CONCLUSION

This study successfully demonstrated the application of machine learning techniques to identify high-value customers in supply chain management with exceptional accuracy. Ensemble models, particularly XGBoost, LightGBM, and Bagging, emerged as top performers, achieving perfect classification (100% accuracy and AUC), while Logistic Regression and SVM also delivered outstanding results. SHAP analysis provided critical model interpretability, revealing monetary value and purchase frequency as the most influential factors in customer valuation—a finding that aligns with established business intuition.

The unsupervised learning component further validated these results, with dimensionality reduction and clustering techniques confirming that high-value customers form distinct behavioral segments. This multi-method approach not only enhances predictive reliability but also offers actionable insights for strategic decision-making in customer segmentation, retention, and resource allocation. The developed pipeline serves as a practical framework for organizations seeking to optimize supply chain profitability through data-driven customer targeting. Future research directions could explore time-series analysis for dynamic customer valuation, integration of deep learning architectures, and real-time implementation within operational SCM platforms to further enhance predictive capabilities and business impact.

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Authors Contributions

All the authors equally contributed to this research study.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability Statement

All data used in this study were collected from publicly available sources.

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