Metaheuristic Optimization Review

ISSN: 2692-4048 Vol: 03, No. 01, 2024 PP. 14–18
Article DOI: https://doi.org/10.54216/MOR.030104

REVIEW ARTICLE

A Review of Machine Learning for Predicting Supply Chain Demand in Retail

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Received: November 29, 2024 Revised: December 18, 2024 Accepted: January 08, 2025 ⋆ Corresponding author

ABSTRACT

This review demonstrates the effectiveness of machine learning (ML) and deep learning (DL) approaches for demand forecasting in the retail supply chain and highlights their superiority over conventional statistical methods. Traditional models are often poorly suited to nonlinear dependencies, outside influences, and fluctuating retail settings. In contrast, ML methodologies such as Random Forest, support vector machines (SVMs), long short-term memory (LSTM), and convolutional neural networks (CNNs) provide strong forecasting accuracy when the temporal and spatial complexity of sales information is captured. The review underlines the importance of data fusion and feature engineering, including macroeconomic indicators, weather, and promotions, for improving forecasts. Issues such as data quality, scalability, and model interpretability are discussed together with solutions related to IoT and blockchain integration. These innovations enable real-time data capture, high reliability, and greater process transparency. The use of evaluation indicators such as MAE, RMSE, and MAPE further shows that model engineering requires careful metric selection. Overall, this systematic review synthesizes recent developments, issues, and trends in applying ML and DL to improve inventory management, pricing, and customer satisfaction in retail.

Keywords: Machine Learning ▪ Deep Learning ▪ Retail Demand Forecasting ▪ Data Integration ▪ Feature Engineering ▪ Supply Chain Management

1. INTRODUCTION

Demand forecasting is an essential practice for managing retail supply chains. Machine learning technologies are changing this field because retailers can predict customer demand more accurately than with many traditional approaches. Earlier statistical models do not fully encompass the dynamic and nonlinear characteristics of retail environments. ML techniques address these limitations by learning from large datasets, discovering hidden patterns, and adapting to changes in market conditions.

The rationale for this review is to identify and synthesize ML approaches for forecasting demand in retail supply chains. It describes the challenges and uses of ML models across retail contexts and explains how external influences, including economic variables, weather patterns, and social media, are incorporated into forecasting models. The review aims to define the current state of knowledge, identify gaps in the literature, and provide directions for future investigation.

1.1 Advancing Demand Forecasting in Retail with Machine Learning

Demand forecasting supports inventory control, cost reduction, and customer satisfaction. Accurate forecasts help retailers maintain stock levels that avoid both overstocking and stockouts. This balance reduces storage costs, improves product availability, enhances customer experience, and increases loyalty [1].

Traditional fixed-interval forecasting techniques, including ARIMA, linear regression, and exponential smoothing, depend heavily on predetermined assumptions and historical patterns. These methods can produce considerable errors in markets where customer behavior changes rapidly and external conditions are influential [2]. Machine learning provides an alternative by processing large volumes of data, finding complex correlations, and updating models as new information becomes available. As a result, ML improves decision-making in inventory management, pricing, marketing, and supply chain responsiveness [3].

1.2 Machine Learning Techniques for Retail Demand Forecasting

Supervised learning algorithms play a critical role in retail demand forecasting. Decision trees, SVMs, neural networks, and ensemble models use historical sales observations and explanatory variables to predict future demand [4]. These models are useful when labeled historical outcomes are available and when relationships between inputs and demand are nonlinear.

Unsupervised learning can also support forecasting by discovering customer segments, product clusters, and hidden demand structures without requiring explicit labels [5]. Deep learning methods such as CNN–LSTM architectures are particularly useful for sequential retail data because they capture temporal dependencies and spatial relationships in sales patterns [6, 7]. Feature engineering further improves demand prediction by incorporating variables such as promotions, holidays, weather, prices, and macroeconomic indicators [8].

Model performance is commonly assessed using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These metrics are defined as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{2}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|. \tag{3}$$

The choice of metric affects model selection and optimization because each metric emphasizes different error properties [9].

1.3 Challenges and Future Opportunities

Several challenges remain in applying ML to retail demand forecasting. Data accuracy is crucial, as missing, noisy, or irrelevant values can reduce forecast reliability. Scalability is also important because retailers often handle large and rapidly updated datasets. Interpretability is another central issue: stakeholders must understand model outputs to trust and use them effectively [10].

Future retail forecasting systems may increasingly integrate IoT and blockchain. IoT supports real-time monitoring of consumer behavior and product movement, while blockchain can improve trust, traceability, and data integrity. Combining these technologies with ML can improve forecasting quality and support more reliable supply chain decisions [11].

2. LITERATURE REVIEW

Demand forecasting is a core component of effective supply management because it affects stock control, spending, and customer satisfaction. Traditional techniques have limited ability to capture important nonlinear patterns and external effects, while ML and DL methods provide more flexible alternatives. This section summarizes representative studies that use diverse datasets, modern algorithms, and hybrid ML/DL strategies for supply chain demand forecasting.

Retail sales and price projections often rely on time series forecasting, but category-specific products can suffer from low forecast accuracy. D'Souza et al. [12] presented a self-learning forecasting rack that dynamically selects the best-performing algorithm for a given context. By incorporating advanced feature engineering, the reported forecast accuracy for Knitwear improved from approximately 60% to 80%.

Ampazis [13] examined machine learning algorithms for supply chain forecasting, while Jahin et al. [14] proposed an explainable multi-channel data fusion network for demand forecasting. Tensor factorization with demand awareness has also been used to improve sales forecasting accuracy by combining product, store, and temporal information [15]. Comparative studies of multivariate time series, tree-based ensembles, LSTM models, hybrid models, and regression methods further demonstrate that the best algorithm depends on data structure, forecasting horizon, and operational context [16, 17, 18, 19].

Associative and recurrent mixture density networks have been proposed for e-retail demand forecasting, while recent deep approximate forecasting and optimized ML models have expanded the range of available approaches [20, 23, 31]. Critical reviews emphasize that despite strong progress, data quality, explainability, and deployment complexity remain central research challenges [26].

The studies summarized in Table 1 emphasize the increasing prominence of ML and DL in demand forecasting. By combining advanced algorithms with multiple data sources, researchers have built models that often outperform conventional methods. Nevertheless, model interpretability, scalability, and data quality remain open issues.

3. DISCUSSION

Forecasting is critical to demand planning in retail supply chains because it guides inventory control, supply chain improvement, and customer satisfaction. Conventional statistical models remain useful but are limited when retail patterns are nonlinear, dynamic, and affected by external variables. ML and DL techniques improve forecasting performance through optimized algorithms, integrated data, and sophisticated feature engineering.

3.1 Potential of Machine Learning for Retail Sales Forecasts

The literature highlights the positive effect of ML algorithms on retail demand forecasting. While conventional models often fail to handle nonlinearity and extrinsic variables, Random Forest, SVM, tensor decomposition, LSTM, CNN, and hybrid approaches can capture temporal and spatial features in sales data. These improvements help retailers make bet-

Table 1. Summary of literature review

Study	Methodology/Algorithm	Dataset/Domain	Main Contribution
[12]	Adaptive algorithm rack with feature engineering	Retail knitwear forecasting	Improved low category-level accuracy through self-learning model selection.
[13]	Classical ML algorithms	Supply chain demand data	Demonstrated the applicability of ML to demand prediction tasks.
[14]	Explainable multi-channel data fusion network	Supply chain demand forecasting	Integrated multiple channels while improving explainability.
[15]	Tensor factorization with demand awareness	Sales forecasting	Improved accuracy by exploiting product–store–time structure.
[16]	Comparative multivariate time-series models	Retail demand data	Compared forecasting performance across multiple variables.
[17]	ML and DL comparative study	Retail industry	Compared modern ML and DL approaches for demand forecasting.
[18]	Tree-based ensembles and LSTM	Retail prediction	Compared ensemble learning with deep sequential models.
[19]	Hybrid ML model	Multi-channel retail company	Presented a hybrid approach for complex retail channels.
[20]	Associative and recurrent mixture density networks	eRetail forecasting	Modeled uncertainty and recurrent demand structures.
[26]	Critical review of ML and DL models	Supply chain management	Synthesized progress and limitations across 119 papers.

ter decisions about merchandise management, pricing, and promotional strategies [28].

3.2 Importance of Data Integration and Feature Engineering

Data quality and diversity are critical to practical ML forecasting. Many studies improve predictions by incorporating macroeconomic indicators such as consumer price indices and unemployment rates, weather variables, promotional campaigns, and product attributes. Feature engineering helps identify relevant predictors and improves the likelihood that models capture real consumer dynamics. Multi-source systems such as ATLAS and ARMDN illustrate how data integration supports richer insight into demand fluctuations [29].

3.3 Evaluation Criteria and Model Performance

Evaluation metrics influence how forecasting models are assessed and optimized. MAE, RMSE, and MAPE are widely used because they provide interpretable indicators of forecast deviation. Deep learning models such as LSTM perform well on sequential data, whereas tree-based ensemble methods such as Extra Trees and Random Forest may be more suitable for certain retail settings, including perishable products. Comparative analyses show that model selection must match the characteristics of the dataset and application [30].

3.4 Deployment Challenges

Despite progress, deployment remains challenging. Noise, missing values, and irrelevant variables reduce forecast accuracy. Scalability is difficult when large datasets and real-time processing are required. Interpretability is also essential because stakeholders need to understand why a model produces a given recommendation. Complex CNN and LSTM hybrids may deliver high accuracy but can be difficult to deploy in routine retail environments because of computational sophistication and limited transparency [31].

4. CONCLUSION

This review examined the role of machine learning and deep learning in predicting retail supply chain demand. The literature shows that ML/DL models can outperform traditional statistical methods by capturing nonlinear relationships, integrating heterogeneous data, and adapting to changing market conditions. The reviewed studies demonstrate strong benefits for inventory management, pricing decisions, promotional planning, and customer satisfaction.

At the same time, practical use of ML in retail forecasting is constrained by data quality, scalability, computational cost, and model interpretability. Future research should focus on explainable forecasting systems, robust multi-source data integration, real-time IoT-enabled pipelines, blockchain-supported data reliability, and hybrid models that balance predictive accuracy with operational usability. These developments can help retailers make more reliable decisions in fast-changing markets.

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