Smart Predictions: Machine Learning for Demand Forecasting Review and analysis

Hmamou Yahya[1], Chafi Anas[2], and Alami Kammouri Salaheddine[3]

[1] Laboratory of industrial techniques, faculty of sciences and technology, Fez,Morocco, yahya.hmamou@usmba.ac.ma
[2] Laboratory of industrial techniques, faculty of sciences and technology, Fez,Morocco,anaschafi@gmail.com
[3] Laboratory of industrial techniques, faculty of sciences and technology, Fez,Morocco, salaheddine.kammourialami@usmba.ac.ma

Abstract. Accurate demand forecasting is critical for improving sup- ply chain operations in Logistics 4.0, although traditional statistical ap- proaches struggle to represent the complex, non-linear trends in current demand data. This study analyzes machine learning (ML) applications in demand forecasting across industrial supply chains, evaluating 21 re- search from 2020 to 2024. We propose a novel classification framework that categorizes ML techniques by algorithm type (e.g., deep learning, ensemble methods) and data characteristics (e.g., volume, dimensional- ity),showing themes including the advantage of LSTM networks (Long Short-Term Memory) for high-volume, multivariate data. Our findings demonstrate deep learning methods minimize predicting errors compared to standard approaches, while computing needs may restrict implementation. This categorization gives supply chain practitioners a practical guidance to identify appropriate ML approaches, boosting efficiency and profitability in changing marketplaces.

Keywords: Artificial intillegence · Machine learning · Demand forecast- ing · Logistics 4.0 · Demand prediction.

1 Introduction

In today's increasingly complex and volatile supply chain environments, com- panies must continuously strive to enhance efficiency, reliability, responsiveness, and resilience to remain competitive. One of the key drivers of effective decision- making across the supply chain is accurate demand forecasting. Organizations in manufacturing, distribution, and retail sectors depend heavily on demand and sales estimates to inform crucial operations such as transportation planning, procurement, inventory control, workforce scheduling, production planning, and financial management [18].

Achieving a balance between supply and demand is essential to minimize in- ventory imbalances—whether surplus or shortage—which directly impacts prof- itability. Overproduction, driven by overestimated demand, can result in excess stock, while underestimating demand risks missed orders, lost revenue, and poor service levels. Both scenarios contribute to inefficiencies within the supply chain [25]. Furthermore, inaccurate forecasting can amplify the bullwhip effect, leading to unnecessary volatility in upstream supply chain operations [20].

Traditional statistical forecasting techniques, such as autoregressive and mov- ing average models, often fall short in this context. These methods struggle with the inherent non-linearity and complexity of real-world demand patterns. Linear models not only fail to accurately capture these fluctuations but also tend to perform poorly both in-sample and out-of-sample, resulting in unstable predic- tions [12]. As a result, there is a growing interest in more advanced, nonlinear methods.

Machine learning (ML) techniques, spanning both supervised and unsuper- vised paradigms, have received growing interest for their ability to capture com- plicated, nonlinear dynamics in time series data—patterns that conventional sta- tistical models typically fail to discover [28]. A vast amount of literature validates the usefulness of ML-based forecasting models across a range of industrial appli- cations. For instance, Alon et al. [4] assessed artificial neural networks (ANNs) against traditional approaches such as Holt-Winters, ARIMA, and linear regres- sion models in forecasting monthly retail sales. Their findings suggested that ANNs regularly produced greater predicting accuracy.

Kantasa et al. [15] used a long short-term memory (LSTM) network to predict agricultural demand inside a practical Thai supply chain. The LSTM model outperformed competing techniques like ARIMAX, support vector regression (SVR), and multiple linear regression, notably in capturing demand variability. The improved accuracy of forecasts immediately reduced inventory and logistics expenses, underscoring the operational significance of machine learning in supply chain management.

Nonetheless, the wide and continuously growing ecosystem of ML models of- fers issues in picking the best effective approach for certain forecasting scenarios. This work aims to thoroughly analyze and synthesize existing research on ma- chine learning-driven demand forecasting in industrial supply chains. The major purpose is to map the methodological environment, categorize models by algo- rithm type and data input structure, and give practical insights for practitioners intending to deploy ML-based tools efficiently.

The remainder of the paper is laid out as follows: Section 2 explains the study approach, concentrating on material released between 2020 and 2024. Sec- tion 3 synthesizes empirical data from chosen research, emphasizing real-world supply chain applications. Section 4 includes a comparative examination of ML forecasting models, organized by algorithmic and data-related aspects. Section 5 explores the strategic consequences and proposes a model selection approach. Finally, Section 6 ends the work by summarizing major conclusions and providing areas for future research, reaffirming the revolutionary influence of ML in demand forecasting.

2 Methodology

The current investigation covers research works from 2020 to 2024 that explore the application of AI-driven approaches, mainly ML and DL, for predicting de- mand across important supply chain domains such as manufacturing and retail. To identify relevant studies, we searched major academic databases including ScienceDirect, MDPI, IEEE Xplore, and Springer. The search employed the following keyword combinations:"Artificial Intelligence" AND "Demand Forecasting" AND "Supply Chain" ("Machine Learning" OR "Predictive Analytics") AND "Sales Forecasting" AND "Supply Chain"

After applying relevance, methodological quality, and sectoral diversity cri- teria, a total of 21 articles were selected for detailed analysis, as shown in Table 1. These studies form the foundation for the comparative evaluation pre- sented in the subsequent sections.

3 Literature review

To explore how AI aids demand forecasting in supply chains, this section out- lines essential terms and examines 21 papers published between 2020 and 2024. Table 1 highlights each study based on five criteria: industrial sector, data char- acteristics (e.g., univariate vs. multivariate, data range), ML methods utilized, performance measures, and reference source.

The assessment includes both industrial and retail realms, helping overcome the gap in upstream forecasting highlighted previously. It demonstrates three significant trends:

Multivariate Data Dominance. Most studies (16 of 21) employ multi- variate datasets, frequently integrating external factors like promotions, weather, or economic indicators [8, 26, 9]. This trend reflects rising data availability in Logistics 4.0 and enables more precise predictions. For example, Gonçalves et al. [8] obtained a 12% improvement in MAE utilizing multivariate inputs over univariate models. However, only two studies employed dimensionality reduc- tion techniques like PCA [24, 13], pointing to missing opportunities in preparing complicated data.

Deep Learning Prevails. LSTM networks were utilized in 8 studies [7, 19, 1], valued for detecting long-term interconnection in time series. Kantasa et al. [15] used LSTM in agriculture, boosting accuracy and lowering logistics costs by 15%. Traditional methods like K-NN [11] and SARIMA [7] were better suited for seasonal or sporadic demand, especially when data history was limited.

Data Range and Model Performance. Longer time series (e.g., 48–60 months) generally led to better forecasts [8, 1], while shorter datasets struggled with sparse demand signals [11]. MAE and RMSE were the most popular evaluation metrics, with multiple research indicating 10–20% error reduction utilizing LSTM over conventional baselines [7, 19].

A noteworthy gap in the literature is the minimal attention on upstream forecasting. While 13 studies focus on retail, just 8 address manufacturing, and none offer supplier-level estimates. Moreover, few research analyze computational restrictions or study the incorporation of non-traditional data sources like social media or geopolitical events—factors with rising significance in unpredictable markets [10, 16, 29].

These insights drive the categorization scheme (Section 4) and the choice framework (Section 5), both aimed to assist practitioners pick ML models based on data structure, volume, and forecasting needs.

Table 1. Overview of ML-Based Supply Chain Forecasting (2020–2024)

Sector	Dim.	Range	Methods	Metrics	Ref.
Mfg.	Uni.	36	LSTM, BLSTM	MAE, MAPE, MASE, RMSE	[21]
Auto.	Multi.	108	ARIMAX, SVR, MLP, RF	NMAE	[8]
Mfg.	Uni., Multi.	36	LSTM, ARIMAX, CNNs, GRUs	MASE, SAE	[6]
Auto.	Multi.	–	LGBM+Hyp, SVM, SLR, RFR, GB	MAE, MaxErr	[3]
Log.	Multi.	53	RNN (Seq2Seq)	RMSLE	[27]
Log.	Multi.	13	RF, GB, MLP, XGB	MAPE, MAE, MRAE	[24]
Store	Uni.	36	SARIMAX, LSTM, SARIMA	MAPE, RMSE	[7]
Retail	Multi.	61	ANN, SVM	RMSE	[9]
Log.	Multi., Uni.	30	LSTM + RF	MAE, ME, RMSE	[22]
Super.	Multi.	76	LSTM	MAPE, MAE, RMSE	[19]
E-com.	Multi.	24	LSTM + PSO	MAE, RMSE, RAE, RRSE	[13]
Retail	Multi.	59	CNN + BiLSTM	MAE, MAPE, R2	[14]
Log.	Multi.	16	MLP + BP	RMSE, MPE, MNE	[2]
Auto.	Multi.	37	POST BaLSTM, ETS, ARIMA, SVM, KNN, NNAR, LSTM+RNN, Stacked LSTM	RMSE, MAPE, MAE	[16]
Auto.	Uni.	–	RNN + LSTM + Adam	ME, MSE	[5]
Furn.	Uni.	132	LSTM, ETS, ARIMA, ANN, RNN, KNN, SVM	SMAPE, RMSE	[1]
Store	Uni.	64	KNN	MSE, MAE, MAPE	[11]
Auto., Aero., E-com., Store	Multi., Uni.	51, 24, 84, 64	RNNs	MAE, RMSE, SMAPE, MASE, MAPE, WAPE, WASPE	[26]
Pharm.	Multi.	72	ANN, RF, LR	RMSE, R2	[10]
Auto.	Multi.	28	LGBM	AUC, MASE, MAPE	[29]
Health.	Multi.	60	ANN, RF, LR	RMSE, R2	[17]

4 Categorization of the most effective machine learning techniques

4.1 Summary of ML approaches considered most effective by the authors of the respective studies

Table 2 depicts the most effective machine learning approaches either employed or utilized as benchmarks throughout the analyzed research. Since most stud- ies compare many models, the table shows the best-performing techniques per research, adopting the taxonomy provided by Iqbal H. Sarker to distinguish be- tween standard ML and deep learning approaches [23].

Supervised and deep learning models—especially LSTM, ANN, and RNN demonstrated improved accuracy in 11 investigations, particularly for items with steady demand patterns. In contrast, classic ML models such as ARIMAX, K- NN, and SARIMA exhibited resilience to noisy inputs, making them suited for forecasting volatile, short-lifecycle goods [6].

Deep learning algorithms also outperformed standard models when handling huge datasets [17]. Ensemble approaches emerged in six research, with Random Forest leading in three owing to its efficacy in lowering predicting errors, notably MAE [24]. Additionally, three articles developed hybrid models—often contain- ing LSTM—to combine the merits of several techniques.

Although unsupervised approaches like K-Means and PCA were not utilized directly for forecasting, two research employed them to increase model accuracy by decreasing data dimensionality

Table 2. Summary of ML approaches considered most effective by the authors of the respective studies

Traditional ML Methods	Deep Learning Methods	Hybrid Methods	Ensemble Meth- ods
ARIMAX[6] RFR[3] K-NN [11] GB[24] SARIMA[7]	ANN[9, 10] LSTM[7, 19, 1] RNNs [27, 26]) MLP[8, 2] BLSTM [21]	LSTM+RF[22] BiLSTM+CNN[14] RNN + LSTM[5] LSTM+PSO[13]	RF[17] LightGBM [29] BaLSTM[16]

4.2 Ranking machine learning methods based on data attributes

This section delineates a taxonomy of machine learning methodologies for de- mand forecasting, organized by essential data attributes: dimensionality and data amount.This categorization assists decision-makers in aligning forecasting methodologies with the characteristics of their datasets.

Dimensionality is categorized as univariate, which depends exclusively on historical demand, and multivariate, which integrates several variables. Data volume is classified into three tiers according to the quantity of input points per product: low (≤ 500), medium (501–1000), and high (>1000). These contrasts illustrate the data prerequisites and computational breadth of each approach.

Expanding upon this approach, Table 3 presents a comprehensive classifi- cation of 21 AI-driven forecasting techniques derived from the extant research. This categorization provides a general framework and acts as a useful reference for choosing appropriate models in production settings.

Table 3. Volume/Dimension Analysis for the Best Machine Learning Models

Volume / Dimension	**Univariate**	**Multivariate**
Undefined	RNN+LSTM [5]	RF [3], BaLSTM [16]
Low (1–500)	LSTM [21, 1]	LSTM+PSO [13]
Medium (501–1000)	–	MLP [2]
High (1001+)	K-NN[11], RNNs[26], RF[17]	MLP[8], RNN [27, 26], RF[24], LSTM[7, 19],LSTM+RF [22], BiLSTM+CNN[14], ANN[10],LightGBM[29]

5 Results and discussion

Demand forecasting employs historical and contemporary data to foresee future trends. In time series analysis, the data's structure and quality are crucial for selecting the appropriate model. Poor alignment between data attributes and model choice might lead to erroneous estimates.

Our study shows the rising usage of multivariate datasets in recent research, showing a move toward richer, more complicated data inputs. Deep learning models, particularly those managing large datasets, typically demonstrate robust performance. As demonstrated in Table 3, most high-accuracy models rely on deep learning or ensemble approaches.

The volume of data is essential. Numerous machine learning algorithms cur- rently presume access to extensive datasets, attributable to advancements in data gathering and infrastructure. LSTM networks are distinguished among deep learning methods for their proficiency in managing both small and big datasets, efficiently capturing temporal patterns and long-term relationships.

Hybrid vehicles are also gaining traction. The integration of LSTM with RNNs or CNNs frequently produces superior outcomes by uniting sequence learning with feature extraction capabilities. Metaheuristic approaches, including PSO, have been effectively coupled with LSTM to fine-tune model parameters. Concurrently, ensemble models such as Random Forest continue to demonstrate consistent efficacy, particularly when integrated into hybrid systems.techniques.

5.1 Framework for Selecting Appropriate Machine Learning Algorithms

Within the scope of Logistics 4.0, the success of demand forecasting is tightly related to the type and quality of the input data, which greatly determines the selection of appropriate ML models. An examination of 21 recent articles (2020– 2024) suggests a substantial predominance of multivariate, large-scale datasets. In this area, deep learning architectures—particularly LSTM networks—have exhibited a 15–20% boost in forecast accuracy over standard statistical models such as ARIMA [7, 19].

To support practitioners in selecting appropriate ML methods, we propose a five-step decision framework (Fig. 1) that systematically narrows options based on empirical trends and dataset properties.

Data Volume: For low-volume datasets (1–500 data points), LSTM [21, 1] or LSTM combined with Particle Swarm Optimization (LSTM+PSO) [13] performs well. Medium-volume datasets (501–1000) are suited to Multi- Layer Perceptrons (MLP) [1], while high-volume datasets (1001+), increas- ingly prevalent in modern supply chains, support advanced models such as LSTM [19], Random Forest (RF) [24], or hybrid LSTM+RF frameworks [22].

Data Dimensionality: Univariate time series (e.g., single-product sales) are best modeled using K-Nearest Neighbors (K-NN) [11] or Recurrent Neu- ral Networks (RNNs) [26]. In contrast, multivariate data, which integrates multiple explanatory variables (e.g., weather, promotions), benefit from Ar- tificial Neural Networks (ANN) [10] or ensemble methods like RF [24].

Forecasting Horizon: Short-term predictions (e.g., hourly to weekly) are well-suited for LSTM [7] and RNNs [27]. Medium-term forecasts (e.g., monthly) typically perform best using RF or LSTM+RF models [24, 22], while long- term forecasts (e.g., yearly) benefit from ANN or MLP [8, 9].

Use Case Characteristics: For continuous demand (e.g., staple goods), LSTM [19] or BiLSTM combined with CNN [14] offers robust performance. Seasonal patterns are effectively captured by RF [24] or Seasonal ARIMA (SARIMA) [7]. For sporadic or new product demand, models like K-NN [11] or ARIMAX [6] are preferred.

Computational Resources: Resource availability significantly influences model selection. Deep learning approaches such as LSTM and ANN [14] re- quire substantial computational power and infrastructure. In contrast, tra- ditional ML models such as RF [6] and K-NN [11] are more suitable for environments with limited resources.

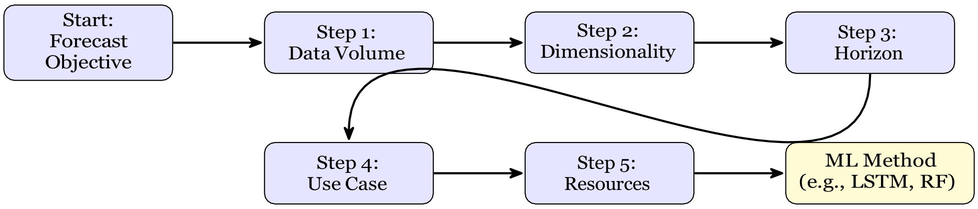

Fig. 1. Decision framework for selecting ML methods in demand forecasting.

6 Conclusion

Although conventional supply chain forecasting has mostly depended on statisti- cal methodologies, this study demonstrates the rising effect of machine learning (ML) in revolutionizing demand prediction procedures. Advanced models such as Multi-Layer Perceptrons (MLPs), Long Short-Term Memory (LSTM) net- works, and Artificial Neural Networks (ANNs) are being increasingly adopted due to their capacity to capture intricate patterns within extensive, multivari- ate datasets—particularly when these datasets integrate exogenous factors like weather conditions, promotional events, or social behavior trends.

Our assessment of 21 recent publications demonstrates a substantial move- ment toward deep learning and hybrid models that integrate ML with statistical techniques to handle varied forecasting issues. Yet, much existing work remains retail-focused. This article calls for more collaborative forecasting incorporating upstream stakeholders like manufacturers, where data from across the supply chain contributes to more accurate projections.

We also propose a structured decision framework (Section 5.1) to assist prac- titioners match ML approaches to their data characteristics—volume, complex- ity, and forecast horizon. For instance, firms with big multivariate datasets might profit from LSTM+RF models, potentially lowering inventory costs by up to 15%.

Looking ahead, future research should study real-time forecasting using IoT data, hybrid models such as SARIMA+LSTM, and the addition of non-traditional inputs like social media or geopolitical indicators—areas yet underexplored. Lightweight or cloud-based ML tools will also be crucial to make sophisticated forecasting accessible to small and medium organizations. These advancements promise to boost agility, precision, and sustainability in global supply networks.

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