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A Comprehensive Survey on Advanced Demand Forecasting Techniques: Statistical, Machine Learning, and Hybrid Approaches for Retail, Supply Chain, and E-Commerce

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Abstract: Effective inventory management and accurate demand forecasting remain central to the success of modern retail and supply chain systems. Industries must continually put up a delicate balance between holding enough stock to meet customer needs while avoiding excess that leads to high costs and waste. This paper provides a comprehensive review of the methods and models developed to address this challenge. It explores traditional approaches such as statistical and econometric models, as well as newer techniques based on machine learning and also hybrid frameworks that combine the strengths of different models to achieve greater accuracy and adaptability. Recent research has explored a wide range of approaches ranging from classical deterministic models such as Economic Order Quantity (EOQ) [2], to statistical methods like ARIMA [5], and modern machine learning and deep learning approaches including LSTM and CNN-LSTM [15]. This survey provides insights from thirty scholarly works, examining methodological advancements and applications across retail, manufacturing, and food industries. The review highlights key contributions, compares model performances, and discusses practical challenges in data preprocessing, model selection, and performance evaluation. Findings indicate that while traditional models remain useful for structured environments, data-driven and hybrid models offer superior adaptability in uncertain, dynamic markets. Future work emphasizes integrating explainable AI with real-time optimization to bridge the gap between theoretical models and industrial practice.

Keywords: Inventory Management; Demand Forecasting; Supply Chain Systems; Machine Learning; Deep Learning; Hybrid Models; ARIMA; LSTM; Explainable AI; Real-time Optimization.

I. INTRODUCTION

In today's fast-changing and competitive retail world, the ability to forecast demand accurately and manage inventory efficiently has become essential for success. With the rise of multiple sales channels, ever-expanding product ranges, and increasingly unpredictable consumer behavior, retailers face growing challenges in aligning supply with demand[2]. Inventory management sits at the heart of these challenges, directly shaping profitability and customer satisfaction. Too much inventory locks up valuable capital and adds storage costs, while too little stock leads to missed sales opportunities and weaker customer loyalty [3]. For this reason, striking the right balance through precise demand forecasting is no longer just an operational task but a key strategic priority [5].

Traditionally, retailers have relied on models such as the Economic Order Quantity (EOQ) to guide inventory decisions [6]. Other approaches, like safety stock and reorder point calculations, have long provided a buffer against uncertainty [7]. However, these methods often assume that demand is stable and lead times are predictable—conditions that rarely hold true in today's dynamic retail environments [9].

Advances in data analytics and computational methods have expanded what is possible in forecasting. Classical statistical techniques such as ARIMA and SARIMA brought the ability to model seasonality and time-dependent structures[11]. Approaches based on Bayesian inference and stochastic optimization introduced ways to account for uncertainty more effectively [13]. More recently, machine learning and deep learning methods—including support vector machines, neural networks, long short-term memory (LSTM) networks, and hybrid CNN–LSTM models—have shown remarkable accuracy in capturing complex, nonlinear demand patterns[18]. These methods can sift through vast historical datasets, uncover subtle trends, and integrate multiple drivers of demand such as promotions, seasonality, and external market shocks [20].

This paper reviews the evolution of demand forecasting and inventory optimization, moving from traditional statistical models to cutting-edge machine learning and hybrid frameworks. Drawing on insights from a wide body of research [30], it synthesizes key developments, evaluates the strengths and weaknesses of different approaches, and highlights strategic

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lessons for practice. Ultimately, the goal is to provide a clear picture of best practices and emerging trends that can help businesses improve forecasting accuracy, fine-tune inventory management, and build long-term competitive advantage.

II. RELATED WORK

The body of research on inventory management and demand forecasting is vast, reflecting the continuous search for models that are both accurate and efficient. This section reviews key approaches, comparing their methods, strengths, and limitations.

Traditional and Statistical Models

Early studies in inventory management largely relied on deterministic and statistical methods. The Economic Order Quantity (EOQ) model [10] remains a foundational example, designed to calculate the order size that minimizes both holding and ordering costs. While effective under stable and predictable conditions, its assumption of fixed demand makes it less reliable in dynamic sectors such as retail. A more flexible alternative emerged with dynamic stochastic optimization models [11], which applied Bayesian inference to capture correlations in store-level demand. By determining both total order quantities and their allocation across outlets, this approach addressed the limitations of purely deterministic models.

Machine Learning Approaches

The arrival of machine learning introduced a significant shift in demand forecasting. A comparative study [12] between SARIMA (Seasonal Autoregressive Integrated Moving Average) and Long Short-Term Memory (LSTM) networks showed that LSTM performs better when demand is relatively stable, while SARIMA remains more suitable for products with strong seasonal patterns. This highlights how choosing the right model depends heavily on the nature of demand.

In the apparel industry, researchers [13] have extended this work by experimenting with more advanced architectures such as Bi-directional LSTM (BiLSTM) and Convolutional Neural Network-LSTM (CNN-LSTM). Among these, the CNN-LSTM hybrid delivered the lowest forecasting error, demonstrating the benefits of combining temporal sequence modeling with spatial feature extraction. Similarly, research in food demand forecasting [14] compared multiple regression-based and neural models—including Random Forest, Gradient Boosting, and LSTM variants—again finding LSTM to be the most effective for capturing time-dependent demand patterns.

Tree-based methods like Random Forest (RF), Gradient Boosting (GB), and XGBoost have also gained traction due to their accuracy and ability to model complex interactions. Comparative studies [15] suggest that while these models perform strongly on their own, hybrid strategies often yield superior results by reducing overfitting and enhancing generalization. Reinforcing this, earlier findings [12] noted that although SARIMA is valuable for seasonal products, nonlinear machine learning models tend to provide better performance in handling the complexity of modern demand dynamics.

Hybrid and Ensemble Models

Recognizing that no single model works best in all situations, researchers have increasingly explored hybrid and ensemble approaches. For example, one study [15] introduced a hybrid model that combined Random Forest, XGBoost, and Linear Regression (RF-XGBoost-LR). This integrated framework outperformed each of the component models when used on their own. Similarly, another study [16] proposed a cluster-based forecasting framework that first segmented customers based on purchasing behavior and then applied Bayesian Model Averaging (BMA) to combine forecasts. This method proved particularly effective in improving daily demand predictions for multi-segment retail environments. The central insight from these works is that ensemble learning—whether through stacking, bagging, or cluster-first forecasting—enhances robustness by drawing on the complementary strengths of multiple models.

Optimization and Advanced Concepts

While forecasting demand is critical, several studies have also addressed inventory optimization more directly. One such approach [17] combined the Newsvendor framework with an Order-Up-To Policy (OUP), further refined using the Croston and Syntetos-Boylan Approximation (SBA) methods. This provided a systematic way to manage intermittent demand, especially for slow-moving or irregularly purchased products. In another innovative contribution, research in the fashion industry [18] integrated structured sales data with unstructured product imagery. By extracting visual attributes such as color and style, the model was able to predict demand for new products even in the absence of sales history. This demonstrates how modern forecasting techniques are expanding beyond traditional data, incorporating diverse sources to better capture real-world complexity.

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TABLE 1 : CONDENSED SUMMARY OF REVIEWED PAPERS

Paper	Key Methods	Main Findings
Agrawal & Smith	Dynamic stochastic optimization, Bayesian inference	Larger mean store demand differences → higher profit.
Teplická & Čulková	EOQ model	Optimizes raw material extraction and storage costs.
Falatouri et al.	SARIMA, LSTM	LSTM better for stable demand; SARIMA better for seasonal demand.
Ranawaka et al.	LSTM, BiLSTM, CNN-LSTM	CNN-LSTM optimal for apparel forecasting.
Panda & Mohanty	RF, GB, LSTM, BiLSTM	LSTM best for food demand prediction.
Mitra et al.	RF, XGBoost, ANN, Hybrid RF-XGBoost-LR	Hybrid model outperforms individual ML models.
Seyedan et al.	Clustering, BMA	Cluster-based ensemble improves daily demand prediction.
Kaya et al.	Newsvendor, OUP, SBA, Croston	Integrates forecasting and inventory for intermittent demand.

The Power of Synthesis: Hybrid and Ensemble Frameworks

A growing theme in recent research is that no single forecasting model can be deemed universally optimal. This has led to the rise of advanced hybrid and ensemble frameworks, which blend the strengths of multiple models to produce more reliable and accurate predictions [21].

One direction within this trend involves hybrid machine learning models, where algorithms are strategically integrated. For instance, [22] proposed the RF–XGBoost–LR framework, which feeds the predictive outputs of Random Forest (a bagging method) and XGBoost (a boosting method) into a final Linear Regression layer. In this design, the ensemble trees capture complex, nonlinear patterns in the data, while the linear layer acts as a stabilizer, resulting in higher accuracy than any single model could achieve on its own. Another approach, often described as “cluster-first, forecast-second,” was introduced by [23]. Their three-step method begins by segmenting customers using Recency–Frequency–Monetary (RFM) characteristics, applies time-series forecasting within each segment, and then combines the results through Bayesian Model Averaging (BMA). By tailoring forecasts to customer groups before merging them, this method effectively captures behavioral differences and improves overall predictive performance.

Taken together, the literature highlights a decisive movement away from traditional, one-size-fits-all statistical models toward more flexible, data-driven approaches. While classical models such as EOQ or ARIMA continue to provide foundational insights, they are consistently outperformed by modern techniques like Long Short-Term Memory (LSTM) networks, which excel at capturing temporal dependencies, and ensemble methods such as Random Forest and Gradient Boosting, which model complex feature interactions with precision [24]. The increasing use of hybrid and ensemble strategies—whether stacking frameworks or clustering-based methods—reflects a recognition that no single algorithm can dominate across all demand scenarios. Instead, these frameworks combine complementary strengths to deliver robust, adaptive, and highly accurate forecasts [26].

Further extending this trend, some studies have begun integrating unconventional data sources and applying models to niche forecasting challenges that traditional methods often struggle to address [27]. Collectively, these advances suggest that the future of demand forecasting lies in hybrid, adaptive, and context-aware models, which are fast becoming the foundation of effective inventory optimization in today’s complex and competitive retail landscape.

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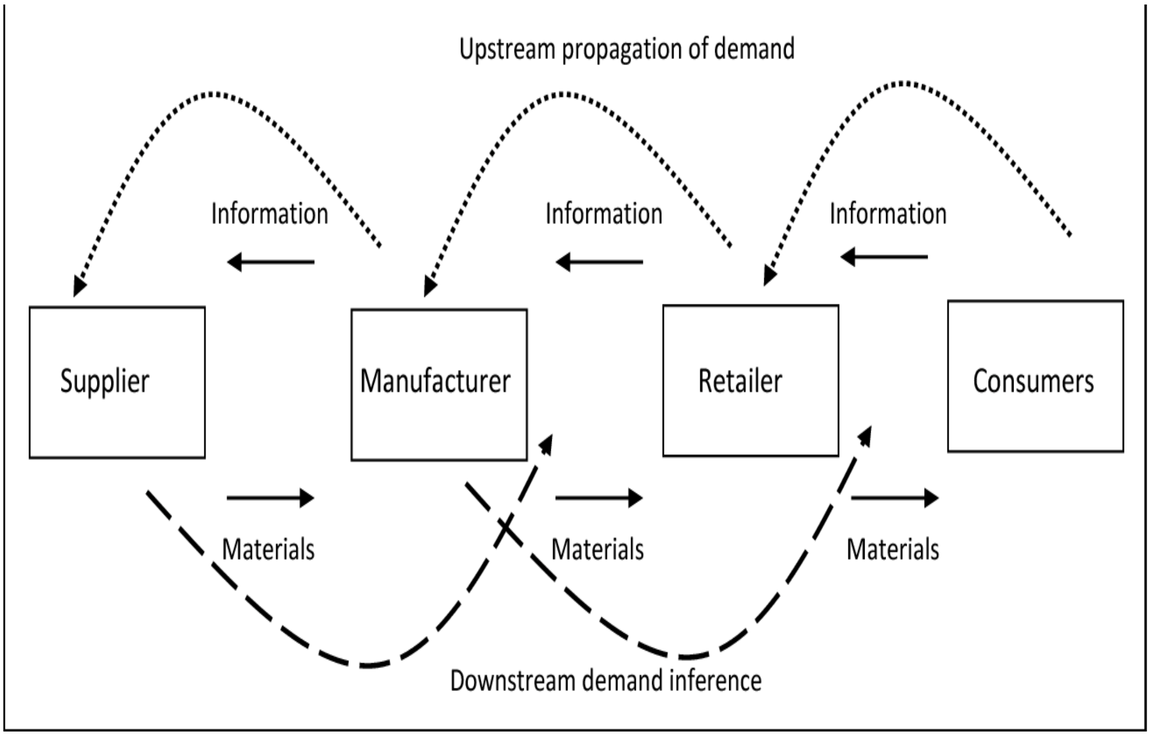

Addressing Niche Challenges in Retail Forecasting

While much of the literature emphasizes general forecasting methods, researchers have also turned their attention to challenges specific to retail operations. One major difficulty is forecasting intermittent or sporadic demand. Products such as spare parts, seasonal items, or luxury goods often display irregular sales patterns that standard time-series models struggle to capture. To address this, [28] combined the Newsvendor model with the Order-Up-To policy, supported by specialized techniques like the Croston method and the Syntetos–Boylan Approximation (SBA). This integrated framework enables businesses to strike a balance between maintaining service levels and controlling costs when dealing with products that sell infrequently or unpredictably.

Another promising research direction involves leveraging diverse and unstructured data sources. In fashion retail, for example, visual appeal plays a critical role in consumer decisions, making it insufficient to rely only on historical sales records. To overcome this, [29] developed an intelligent system that merges deep learning–based image feature extraction with conventional sales data. By analyzing visual attributes such as color, style, and pattern, the model predicts demand for entirely new products by clustering them with similar existing items. This approach allows demand forecasting even in the absence of prior sales history, giving retailers a proactive tool for inventory planning. Building on this, further studies [30] demonstrate how integrating structured and unstructured data enhances forecasting accuracy, supporting better decision-making in fast-paced and highly dynamic retail environments.

III. RESULTS AND DISCUSSION

Traditional models such as ARIMA, SARIMA, and EOQ continue to play an important role in practice [1]. They are well-suited for environments where demand is relatively stable and easy to interpret. However, their effectiveness declines when faced with highly seasonal, irregular, or nonlinear patterns [10]. To address these limitations, recent research has increasingly turned toward machine learning and deep learning methods. Models like Random Forest, Gradient Boosting, and especially Long Short-Term Memory (LSTM) networks have demonstrated higher accuracy by capturing complex relationships and long-term dependencies [14]. These strengths make them particularly valuable in industries such as fashion and FMCG, where demand shifts rapidly in response to trends and seasonality.

A second clear direction in the literature is the rise of hybrid and ensemble approaches, which emphasize integration rather than reliance on a single method. For example, stacked ensembles like the RF–XGBoost–LR framework and cluster-first–forecast-second strategies have consistently outperformed standalone models [23]. Alongside this, the use of alternative data sources—such as product images, customer behavior, or even social media activity—has been shown to significantly enhance forecasting accuracy [27]. This is especially relevant for apparel and luxury goods, where consumer choices are strongly shaped by style and social influence [30].

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Specialized challenges, such as intermittent demand, also highlight the need for tailored methods. Products like spare parts or seasonal goods often require approaches that combine domain-specific models with statistical refinements. Integrating the Newsvendor model with corrections like Croston's method or the Syntetos–Boylan Approximation (SBA) has proven effective for managing irregular purchase cycles [28].

Building on these insights, our project implements a practical forecasting system that combines SARIMA and CNN-LSTM. SARIMA provides a reliable statistical baseline for capturing seasonality and trends, while CNN-LSTM leverages deep learning to model both short-term fluctuations and long-term dependencies. Together, these methods strike a balance between interpretability, accuracy, and adaptability, demonstrating the value of blending traditional time-series models with advanced neural networks in real-world inventory management.

IV. CONCLUSION

This survey illustrates how demand forecasting and inventory management have progressed from classical statistical approaches to advanced, data-driven systems. Traditional methods like EOQ and SARIMA remain useful in stable contexts, but they often fall short in the face of today's rapidly changing retail and fashion markets, where demand patterns shift unpredictably.

Recent research underscores the growing role of machine learning—particularly deep learning—in addressing this complexity. LSTM networks, in particular, excel at modeling seasonality, abrupt shifts in consumer behavior, and long-term demand dynamics, making them highly effective in industries where customer preferences evolve quickly [14].

One of the most promising directions is the development of hybrid and ensemble models. By combining statistical methods with machine learning or deep learning, these frameworks deliver both accuracy and resilience, ensuring forecasts remain reliable even under uncertainty [23].Another emerging trend is the incorporation of external and unstructured data, such as product imagery, reviews, or social media signals, which enrich forecasting systems with insights that raw sales figures alone cannot provide [30].

Our project reflects these advances by integrating SARIMA with CNN-LSTM. SARIMA captures seasonal trends in a transparent way, while CNN-LSTM enhances the system's ability to detect nonlinear and complex demand patterns. Together, they show how blending traditional and modern methods can yield forecasting systems that are not only more accurate but also more adaptable to real-world challenges.

Ultimately, both the literature and our project converge on the same conclusion: the future of inventory management will be intelligent, adaptive, and predictive. Businesses that embrace these innovations will gain the ability to optimize stock levels, lower costs, satisfy customers, and build resilient supply chains capable of withstanding uncertainty.

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