



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

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Abstract

This review aims to demonstrate the effectiveness of the ML and DL approaches to demand forecasting in the retail supply chain, proving the superiority of the approaches over conventional statistical methods. Traditional models suit themselves poorly in the face of nonlinear dependencies, outside influences and fluctuating settings, especially in retail. At the same time, Machine Learning methodologies like RandomForest, SVMs, LSTM, and CNN provide astonishing accuracy once the temporal and spatial complexity characteristics of sales information are discovered. The review underlines the consideration of data fusion and feature construction, including macroeconomic indexes, weather, and promotions, in extending the forecasts. Issues like data quality, scalability and interpretability of the model are deliberated upon along with the solutions related to incorporating IoT and blockchain. These innovations imply real-time data capture, high-reliability levels and greater process transparency. On the same note, using enhanced value assessment indicators, usually MAE, RMSE, and MAPE, highlights that model engineering requires careful, distinct selection methods. Thus, this systematic review has put together and analyzed the most recent developments, issues, and trends in applying ML and DL in enhancing inventory management, pricing, and customer satisfaction in the retail industry to stimulate better performance and competitiveness in today's fast-growing market environment.

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

1. Introduction

Demand forecasting is a reasonable and essential practice for managing the supply chain in retail stores. ML technologies are changing this field as retailers can predict customer demand more accurately. Traditional statistical models used in previous work do not encompass all the aspects of dynamic and nonlinear retail environments daily. ML techniques overcome such limitations because the latter works based on large datasets, finds concealed features, and considers the changes in the market environment.

The rationale for conducting this review is to identify and synthesize various ML approaches for forecasting demand in the supply chain retail environment. The potential challenges and potential uses of ML models in different retail contexts are described in the review. It also describes ways external influences, including economic variables, weather patterns and social media, are incorporated into demand forecasting models.

The layout of this review corresponds to the following key objectives: to define the present state of knowledge regarding demand forecasting in the context of ML applications in the retail industry, to establish the gaps in existing literature, and to provide perspective avenues for further -investigation.

1. Advancing Demand Forecasting in Retail with Machine Learning

Demand forecasting is an important aspect of the retail supply chains since it can be accurate or inaccurate. This gives efficient inventory control, reduces costs, and improves the satisfaction of target customers. The following is how retailer stocking can benefit from demand forecasting, ensuring they have a good stock to avoid overstock or running out. This balance helps save on storage and availability, enhancing customer experience and increasing customer loyalty [1].

Problems exist with traditional fixed-interval forecasting techniques, including ARIMA, linear regression, exponential smoothing, etc. The best-performing models take a deterministic approach to pattern recognition and rely heavily on predetermined parameters often preset from historical data with little influence from more complicated patterns than simple linear progressions. It can cause significant errors, which may not be helpful in contemporary markets that undergo considerable changes within a short period regarding customers' actions. Further, self-generated methods are limited in their ability to integrate the external environment, such as economic signs or real-time data, which formally lowers the effectiveness of the methods [2].

Machine learning provides an answer to these problems. ML models are effective when used in a rapidly changing environment such as retail because they can compare large amounts of data, find complex correlations, and filter and update data. This brings another point: ML interacts with diverse sources of data inputs, including real-time data, for better and improved forecasts. This improvement means improved decision-making on inventory, pricing, and marketing strategies, so the supply chain makes important improvements toward being more responsive [3].

2. Machine Learning Techniques for Retail Demand Forecasting

Supervised learning algorithms play a critical role in retail demand forecasting. Decision trees, SVMs, and neural networks are the best ways to understand the past sales data needed to forecast future trends. Data is split along feature values, whereas the decision tree traces the decision paths leading to a demand forecast. As for data classification, SVMs use the best hyperplane to segment other demand levels without having high dimensionality problems. Numerical models built on the premise of the human brain, the neural networks help discover these patterns by layers of connections and help capture complex sales data relationships. These algorithms have been used successfully in different retail contexts with the aim of improving the stock and selling processes [4].

Clustering analysis methods, belonging to the unsupervised learning group, search for patterns in sales data without prior knowledge of these patterns' classification. Techniques such as k-mean clustering help categorize products used in demand clustering to segment items to suitable forecasting approaches. Then, Ensemble learning methods use different distinct models to increase reliability by canceling the biases. Such methods as bagging, boosting or making predictions from multiple models and then taking the average, thereby developing better demand forecasts. It is revealed that implementing these approaches enhances forecasting performance in a retail environment to enhance decision-making [5].

Retail demand prediction has benefitted from deep learning models such as LSTM and CNN through temporal and spatial dependencies in data. The selected LSTMs are an example of recurrent neural networks, and one of the significant strengths of the approach is the capacity to handle long-term dependencies in sales time series. CNNs, apt for finding spatial hierarchies, have been trained to discover the local structure of the sales data. CNN and LSTM combined models have outperformed other models in describing the dynamics of retail demand, including all the complexities of finally achieving a MAPA [6].

3. Advancing Retail Demand Forecasting with Deep Learning and Data Integration

Specifically, the LSTM network and CNNs have greatly enhanced the performance of retail demand forecasting. One of the most important advantages of LSTMs is the ability to process sequence data, which

is why LSTMs are suitable for time series data in sales data. CNNs, however, are extremely good at identifying spatial patterns from data. CNN and LSTM Models combined in the CNN LSTM lead to improved prediction accuracy by seeking temporal and spatial features. For instance, a current work pointed out that a CNN-LSTM model holds high potential for predicting retail demand, out-competing other models with an RMSE of 18 [7].

It is, therefore, important that, through feature engineering, external data is included in forecasting demand. Promotions, holidays, and weather are some factors that significantly affect decisions. Introducing these variables provides a valuable mechanism for improving the predictive models' accuracy in forecasting demand oscillation. A holistic approach of broaching internal sales data accompanied by some external aspects results in more accurate projections, unlike random guessing, which makes Macy's able to make the proper inventory and marketing decisions. For instance, one of the studies delineated feature engineering for enhancing predictive sales models [8].

Measuring the performance of the demand forecasting models is done by the use of suitable measures. MAE, MAPE, and RMSE are the most used evaluation measures in various fields and applications. MAE measures the deviations between the actual and forecasted values without any regard to sign, resulting in a relatively straightforward interpretation of the accuracy of the forecast. MAPE comes up with errors in percentage form, thereby giving us a perception of the size of individual errors. RMSE is much worse when significant errors occur because it directly squares the difference 'striking at the outliers. The choice of the correct metric is important as it decides model selection and optimization. This paper's comparative analysis aids practitioners in identifying the optimal metric for a given forecasting environment [9].

4. Overcoming ML Challenges and Future Opportunities in Retail Forecasting

There are several challenges with using machine learning (ML) in retail demand forecasting. Data accuracy is crucial; irrelevant or missing values will result in the prediction of false results. Two important limitation areas include scalability and complexity in dealing with large sets of training data for retail businesses. Model interpretability is also important; people should be able to explain how the models come up with the results they make so that they can trust and apply the information provided by the ML models [10].

Next, the use of ML for retail forecasting may include IoT and blockchain. It has also realized the need for real-time monitoring of consumers' behavior, which helps improve estimates concerning demand. Since blockchain technology independently serves as a database, it helps maintain the data's accuracy and makes them trustworthy regarding ML forecasts. Further studies on integrating these technologies with ML showed that accurate forecasting models could be developed if these technologies were incorporated into the models [11].

In conclusion, despite the immense benefits ML has the potential in increasing the efficiency of the retail supply chain through accurate demand forecasting, the following research questions pose significant challenges, as seen above, regarding data quality, scalability and interpretability. Future research proposals include a more detailed investigation of the relationship between IoT and blockchain as relatively novel technologies. Through these changes, retailers can realize the benefits of ML in supporting the correct decisions and improving inventory management in order to satisfy the consumer's needs.

Literature Review

Forecasting requirements is one of the strong pillars of efficient supply management since it determines stock control, spending, and customer satisfaction. Traditional techniques have significant limitations in capturing the most important patterns and externalities, which can only be overcome using machine learning (ML) and deep learning (DL) skills. This literature review focuses on Upgrading forecasting methodologies, where intelligent artificial intelligence procedures replace traditional statistical techniques. This section draws the potential of the field to improve its forecasting capabilities by summarizing studies that use diverse data, new methods and algorithms, and the mixed use of ML and DL. The findings derived seek to present a synthesis of knowledge about the current state and changes in demand forecasting in supply chain management.

Retail sales and price projections often rely on time series forecasting, but specific product categories face challenges with low forecast accuracy. In the research presented in [12], a proactive approach was explored to improve the demand forecast accuracy for the Knitwear category, which previously achieved only 60% accuracy using non-AI models. The study introduced a decision model employing an algorithm rack that dynamically selects the best-performing algorithm for a given context. By incorporating advanced feature engineering into the AI/ML forecasting model, the forecast accuracy for Knitwear improved by 20%, reaching 80%. This adaptable algorithmic approach highlights the potential of machine learning to address forecasting inefficiencies while tailoring solutions to specific customer contexts.

Managing inventory in a multi-level supply chain structure is particularly complex due to the difficulty in accurately predicting demand for most items. In the analysis conducted in [13], machine learning approaches such as Artificial Neural Networks (ANNs) trained with a second-order algorithm and Support Vector Machines (SVMs) for regression were employed to predict customer demand at the first level of a supply chain. The study utilized public data from Netflix's online DVD rental platform to forecast movie rental demand during the critical Christmas season. Additionally, data from external sources, including Rotten Tomatoes and Flipster, were integrated to enhance predictive accuracy. This combination of advanced machine learning techniques and multi-source data integration effectively reduced uncertainty in demand forecasting, demonstrating its potential to optimize inventory management in retail supply chains.

Accurate demand forecasting is crucial for optimizing supply chain management, particularly in capturing complex patterns influenced by seasonal variability and special events. In the research presented in [14], the Multi-Channel Data Fusion Network (MCDFN) was introduced as a hybrid deep learning architecture integrating Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU). This approach extracted spatial and temporal features from time-series data, achieving superior predictive performance compared to seven other deep-learning models. Benchmarking results demonstrated MCDFN's effectiveness, with metrics including MSE (23.5738), RMSE (4.8553), MAE (3.9991), and MAPE (20.1575%). The study enhanced model interpretability by using explainable AI tools like ShapTime and Permutation Feature Importance while confirming prediction accuracy through statistical validation, such as a paired t-test and 10-fold cross-validation. The findings provide practical insights for integrating MCDFN into supply chain systems and outline future research directions for scalability and usability.

Due to the availability of extensive data collections from consumers, products, and stores, advanced sales forecasting capabilities have gained significant attention in the retail industry for their critical role in decision-making. The analysis conducted in [15] introduced a novel method called the Advanced Temporal Latent-factor Approach to Sales Forecasting (ATLAS). This approach employs tensor factorization methodologies, initially designed for personalized context-aware recommender systems, to enhance the accuracy and individualization of sales predictions across multiple stores and products. ATLAS integrates a tensor framework to leverage information across stores and products, a novel regularization function incorporating demand dynamics. It extrapolates tensor predictions into future periods using seasonal ARIMA models and recurrent neural networks. The effectiveness of ATLAS was demonstrated through analysis of over 165 million weekly sales transactions spanning 15,560 products across 1,500 grocery stores, achieving substantial improvements in forecasting accuracy and showcasing its potential for retail applications.

Accurate demand forecasting in the retail industry is critical to financial performance and supply chain efficiency. In the study referenced as [16], the limitations of relying solely on historical sales data were addressed by incorporating macroeconomic variables such as the Consumer Price Index (CPI), Index of Consumer Sentiment (ICS), and unemployment rates into time-series forecasting. This enriched dataset was used to develop and compare various regression and machine learning models to improve retail demand predictions. By bridging the gap between traditional forecasting and the influence of macroeconomic conditions, the study provided a more comprehensive framework for understanding consumer behavior and enhancing forecasting accuracy in dynamic retail environments.

Demand forecasting is a critical challenge in the retail industry, as it directly impacts cost minimization, inventory management, and the reduction of out-of-stock situations. In the analysis conducted in [17], a

comparative evaluation of Machine Learning (ML) and Deep Learning (DL) techniques, including Random Forest, Gradient Boosting Regression, and Long Short-Term Memory (LSTM), was performed to forecast product demand using extensive time-series historical data. The study assessed the models' performance using metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The findings revealed that Random Forest demonstrated superior efficiency and accuracy compared to the other techniques, establishing its potential as a reliable forecasting method in dynamic retail environments.

The analysis conducted in [18] explored the importance of accurate forecasting in retail supply chain management, focusing on tree-based ensemble forecasting methods and deep learning techniques. This study utilized over six years of historical demand data, encompassing daily metrics for over 330 products and integrating external factors such as meteorological and COVID-19-related data. The evaluation of three perishable product categories revealed that the Extra Tree Regressor (ETR) outperformed Long Short-Term Memory (LSTM) networks in key metrics such as MAPE, MAE, RMSE, and R², with the performance gap most significant for fresh meat products and marginal for fruit products. Additionally, ETR results were compared with three other tree-based ensemble methods—XGBoost, Random Forest Regression (RFR), and Gradient Boosting Regression (GBR)—highlighting their robust predictive capabilities compared to LSTM. These findings underline the potential of tree-based ensembles in addressing forecasting challenges and encourage further exploration of their comparative performance with deep learning models across different forecasting horizons.

As detailed in the paper [19], demand forecasting is pivotal in operational strategy for managing inventory and enhancing customer satisfaction. This study evaluated the performance of five machine learning regression techniques—Random Forest (RF), Extreme Gradient Boosting (xgboost), Gradient Boosting, Adaptive Boosting (AdaBoost), and Artificial Neural Network (ANN)—in comparison to a proposed hybrid RF-XGBoost-LR model for sales forecasting in a retail chain. Using weekly sales data from a U.S.-based retail company, the analysis incorporated attributes such as regional temperature and store size to assess forecasting accuracy. The findings revealed that the hybrid RF-XGBoost-LR model outperformed individual models across multiple performance metrics, showcasing its potential to provide more reliable sales forecasts. These insights can guide industry decision-makers in adopting advanced forecasting methodologies for improved operational efficiency.

The article denoted as [20] addressed the limitations of traditional time series and regression methods in addressing the significant, non-stationary shifts in demand for online retail organizations. To overcome these challenges, the study proposed Neural Network architecture, AR-MDN, designed to simultaneously model associative factors, time-series trends, and demand variance. The architecture utilized feature embeddings, Multi-Layer Perceptrons (MLPs), and Long Short-Term Memory networks (LSTMs) to represent causal features, with the output density modeled as a mixture of Gaussian distributions. This end-to-end trainable approach was tested on a dataset spanning a year of demand for tens of thousands of products from Flipkart. The results demonstrated a significant improvement in forecasting accuracy compared to traditional methods, underscoring the potential of AR-MDN in enhancing demand prediction in the dynamic online retail environment.

The publication identified as [21] explored the potential of advanced sales forecasting to influence critical business decisions in the retail industry. The study introduced the Advanced Temporal Latent-factor Approach to Sales Forecasting (ATLAS), a novel methodology leveraging tensor factorization to enable accurate and individualized predictions across multiple stores and products. ATLAS integrates a tensor framework to exploit cross-store and product information, incorporates a new regularization function to account for demand dynamics, and uses state-of-the-art models such as seasonal ARIMA and recurrent neural networks for extrapolation into future periods. The method was validated using eight product category datasets from Information Resource, Inc., encompassing 165 million weekly sales transactions across 1,500 grocery stores and over 15,560 products. The results demonstrated ATLAS's capability to improve sales forecasting accuracy, offering valuable insights into inventory management and supply chain optimization.

As outlined in [22], as a core of retail business, demand forecasting is a key aspect that significantly impacts both the financial outcomes for a business and supply chain realities. The study eliminated some of the

traditional methods into time-series datasets, where the primary tool was used for the pre-economic variables, such as the Consumer Price Index (CPI), Index of Consumer Sentiment (ICS), and unemployment rates. By enriching the predictive models with these macroeconomic indicators, the research developed and compared various regression and machine learning techniques to enhance forecasting accuracy. This comprehensive approach demonstrated the importance of integrating broader economic conditions into retail demand prediction models to give businesses a competitive edge in increasingly interconnected global markets.

In the research presented in [23], a uni-regression deep approximate forecasting model was developed to address the challenges of complex patterns, external factors, and nonlinear relationships in supply chain demand forecasting. The model integrates bidirectional long short-term memory (BiLSTM) networks and nonlinear autoregressive with exogenous inputs (NARX), creating a robust deep learning framework for regression-based approaches. This combination allows the model to capture intricate dependencies and patterns that traditional methods often fail to recognize. The uni-regression approach demonstrated superior performance, achieving the lowest error rates among competing models, with a mean average error (MAE) of 1.73, mean square error (MSE) of 4.14, root mean square error (RMSE) of 2.03, root mean squared scaled error (RMSSE) of 0.020, and an R-squared value of 0.94. These results highlight the model's effectiveness in dynamic supply chain environments. By optimizing inventory management and enhancing supply chain resilience, the uni-regression model offers a valuable tool for practitioners and contributes to advancing demand forecasting methodologies.

The analysis conducted in [24] explored the critical role of machine learning techniques in overcoming supply and demand challenges within organizations, focusing on demand forecasting. Weekly sales data from a multinational retail chain covering 45 stores over three years in the United States was used to evaluate the performance of machine learning models, including Random Forest, Gradient Boosting, and XGBoost. Other variables in the study regarding sales include the store size and the Consumer Price Index. The performance of the models was compared to evaluate distances cross entropy against distance respectively based on metrics such as Mean Absolute XGBoost, which demonstrated superior performance, producing the most accurate predictions among the evaluated models and highlighting its effectiveness for demand forecasting in retail supply chains.

As discussed in [25], managing inventory within a multi-level supply chain is particularly challenging for large retail stores due to the complexity of predicting demand across numerous items. The study explored the potential of machine learning techniques, specifically Artificial Neural Networks (ANNs) trained with a second-order algorithm and Support Vector Machines (SVMs) for regression, as effective methods for demand forecasting at the first level of the supply chain. Public data from the Netflix movie rental service was used to predict demand during the critical Christmas season, incorporating external data sources such as Rotten Tomatoes and Flixster to enrich the analysis. By integrating diverse data sources and leveraging advanced machine learning models, the approach demonstrated a significant reduction in uncertainty, highlighting the capability of such methods to improve demand forecasting and inventory management in dynamic retail environments.

In the article denoted as [26], a comprehensive review of machine learning (ML) and deep learning (DL) models for demand forecasting in supply chain management was conducted. The study analyzed 119 papers from the Scopus database spanning 2015 to 2024, offering both macro and micro-level insights into the application of AI-based methodologies. At the macro level, the review examined trends and the overall trajectory of ML and DL applications, while the micro-level analysis delved into the distinctions and advantages of specific models. By synthesizing insights from this extensive literature, the study provides a valuable resource for leveraging ML and DL techniques to enhance demand forecasting in supply chain management, paving the way for future advancements in the field.

As outlined in [27], the critical role of supply chain management and demand forecasting in business operations was examined, focusing on the transition from traditional forecasting methods to advanced statistical and machine learning approaches. The study utilized machine learning regressors to predict orders for a Brazilian logistics company, employing the PyCaret Python library to develop robust regression models and validate key contributing features through feature importance plots. The performance of 18 regression

models, including Ridge, LASSO, XGBoost, Bayesian Ridge, Linear Regression, Gradient Boosting, KNN, and Random Forest, was evaluated using the Mean Absolute Error (MAE) metric. The findings highlight the effectiveness of these advanced approaches in improving demand forecasting accuracy, contributing valuable insights to the logistics sector.

A detailed comparison of various machine learning and deep learning-based demand forecasting papers is provided in Table 1. It also touches on different approaches that may be used, including those based on combinations like RF-XG Boost-LR and more complex network structures like MCDNF and AR-MDN, which are appropriate for retail forecasting when the environment is more dynamic. The papers employ various databases, including sales transaction records and macroeconomic databases, to enhance predictive foresight and decision-making. Measures of performance that include RMSE, MAE, or MAPE demonstrate the usefulness of these models, as results are usually better than those of traditional forecasting methods. The analysis also identifies the importance of feature selection and construction, fusion of multiple data sources, and using both models to improve the accuracy and generalization capability of forecasts. The table helps gain insights into present-day advancements and future research in retail demand forecasting.

Table 1: Summary of Literature Review

Study	Methodology/Algorithm	Dataset/Domain	Performance Metrics	Key Insights
[12]	Decision model with feature engineering	Knitwear retail sales	Accuracy improvement (20%)	Adaptive algorithmic approach tailored solutions to specific contexts.
[13]	ANN, SVM regression	Netflix data with Rotten Tomatoes and Flipster integration	Enhanced predictive accuracy	Multi-source data integration reduced demand forecasting uncertainty.
[14]	MCDNF (CNN, LSTM, GRU)	Time-series retail data	MSE: 23.57, RMSE: 4.85, MAE: 3.99, MAPE: 20.15	Hybrid architecture excelled in capturing spatial and temporal features.
[15]	ATLAS (Tensor Factorization)	Grocery sales (165M weekly transactions)	Substantial forecasting accuracy improvements	Leveraged cross-store and product information.
[16]	Regression and ML models integrating macroeconomic variables	Consumer Price Index, ICS, unemployment rates	Enhanced prediction accuracy	Bridged traditional methods with economic indicators.
[17]	Random Forest, Gradient Boosting, LSTM	Extensive time-series data	RMSE, MAPE	Random Forest outperformed in dynamic retail environments.
[18]	Extra Tree Regressor (ETR) and ensemble methods	Historical demand data (330 products, external factors)	MAPE, MAE, RMSE, R ²	Tree-based ensembles outperformed

			deep learning for perishables.	
[19]	Hybrid RF-XGBoost-LR	U.S. retail weekly sales	Improved accuracy across metrics	Demonstrated hybrid model's reliability for retail sales forecasting.
[20]	AR-MDN (Neural Network)	Flipkart sales data	Significant accuracy improvements	Modeled associative factors, trends, and variance.
[21]	ATLAS (Tensor Framework)	Grocery sales (165M weekly transactions)	Enhanced accuracy and individualization	Showcased application of advanced factorization techniques.
[22]	Regression and ML integrating macroeconomic variables	CPI, ICS, unemployment rates	Improved accuracy over traditional methods	Highlighted the role of economic conditions in retail predictions.
[23]	BiLSTM and NARX	Supply chain demand data	MAE: 1.73, MSE: 4.14, RMSE: 2.03	Captured intricate dependencies and optimized inventory management.
[24]	Random Forest, Gradient Boosting, XGBoost	Weekly sales (3 years, 45 stores)	XGBoost most accurate	Emphasized the robustness of ensemble methods for retail.
[25]	ANN, SVM regression	Netflix movie rental data	Significant uncertainty reduction	Leveraged external data to enhance predictive accuracy.
[26]	ML and DL model analysis	Scopus database (119 papers)	Literature synthesis	Provided macro and micro-level insights into ML/DL forecasting.
[27]	Regression models (18 types, PyCaret)	Brazilian logistics company data	MAE evaluation	Showcased ML regressors' effectiveness in logistics forecasting.

These reviewed papers emphasize the increasing prominence of ML and DL in floating the demand forecasting area, providers with a significant enhancement in prediction quality and versatility. Hence, by combining highly complex algorithms with various data sources, researchers have established strong models that perform better than conventional methods in various supply chains. Still, there are issues of model interpretability, scalability, and data quality, which remain challenges that still hold further potential for

innovation. This literature review also looks at the current accomplishments of the previous research and the possibility of future developments to improve the applicability of these models. The work provides a basis for practitioners and researchers to assess and apply advanced forecasting techniques in complex supply chain contexts.

Discussion

Forecasting is critical to demand planning in the retail supply chain since it guides inventory control for supply chain improvement and customer satisfaction. Conventional models of analysis based on statistics are limited in explaining contemporary nonlinear and dynamic patterns characteristic of retail settings. This review benefits from presenting the potential of Machine Learning (ML) and Deep Learning (DL) techniques in enhancing the overall forecasting performance through optimized algorithms, integrated data, and, most effectively, sophisticated feature engineering. The analysis focuses on the evolution, prospects, and potential problems of using these technologies and outlines the key directions for their effective implementation. This review can direct researchers and practitioners toward better solutions for demand forecasting-related issues by coalescing findings of prior studies on supply-side and demand-side perspectives.

1. Studying the Potential of Machine Learning for Sales Forecasts in Retail resizing

The literature discussed above highlights the positive effects of applied machine learning (ML) algorithms on retail demand forecasting. While conventional models fail to handle nonlinearity and extrinsic variables, ML techniques like Random Forest, Support Vector Machines (SVM), and other hybrid models have outperformed others with a remarkable rise in forecasting precision. Other techniques, such as tensor decomposition and neural models like LSTM and CNN, enhance these features by discovering temporal and spatial features in sales data. These advancements help retailers make the right decisions on merchandise management, pricing, and promotional strategies to handle customers, which contributes to the retail business's operational effectiveness and profitability [28].

2. Data integration and feature engineering are important aspects of the current world of technology.

It has also come from the findings that data quality and diversity are critical to the practical application of ML models to demand forecasting. To enrich prognoses, many studies embrace extensive indicators, including macroeconomic indexes (CPI, rates of unemployment etc.), weather factors, and promotions. Feature engineering practices have been seen to be crucial in the determination of what features are relevant. This has increased the likelihood of the models getting the dynamics of consumers right. As shown in the case of ATLAS and AR-MDN, multi-source data enhances this process apart from providing rich insights into demand fluctuations in different contexts [29].

3. Information About the Evaluation Criteria and Model Performances

That is the case because the choice of evaluation metrics defines how forecasting models are assessed and optimized. Some of the easily measurable parameters by genuine statistically significant evaluation methodologies include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and others. As research suggests, when it comes to sequential data, such as our case of the forecast of products, deep learning models, specifically LSTM, show excellent results. In contrast, tree-based ensemble methods like Extra Tree Regressor or Random Forest may be more suitable for certain retail situations, such as perishable products. The comparative analyses prove that it is crucial to choose models appropriate for the given data's traits and the application's nature [30].

4. Difficulties that Arise when Deploying Machine Learning Techniques

Progress has been made in the development of ML models; however, there are issues with using these models. The phenomenon of noise and data quality also threatens the accuracy of forecasts due to potentially missing values or the inclusion of non-relevant informative variables. As mentioned above, scalability is still an issue,

especially when dealing with large datasets and real-time processing. Furthermore, another type of model that needs much attention is model interpretability, which is important in helping stakeholders in decision-making. Problems of this class, like CNN and LSTM hybrids, are not always used in retail settings due to their high computational sophistication despite their high accuracy levels [31].

5. They are as follows: Emerging technologies and future direction.

The application of emerging technologies like IoT and blockchain in combination with ML to recharge the demand forecasting area in the retail industry. Internet of Things ensures data capture their data are real-time, while blockchain ensures their data is reliable and traceable. Subsequent studies should incorporate these technologies with ML models to address issues such as data scalability and interpretability. Additionally, a rise in the application of Explainable AI tools can enhance model interpretability, enhancing its use across the retail industry [32].

6. Business Relevance for Retail Supply Chain Management

Furthermore, the conclusions arrived at by this review have important implications for practice in the context of retail supply chains. Modern demand forecasting contributes to inventory management, cost control, and improvement of the overall satisfaction among consumers. Moreover, by utilizing sophisticated techniques in the ML field, retailers can forecast market demand, eliminate out-of-stock situations, and decrease the quantity of overstock or potentially lost sales. The inclusion of external data and the use of works in progress help maintain competitiveness in the current retail environment conditions to provide a reliable framework for organizing business activities [33].

The current and potential use of ML and DL in retail demand forecasting can offer significant progress from conventional methods, as the following arguments will illustrate: Compared with traditional models, which analyze one or two potential factors, these models also manage complicated patterns and influence from outside. However, issues including data quality, the scalability of these methods, and the interpretability of the models have to be addressed for them to become widely adopted. That is why IoT and blockchain can be seen as promising in eliminating these shortcomings and enhancing the effectiveness of forecasts. To sum up, this work proves the necessity of further development of ML-based forecasting, ensuring retail companies' readiness as market participants in today's highly competitive environment.

Conclusion

Analytically, ML and DL have been shown to improve the demand forecast for the retail industry significantly. Hence, these techniques allow for better management of dynamic and nonlinear patterns, which are not well captured in traditional forecasting approaches, including linear models and inadequate external factors. Although RF, SVM, and neural networks such as LSTM and CNN have been fascinating in detecting temporal and spatial patterns in selling information, which aids in stocking, strategic pricing, and promotional campaigns.

The combination of multiple data sets has also boosted the forecast further. Using macroeconomic factors, weather data and promotions informs the ML models of other factors that may affect consumers. Therefore, the feature engineering approach has proved important in selecting features, fine-tuning the model, and accurately capturing demand variability. It has been used in models including ATLAS and AR-MDN that use multiple source data to gain more insight into the retail demand.

However, some issues relate to using ML models in forecasting the retail environment. There are barriers regarding data quality, the interpretability of the model and the scalability. Using outdated data or providing too little will create less reliable forecasts, and highly complex models are often complicated for stakeholders to interpret and believe in. Also, as data grows, the problem of real-time processing of large data sets does not quickly scale. To overcome these barriers, the help of new technologies like IoT and blockchain should be included, which will allow us to capture data in real-time, have reliable information, and trace it.

Therefore, the future of ML-based demand forecasting remains in prospecting for ways to fine-tune such models to counter existing constraints. Mitigating and addressing business and technical risks with IoT, blockchain, and explainable AI tools will improve the scalability, transparency, and efficacy of the current advanced Internet of Things models. These advancements will foster competitiveness within the evolving retail environment by offering a sound base for enhancing operational performance and satisfaction among shoppers. Future studies and advancements are still needed to optimize this field and augment the use of ML in reforming retail demand forecasting.

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