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A Review and Comparative Analysis of Predictive Models for Supply Chain Demand Forecasting

Rehab IbrahimAhmed Omer
Department of Computer Science
International Islamic University Malaysia
Kuala Lumpur, Malaysia
Rehab.iao@hotmail.com

Raini Hassan
Department of Computer Science
International Islamic University Malaysia
Kuala Lumpur, Malaysia
hrai@iium.edu.my

Madihah Sheikh Abdul Aziz
Department of Information Systems
International Islamic University Malaysia
Kuala Lumpur, Malaysia
madihahs@iium.edu.my

***Abstract*— Accurate demand forecasting is critical to supply chain optimization, influence inventory management, production scheduling, and customer satisfaction. This paper presents a comparative analysis of traditional forecasting models and machine learning approaches for supply chain demand prediction. This study reviews key techniques, including statistical time-series models, supervised and unsupervised learning algorithms, ensemble methods, and deep learning architectures. Empirical evidence from retail, manufacturing, healthcare, and food sectors demonstrates their relative performance and practical applicability. Challenges such as data quality, model interpretability, and system integration are analysed, along with emerging trends in real-time adaptability, hybrid modelling, and explainable AI. By synthesizing current research and implementation insights, this work provides a comprehensive evaluation of existing methods, identifying their strengths, limitations, and future research directions to enhance data-driven demand forecasting in modern supply chains.**

Keywords— Predictive analytics, Machine learning, Supply chain.

I. Introduction

Global supply chains are becoming more complicated, unstable, and unpredictable. To reduce costs, increase customer satisfaction, and remain competitive, accurate demand forecasting is essential in supply chain management. Traditional forecasting methods, such as moving averages, exponential smoothing, and ARIMA models, have long supported planning and decision-making, yet they often struggle to adapt to today's dynamic markets, where data sources are diverse, fast changing, and often unstructured.

Advances in predictive analytics and machine learning (ML) have expanded the forecasting techniques, enabling the extraction of patterns from large, complex datasets that include both structured and unstructured inputs such as social media and IoT sensor data. These approaches, ranging from regression analysis and decision trees to ensemble methods and deep learning, offer new levels of accuracy, adaptability, and insight for supply chain decision-making.

This paper utilizes a targeted literature review approach by selecting 17 papers published between 2019 and 2025 from different databases such as IEEE Xplore, Scopus, and ScienceDirect, focusing on supply chain demand forecasting using predictive techniques. The goal is to clarify the strengths, limitations, and potential of different approaches, highlight implementation challenges, and identify promising directions for future research and practice in supply chain demand forecasting.

The remainder of this paper is organized as follows. Sections II and III introduce the fundamental concepts and describe various demand forecasting methods, including traditional forecasting approaches and predictive analytics techniques, discussing real-world applications across industries and illustrating how machine learning techniques enhance forecasting accuracy and decision-making. Section IV presents a comparative analysis of the reviewed studies on predictive analytics. Section V identifies the existing challenges and research gaps in literature. Section VI explores current trends, emerging technologies, research directions, and future opportunities in the field. Finally, Section VII concludes the paper by summarizing the key insights and emphasizing the transformative potential of advanced analytics in supply chain operations.

II. Traditional Forecasting Techniques in SCM

For a long time, traditional forecasting techniques in supply chain management (SCM) have served as a foundation for planning and decision-making.

A. Overview of Classical Forecasting Models

Traditional forecasting in supply chain management (SCM) is primarily rooted in statistical time-series analysis, using historical data to predict future outcomes [1], [2]. These models operate under the assumption that the future will be an extension of the past, a principle long applied to inventory management and production planning. Key classical models include:

- **Moving Averages and Exponential Smoothing**: Fundamental techniques for smoothing data and identifying trends. Moving averages reduce short-term fluctuations, while exponential smoothing assigns higher weights to recent observations to capture trends and seasonality [3].

- **ARIMA (Autoregressive Integrated Moving Average)**: A strong and widely used model combining autoregression, differencing for stationarity, and moving averages to capture temporal structures [2].

B. Limitations in Adapting to Volatile Market Trends

While effective in stable environments, traditional forecasting models exhibit significant limitations when faced with the complexity and volatility of modern markets [4]. Their weaknesses are inherent to their core assumptions and architecture.

- **Linearity Assumption:** These models' cores are linear and assume that statistical properties of a time series, such as its mean and variance, are constant. This makes them insufficient in handling the non-linear patterns that are generated from sudden spike demand, promotional impacts, or unforeseen disruptions caused by today's dynamic market. As a result of the rapid shift in the condition of the market, historical data has become a poor predictor for the future, leading to inaccurate demand forecasting. [5], [6].
- **Limited Variable Inclusion:** Traditional methods are typically univariate which means they only look at data in past demand. They often do not consider external factors or complex, non-linear relationships that influence demand, such as economic conditions, social media trends, or competitor actions. [5].
- **Poor Handling of Intermittent Demand:** A significant issue for conventional models is predicting intermittent demand, characterized by brief periods of zero demand followed by unexpected, diversified demand increases. These types of models remain constrained when compared to more adaptable machine learning approaches [3].

C. Gap in Responsiveness and Scalability

The architecture of classical forecasting models creates a significant gap in their ability to respond quickly to new information and to scale with the volume of modern data.

- **Adaptability:** Static models cannot adjust quickly to real-time changes. They cannot dynamically adjust to real-time information, such as sudden supply chain disruptions or shifts in consumer behaviour, unlike ML [3], [4].
- **Scalability:** Traditional methods are not optimized for big data environments, limiting their ability to process high-volume, high-velocity datasets [2].

III. Predictive Analytics For Demand Forecasting Techniques in SCM

Predictive analytics has transformed how supply chain management (SCM) works by turning demand forecasting from an educated guess into a complex, data-driven science. Using historical data and advanced predictive techniques, organizations can anticipate future demand with greater accuracy, enabling proactive decision-making that optimizes supply chains. [4].

A. Definition and Role of Predictive Analytics

Predictive analytics is a branch of advanced analytics that uses historical data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes [7]. In SCM, it enables a shift from descriptive analytics to proactive decision-making.

B. Models Used

A diverse set of tools and models are employed in predictive analytics for demand forecasting, ranging from traditional statistical models to complex machine learning algorithms. The performance of these models is precisely evaluated using a standard set of metrics. The choice of model often depends on the complexity of the data, the desired accuracy, and the specific business context.

1) Foundational Statistical and Regression Models

While modern analytics has shifted towards machine learning, traditional models still serve as important benchmarks for performance comparison.

- **Regression Models**: These models Link demand to variables such as price, promotions, and seasonality. They create a mathematical link between demand (the dependent variable) and a number of factors that have an effect on it (independent variables) [2].
- **Time-Series Models**: Classical models like ARIMA (Autoregressive Integrated Moving Average) are used to analyse and forecast time-series data based on its own past values. However, like regression, they struggle to incorporate a wide range of external variables or capture intricate non-linear patterns [3].

2) Machine Learning (ML) Algorithms

Machine learning is the most advanced type of predictive analytics today. It is a collection of powerful algorithms that can learn complicated patterns from huge datasets. Predictive analytics for demand forecasting uses a range of models that can be generally grouped into supervised and unsupervised learning. Each category and its models have their own strengths when it comes to understanding and predicting future demand patterns [2].

- **Linear Regression**: This is one of the simplest supervised learning algorithms, used to predict a continuous dependent variable based on one or more independent variables. It assumes a linear relationship between inputs and outputs, making it easily interpretable but often limited in capturing complex market dynamics [4].
- **Decision Trees**: Decision trees work by creating a tree-like structure where internal nodes represent tests on attributes, branches represent the outcome of the test, and leaf nodes represent the predicted class label or value. They are effective for both classification and regression tasks and are relatively easy to interpret [2]. However, single decision trees can be likely to overfitting the training data [8].
- **Support Vector Machines (SVM)**: SVM is a powerful algorithm that aims to find a function that approximates the

dataset with a certain tolerance for error. It works by mapping data into a high-dimensional feature space and finding a linear relation there. SVR works well for problems with complex, non-linear relationships. It is also noted for being able to represent complicated boundaries with a lot of accuracy and not being as likely to overfit. Particularly SVR, are highlighted for their ability to model complex, non-linear relationships, even with smaller datasets, and often show good performance in demand forecasting tasks [3], [5].

- **K-Nearest Neighbours (K-NN)**: K-NN is a non-parametric, instance-based learning algorithm. For prediction, it finds the 'k' training examples closest to the new data point and uses the majority class (for classification) or the average value (for regression) of these neighbours to make its prediction. It's simple and effective but can be computationally expensive for large datasets and sensitive to the scale of features [2].
- **K-Means Clustering**: This is a popular clustering algorithm used to partition data points into a predefined number of clusters ('k'). Points within each cluster are like each other, and dissimilar to points in other clusters. K-means is useful in SCM for segmenting customers based on purchasing behaviour, categorizing inventory, or identifying patterns in logistics data [4].

While the models listed above are primarily associated with supervised or unsupervised learning, some, like Decision Trees, can be adapted for both tasks. The choice of model depends heavily on the specific characteristics of the demand data and the forecasting objectives.

3) Ensemble Methods

These techniques combine multiple individual models to produce a single, more accurate prediction.

- **Random Forest (RF)**: An ensemble method that builds multiple decision trees on different subsets of the data and features, then aggregates their predictions. This approach significantly reduces overfitting and improves generalization performance compared to single decision trees, making it a strong choice for demand forecasting [13], [15].
- **Gradient Boosting Machines (GBM)**: This is a more advanced ensemble technique in which models are produced one after the other, with each new model fixing the mistakes of the one before it. GBM recognized for its high accuracy and speed, making it widely used in real-time forecasting. Models like XGBoost and attention-based GBMs are known for their high performance and are frequently used in state-of-the-art forecasting systems [8].

4) Deep Learning (Neural Networks)

Deep Learning (DL) is a subset of machine learning that uses neural networks with multiple layers (deep architectures) to learn representations of data at varying levels of abstraction. DL models have shown superior performance in many fields, including time-series forecasting. These models are inspired by the structure of the human brain and can learn complex, non-linear relationships. They consist of interconnected layers of nodes (neurons). Deep learning models are particularly well-suited for modelling the complex, sequential nature of demand data.

- **Recurrent Neural Networks (RNNs)**: These networks are designed to work with sequence data, making them a natural fit for time-series forecasting.
- **Long Short-Term Memory (LSTM) Networks**: A specific type of recurrent neural network (RNN) particularly adept at learning from sequential data. LSTMs have internal mechanisms (gates) that allow them to remember or forget information over long periods, making them ideal for time-series forecasting where historical context is critical. LSTMs particularly noted for their effectiveness in handling time-series data with long-term dependencies, outperforming simpler neural networks and traditional methods in many applications [9].
- **Bidirectional RNNs (Bi-RNNs)**: These models process data in both forward and backward directions, allowing them to use both past and future context to make more accurate predictions. Studies have shown Bi-RNNs can outperform other advanced models like ARIMA and standard LSTMs [6].

Table I. shows the comparison between model accuracy and complexity based on the reviewed literature.

TABLE I. TECHNIQUES VS. ACCURACY VS. COMPLEXITY

Model / Technique	Accuracy	Complexity
Traditional (ARIMA, MA, ETS)	Lower; prone to errors with complex/volatile data [8], [10], [11].	Simple to moderate implement and understand but struggles with complex, non-linear data and requires manual feature engineering; requires some statistical knowledge. [8], [9].
Linear Regression	Moderate; struggles with non-linear relationships [10].	Simple; easy to understand and implement [4].
SVM/SVR	Good; effective with non-linear data and high dimensions. May yield a 12% reduction in forecast error rate compared to linear models [5],[13].	Moderate to High; requires careful parameter tuning (kernels) [5],[13],[14].
Decision Trees	Moderate; can be prone to overfitting if not pruned [7].	Simple; easy to interpret [7].
Random Forest (RF)	High; robust, reduces overfitting, and handles many variables well [13], [15]	Moderate; more complex than single Decision Trees [13].
Gradient Boosting (GBM/XGBoost)	Very High; often achieves state-of-the-art results, especially with large datasets [4], [15]	High; requires significant expertise for tuning and implementation [4]
Neural Networks (NN)	High; capable of learning complex non-linear patterns [12]	High; requires significant data and computational

		resources; tuning is complex [14]
Deep Learning (LSTM, CNN)	Very High; excels at time-series data, capturing long-term dependencies and complex temporal patterns [4],[13],[8]-[10].	Very High; computationally intensive, complex to implement and interpret, "black box" nature. [4],[13], [8]-[10].
Ensemble Models	Very High; combines strengths of multiple models for superior accuracy and robustness [15]	Very High; integrates complexity of multiple models, computationally demanding. [3], [4],[9].

C. *Performance Evaluation Metrics*

Metrics are essential for quantifying the performance of a forecasting model. They provide an objective basis for comparing different algorithms and for understanding a model's strengths and weaknesses.

- **Mean Absolute Error (MAE)**: This metric calculates the average absolute difference between the forecasted and actual values. It is easy to understand.
- **Root Mean Square Error (RMSE)**: RMSE is the square root of the average of the squared errors. Because the errors are squared before being averaged, RMSE gives a relatively higher weight to large errors.
- **Mean Absolute Percentage Error (MAPE)**: MAPE measures the average absolute error as a percentage of the actual values. This makes it a scale-independent metric, which is very useful for comparing forecast performance across different products or time series with varying scales.
- **R-squared (R^2)**: R^2 measures the proportion of the variance in the demand that is explained by the model. A value closer to 1 indicates a better fit, meaning the model captures a larger portion of the demand's variability.

D. *Application examples from various industries*

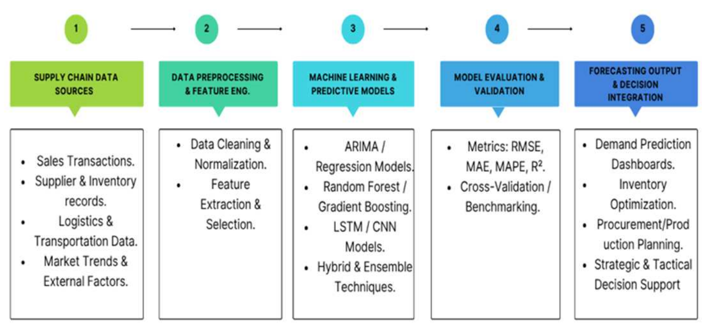
Predictive analytics for demand forecasting is being applied across numerous sectors to solve industry-specific challenges:

- **Retail and E-commerce**: This is one of the most prominent application areas. Retailers use predictive analytics to forecast demand for thousands of Stocks Keeping Units (SKUs) across both physical and online stores. This includes predicting the impact of promotions, holidays, and seasonal trends on products ranging from Fast-Moving Consumer Goods (FMCG) to electronics and apparel [2],[3],[9].
- **Pharmaceutical and Medical Supply Chains**: In the medical field, accurate demand forecasting is critical for patient safety and regulatory compliance. Pharmaceutical companies use predictive analytics to manage inventory for life-saving drugs, ensuring availability while avoiding the high costs of overstocking temperature-sensitive products. It also helps in segmenting customers based on health needs to better predict demand for specific treatments [16].
- **Manufacturing and Spare Parts**: Predictive analytics is used to forecast the demand for spare parts, which is often intermittent and difficult to predict with traditional methods. For example, a bus fleet operator might use machine learning to predict the need for specific parts to minimize vehicle downtime and optimize maintenance schedules [14].
- **Food and Beverage Industry**: For perishable goods, accurate forecasting is essential to minimize spoilage and waste. Food companies use predictive models to align production with consumer demand, ensuring product freshness and availability while controlling inventory costs. These forecasts help manage the entire supply chain, from procuring raw materials to distributing finished goods [2].

E. *Conceptual Framework*

Fig. 1 presents the proposed conceptual framework, which is derived from insights gathered across the reviewed studies on demand forecasting. It integrates common elements identified in the literature—input data sources, model types (ARIMA, machine learning, and deep learning), evaluation metrics, and forecasting outcomes—to illustrate the overall analytical process. This framework reflects the consensus approach adopted in prior research for assessing and comparing forecasting model performance in supply chain contexts.

Fig. 1. Conceptual framework for predictive models based on supply chain demand forecasting



IV. ANALYSIS

The findings across the literature show significant agreement regarding the general superiority of machine learning over traditional methods, but they also reveal critical conflicts and nuances concerning which advanced model performs best under specific data conditions or for particular applications.

A. *Areas of Strong Agreement*

The most common agreement in all the resources is that sophisticated machine learning (ML) and deep learning (DL) models are usually more accurate and make fewer mistakes than standard statistical methods, especially when working with complicated data and non-linear relationships.

This superiority is due to ML's capacity to find complicated and non-linear correlations that regular models often miss. In addition, the majority agree that ensemble approaches and hybrid models (which combine many models or use deep learning and machine learning with statistical methods) are more accurate and more reliable than any one model on its own. In most studies, ensemble and deep learning approaches like GBM, LSTM, and hybrid CNN-LSTM consistently do better than traditional time-series models, getting RMSE declines of 10–25%.

B. *Areas of Conflict and Conditional Performance*

Conflict arises when comparing specific advanced models to each other, or when traditional models unexpectedly perform well under certain conditions.

- **The Volatility/Complexity Condition (LSTM vs. ARIMA)**
  Although the literature does not provide a definitive agreement that LSTM only outperforms ARIMA under high volatility, it strongly links the advantage of LSTM to the presence of complexity and high volatility.

- **Efficiency Trade-off (CNN/LSTM vs. ARIMA)**
  A clear conflict emerges when considering computational cost for short-term forecasting, while CNN and LSTM achieve superior accuracy (low RMSE), ARIMA is the most efficient model in terms of training time and consumed energy. If model size is large, ARIMA might be preferred due to this efficiency.

C. *Performance Comparison*

Table II presents a comparative summary of RMSE and MAE values reported in key studies from the reviewed literature. The table highlights the relative performance of different forecasting models. This comparison provides insight into the accuracy and consistency of each model type as evaluated in prior research.

TABLE II. COMPARING RMSE/MAE VALUES FROM KEY STUDIES

Study / Year	Model(s) Evaluated	RMSE	MAE
Bousqaoui et al., 2021	CNN, LSTM, MLP, ARIMA	485.690 ARIMA 464.261 MLP 457.958 LSTM 457.079 CNN	N/A
Krishna et al., 2025	Attention-based GBM, Random Forest, SVM	0.2 (Attn-GBM). 0.4 (RF). 0.3 (SVM)	0.18 0.3 0.25
Seyedan et al., 2023	Proposed Ensemble (MLP+LSTM+1D-CNN), LSTM, MLP, 1D-CNN	(Electronics) 4.99 Ensemble 5.93 MLP. 5.21 LSTM 7.96 1D-CNN	 3.56 5.05 4.18 6.20
Ahlawat et al., 2024	Bi-RNN, LSTM, RF, SARIMA, ARIMA, SES	4.2 (Bi-RNN). 6.5 (LSTM). 9.0 SARIMA 10.5 (ARIMA) 8.2 RF 9.8 SES	3.4 5.0 6.8 8.0 6.0 7.5
Li, Foshang, 2022	SVM, Improved Bass Model	1.5316 (SVM-Retail). 32.0485 (SVM-Network). 4.7442(Improved Bass-Retail) 92.2839(Improved Bass-Network).	N/A

V. CHALLENGES AND GAPS IN THE LITERATURE

The literature on predictive analytics and machine learning in supply chain management highlights several persistent challenges and gaps. Addressing these issues is crucial for advancing the field and enabling more effective, data-driven decision-making.

A. *Data Quality and Integration*

- **Data Quality and Integration**: The effectiveness of machine learning models is directly tied to the quality of the data used for training. Unreliable data sources, biases, missing values, and inconsistencies can significantly impair prediction accuracy and model performance. Supply chains generate data from diverse sources (e.g., ERP systems, IoT sensors, sales records). Integrating these datasets, which often have different formats and exist in silos, is a significant issue. This lack of a unified view complicates the effective flow of information and the consistent application of ML models [4], [17].
- **Data Scarcity**: For specific applications, such as demand forecasting for short-life cycle products or in certain industries, there can be a lack of sufficient historical data, which is critical for training complex ML models [5].

B. *Lack of Interpretability in Complex ML*

While advanced models like deep learning and ensemble methods offer superior predictive power, their "black box" nature presents a significant challenge:

Model Interpretability: Many sophisticated ML models, particularly deep learning architectures, are complex and difficult to interpret. This lack of transparency can be problematic, especially in industries that require explainable decision-making for regulatory compliance or to build trust among stakeholders [1], [17]

C. Underrepresentation of Low-Resource Regions and SMEs

The current body of research often focuses on large-scale, well-resourced environments, leading to a gap in understanding how ML can be effectively applied in other contexts:

- **Limited Focus on Specific Sectors/Regions**: Several reviews note that while ML applications are growing in sectors like industry and services, there is a lack of research focusing on specific areas like agriculture, low-resource regions, or small and medium-sized enterprises (SMEs) [12], [17].
- **Scalability and Cost Barriers for SMEs**: The implementation of advanced ML solutions can be financially demanding, posing a significant barrier for smaller enterprises. These organizations may struggle

to balance the potential benefits against the required investment in infrastructure and expertise [4], [17].

VI. Future Research Directions

The literature consistently identifies opportunities for developing more dynamic and integrated forecasting systems:

- **Integration with IoT and Blockchain**: The synergistic use of ML with other advanced technologies, such as IoT for real-time data collection and blockchain for enhanced transparency and security, presents significant opportunities for more integrated and reliable forecasting systems [4].

  Addressing these challenges and leveraging these opportunities through further research and development will be critical for unlocking the full potential of predictive analytics and machine learning in supply chain management [17].

- **Real-Time Adaptability**: There is a need for forecasting models that can adapt in real-time to evolving market conditions, demand fluctuations, and external factors. While models like LSTM show promise, many studies do not adequately address this need for real-time adaptability [3].

- **Hybrid Approaches**: Combining statistical, ML, and expert judgment or blending various ML algorithms (e.g., LSTMs with Random Forests, or using ensemble methods), which is highlighted as a promising avenue for improving accuracy and robustness [2], [3], [9]. The integration of human judgment with ML models is also seen as an opportunity to enhance long-term planning and address situations where data is limited or market dynamics are complex [2].

- **Explainable AI (XAI)**: A significant focus for future research is XAI, which seeks to enhance the transparency and interpretability of machine learning and deep learning models [13]. This will cultivate trust and promote adoption, particularly in regulated settings.

VII. Conclusion

This study compared several machine learning models for supply chain demand forecasting and found that ensemble and deep learning methods are generally more accurate and adaptable than traditional statistical models. However, their performance depends on data quality, feature design, and domain context. Challenges like interpretability and computational complexity still hinder large-scale use. Future research should focus on hybrid and explainable AI approaches to make supply chain forecasting more transparent, scalable, and robust.

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