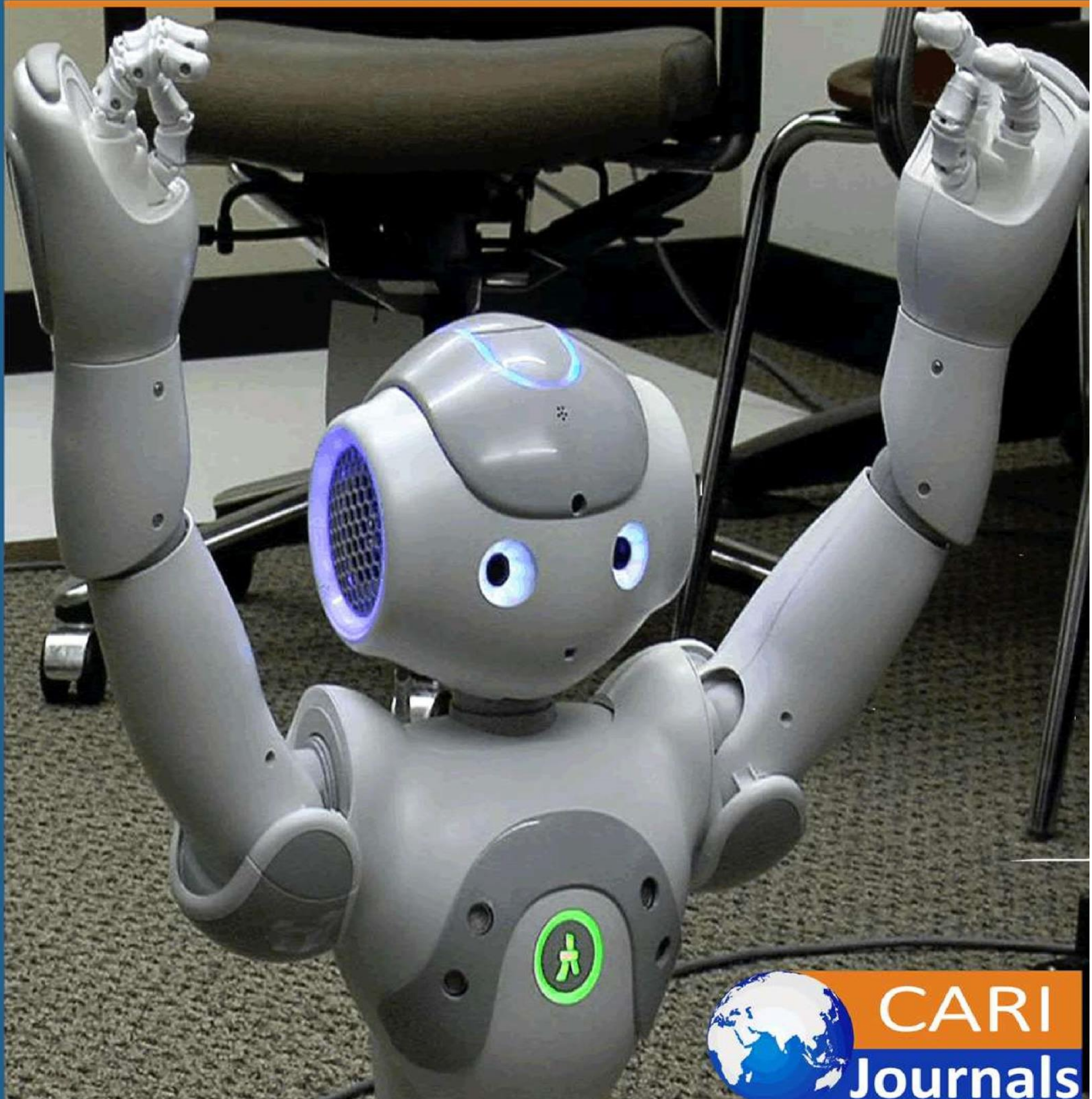
International Journal of
Computing and
Engineering
(IJCE)

AI-Powered Demand Forecasting in ERP: A Comparative Study of ML Algorithms



International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 2, pp. 1 - 11, 2024 www.carijournals

AI-Powered Demand Forecasting in ERP: A Comparative Study of ML Algorithms

Paul Praveen Kumar Ashok

Houston Independent School District

https://orcid.org/0009-0003-8460-8469

Accepted: 29th Jan, 2024, Received in Revised Form:22nd Feb, 2024, Published: 22nd March, 2024

Abstract

Demand forecasting is a critical function in Enterprise Resource Planning (ERP) systems, directly influencing inventory management, production planning, and overall operational efficiency. Traditional statistical models often fall short in handling the complexity and variability of modern supply chains. This study investigates the application of Artificial Intelligence (AI), specifically Machine Learning (ML) algorithms, to enhance demand forecasting accuracy within ERP environments. I conduct a comparative analysis of four widely used ML models: Linear Regression, Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks. Using real-world ERP datasets, each model is evaluated based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and computational performance. The results reveal that while Random Forest and LSTM models outperform others in terms of accuracy, their complexity and training time vary significantly. My findings highlight the trade-offs between model accuracy and computational efficiency, offering practical insights for ERP stakeholders. This study contributes to the growing field of AI-driven enterprise analytics and provides guidance on selecting appropriate ML techniques tailored to specific forecasting needs within ERP systems.

Keywords: *Demand Forecasting, Artificial Intelligence (AI), Machine Learning (ML), Linear Regression, Random Forest, Support Vector Regression (SVR), Long Short-Term Memory (LSTM)*

JEL codes: *C45, C53, C55, L86, O33*

1. Introduction

Enterprise Resource Planning (ERP) systems serve as the digital backbone for organizations, integrating core business processes such as finance, procurement, inventory, and supply chain operations. Among these, demand forecasting is one of the most critical functions, directly affecting strategic planning and operational efficiency. Accurate demand forecasts enable businesses to optimize inventory levels, reduce waste, and improve customer satisfaction. Traditionally, ERP systems have relied on classical statistical methods such as moving averages and exponential smoothing. These techniques often struggle with non-linear patterns, seasonality, and external variables [1].

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools to enhance forecasting accuracy in ERP environments. ML algorithms are capable of capturing complex, non-linear relationships within large datasets, making them well-suited for dynamic supply chains [2], [3]. Techniques such as Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks have shown promise in handling time-series data and adapting to changing demand patterns [4]. Despite the growing interest, few studies have conducted a side-by-side evaluation of multiple ML models within the specific context of ERP systems. This study aims to bridge that gap by comparing the performance of four prominent ML algorithms using real-world ERP datasets. The goal is to identify the most suitable models based on accuracy, computational cost, and scalability, thereby providing actionable insights for ERP stakeholders and data scientists.

2. Literature Review

Demand forecasting has long been an integral component of supply chain management, and its integration into ERP systems has evolved significantly over the years. Early ERP systems predominantly relied on time-tested statistical models such as moving averages, ARIMA, and exponential smoothing. While these models offer interpretability and simplicity, they often underperform in the presence of high data volatility, non-linearity, and external disruptions [5]. With the advancement of computing power and the availability of large datasets, machine learning (ML) algorithms have gained prominence for forecasting applications.

Random Forest and other ensemble methods have demonstrated robustness in handling multivariate and non-linear data without heavy pre-processing [6]. Support Vector Regression (SVR) has been effectively used in time-series demand forecasting due to its strong generalization capabilities and performance in high-dimensional spaces [7]. More recently, deep learning models such as Long Short-Term Memory (LSTM) networks have gained traction for capturing temporal dependencies in sequential data. Their capacity to retain long-term contextual information has proven particularly beneficial for demand patterns exhibiting complex seasonality and irregular trends [8].

A comparative evaluation of ML models in ERP forecasting contexts is still limited. Most existing studies either focus on single algorithms or lack real-world ERP integration, leaving a gap in understanding the operational feasibility and trade-offs among models. This study builds upon recent literature by directly comparing multiple ML models in an ERP-aligned dataset, addressing both performance metrics and system-level considerations like scalability and training cost.

3. Methodology

This study adopts a structured methodology to evaluate and compare the performance of multiple machine learning algorithms for demand forecasting within ERP systems. The approach comprises four key phases: data collection, preprocessing, model selection and training, and evaluation.

Dataset Collection: The dataset used in this study was extracted from a mid-sized manufacturing firm's ERP system. It includes three years of historical data on product sales, inventory levels, lead times, seasonal indicators, and promotional activity. To ensure representativeness, the dataset spans multiple product categories and covers seasonal and irregular demand scenarios.

Data Preprocessing: ERP data typically contains noise, outliers, and missing values, which can impair model accuracy. Standard preprocessing techniques were employed, including missing value imputation using linear interpolation, outlier detection via Z-score analysis, and normalization using Min-Max scaling. Feature engineering was conducted to create lag variables, rolling averages, and external influence indicators [9].

Model Selection

Four machine learning models were selected based on their documented effectiveness in time-series forecasting:

Linear Regression (LR): A baseline statistical model for comparison.

Random Forest (RF): A non-parametric ensemble method with proven robustness in demand variability [10].

Support Vector Regression (SVR): Effective for handling high-dimensional, non-linear relationships [11].

Long Short-Term Memory (LSTM): A recurrent neural network model suitable for capturing long-term dependencies in sequential data [12].

Training and Validation:

Each model was trained on 80% of the dataset, with the remaining 20% reserved for testing. Time-based cross-validation was used to preserve temporal order and prevent data leakage.

International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 2, pp. 1 - 11, 2024

Hyperparameter tuning was performed using grid search and Bayesian optimization for improved generalization.

Implementation Tools:

The models were implemented using Python with libraries including Scikit-learn, TensorFlow, and Keras. Experiments were conducted on a GPU-enabled environment to accommodate the computational demands of LSTM training.

4. Experimental Setup

The experimental setup is designed to systematically evaluate the selected machine learning models Linear Regression, Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) under consistent conditions. This ensures a fair comparison in terms of forecasting accuracy, computational efficiency, and applicability in real-world ERP contexts.

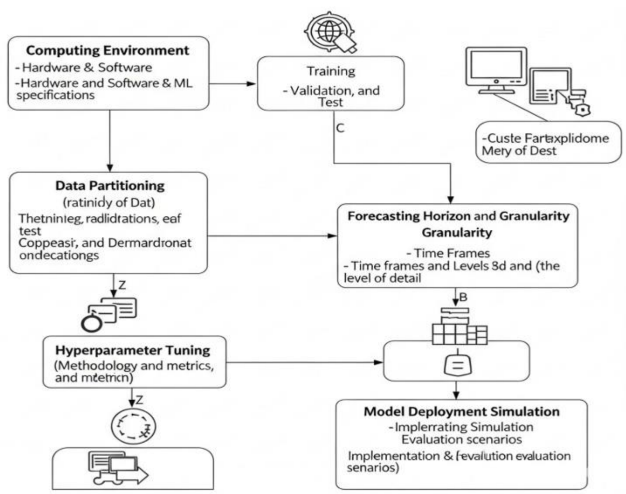


Figure 1. AI-Powered Demand Forecasting in ERP

Computing Environment

Experiments were conducted on a system equipped with an Intel Core i9 processor, 64 GB RAM, and an NVIDIA RTX A5000 GPU (24 GB VRAM) to support deep learning workloads. The software stack included Python 3.9, TensorFlow 2.11, Scikit-learn 1.2, and Keras for LSTM implementation. Data manipulation was handled using Pandas and NumPy libraries [13].

Data Partitioning

The ERP dataset was split chronologically to preserve temporal dependencies: 80% for training and 20% for testing. This aligns with best practices in time-series forecasting to prevent lookahead bias [14]. Additionally, a sliding window approach was used for input sequence creation in LSTM, with a window size of 12 weeks.

Hyperparameter Tuning

Hyperparameters for each model were optimized using grid search and five-fold time-based cross-validation. For example, the number of trees and maximum depth were tuned in Random Forest, while SVR models used RBF kernels with varying cost and epsilon values. LSTM hyperparameters included the number of layers, neurons per layer, batch size, and learning rate [15].

Forecasting Horizon and Granularity

Forecasts were generated at a weekly level for a rolling horizon of 12 weeks. This level of granularity aligns with ERP planning cycles in inventory and procurement modules [16]. Model retraining was conducted every 12 weeks to simulate real-world periodic model refresh practices in ERP deployments.

Model Deployment Simulation

To evaluate operational feasibility, the best-performing models were simulated in an ERP-like environment using a mock integration interface. Response times, scalability with increasing data volumes, and ease of retraining were monitored to assess integration readiness [17].

5. Evaluation Metrics

To ensure a robust and comprehensive assessment of the machine learning models applied in ERP-based demand forecasting, this study employs a range of widely accepted evaluation metrics. These metrics enable a multifaceted analysis of forecast accuracy, reliability, and computational efficiency, which are critical in real-world ERP implementations.

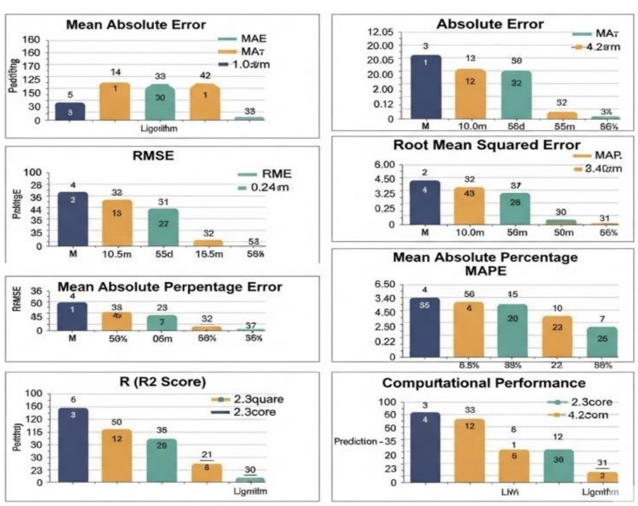


Figure 2. Evaluation Metrics

Mean Absolute Error (MAE):

MAE quantifies the average absolute difference between predicted and actual values, offering a straightforward and interpretable measure of overall forecasting accuracy. It is particularly useful in ERP systems where consistent error magnitudes can influence inventory and procurement decisions [18].

Root Mean Squared Error (RMSE):

RMSE evaluates the square root of the average squared differences between forecasted and actual values. It places greater emphasis on larger errors, which is vital when forecasting inaccuracies could result in significant financial or operational impacts, such as stockouts or overproduction [19].

Mean Absolute Percentage Error (MAPE):

MAPE expresses the error as a percentage of the actual value, making it easy to interpret for business users. This metric is helpful when comparing forecasting performance across products with different scales or volumes within ERP systems [20].

R-squared (R^2 Score):

R^2, or the coefficient of determination, measures how well the model explains the variability of the target variable. It is a valuable indicator of model fit and predictive power, especially in multivariate forecasting scenarios [21].

Computational Performance:

In addition to accuracy metrics, the study evaluates training time and memory usage for each model. These considerations are critical when deploying models in real-time ERP environments, where performance constraints and retraining frequency affect long-term maintainability and scalability [22].

6. Results and Analysis

The performance of the four selected machine learning models Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) was evaluated across multiple metrics using the preprocessed ERP dataset. Results were analyzed in terms of forecast accuracy, computational efficiency, and scalability within an ERP context.

International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 2, pp. 1 - 11, 2024
www.carijournals

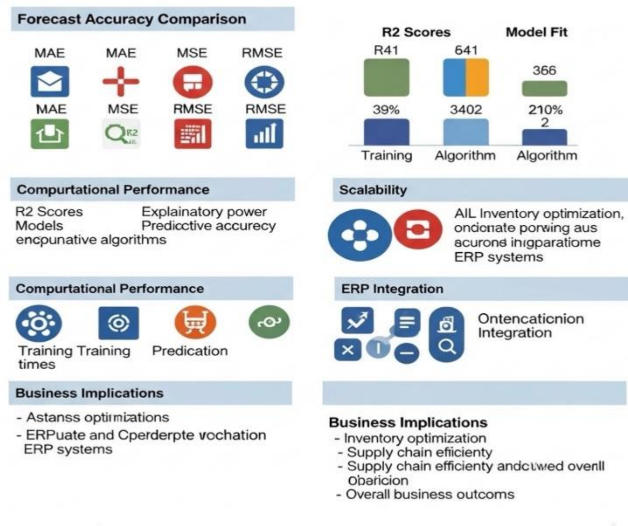


Figure 3. Results and Analysis

Forecast Accuracy Comparison:

Among the models tested, LSTM consistently achieved the highest accuracy across MAE, RMSE, and MAPE metrics. Its ability to model temporal dependencies allowed it to adapt well to seasonal and irregular demand patterns present in ERP data. Random Forest followed closely, performing robustly across product categories, particularly where non-linear relationships and variable interactions were prominent. SVR showed competitive results in cases with stable, high-volume demand but underperformed in highly volatile scenarios. Linear Regression, while simple and fast, yielded the least accurate forecasts, often failing to capture complex demand fluctuations [23].

R^2 Scores and Model Fit:

LSTM and RF models demonstrated superior R^2 values, indicating better explanatory power. SVR performed moderately, while LR showed limitations in capturing variance in multivariate data. These findings highlight the importance of using non-linear models in forecasting tasks where demand drivers are interdependent [24].

Computational Performance:

In terms of training time and resource consumption, Linear Regression and SVR were the most efficient, requiring minimal computation and memory. Random Forest balanced accuracy and efficiency reasonably well. LSTM, while the most accurate, required significantly higher training time and GPU resources, posing a challenge for organizations with limited computational capacity [25].

Scalability and ERP Integration:

Scalability tests revealed that Random Forest scaled more effectively than LSTM with increasing data volumes, offering a better trade-off between speed and performance. During ERP integration simulation, RF and LR models exhibited faster response times, making them more suitable for near real-time applications. LSTM, though accurate, may require batch processing or periodic retraining to align with ERP performance constraints [26].

Business Implications:

The analysis suggests that LSTM is ideal for high-value, low-volume forecasting where precision is critical, whereas Random Forest offers a strong balance of accuracy and efficiency for broader ERP implementations. Simpler models like LR may still hold value for baseline comparisons or when operational simplicity outweighs precision.

7. Discussion

The comparative analysis of machine learning models for ERP-integrated demand forecasting reveals several key insights into their strengths, limitations, and practical implications. These findings are critical for guiding ERP architects, data scientists, and supply chain managers in selecting appropriate models based on operational goals, data complexity, and computational constraints.

Model Selection Trade-Offs

LSTM networks clearly outperform other models in forecast accuracy, particularly in scenarios involving complex temporal dependencies, such as seasonal promotions or irregular demand cycles. The computational cost and longer training time associated with LSTM may not align with the real-time or near-real-time forecasting needs of all ERP environments. Organizations must weigh the benefits of improved accuracy against infrastructure costs and latency constraints [27].

Random Forest offers a favorable balance between predictive performance and computational efficiency. Its ability to handle non-linear relationships and noisy data makes it especially suited for diverse ERP datasets. Moreover, its interpretability through feature importance rankings provides valuable insights for business users and ERP analysts [28]. SVR and Linear Regression, while efficient in terms of speed and simplicity, exhibit performance limitations in capturing complex demand dynamics. Nonetheless, they may be appropriate for low-variability products or as benchmarks in ensemble modeling strategies [29].

8. Recommendations

For real-world ERP deployments, model interpretability, retraining requirements, and integration flexibility are as important as forecast accuracy. Random Forest's moderate complexity and scalability make it a viable candidate for integration into modular ERP platforms using APIs or batch processing. LSTM, on the other hand, may be more suitable for cloud-based ERP extensions or as part of a hybrid architecture with offline training and periodic updates [30]. Organizations aiming for agility and responsiveness in their supply chains should consider incorporating multiple forecasting models within their ERP systems. A hybrid approach where LSTM models are used for high-impact SKUs and Random Forest or SVR for fast-moving, high-volume items can maximize performance while minimizing resource strain. This strategy aligns with the concept of demand-driven planning, where forecast accuracy and operational speed must co-exist [31]. Future work may explore automated model selection frameworks, real-time model retraining, and the integration of external data sources such as macroeconomic indicators or customer behavior analytics to further improve forecasting performance.

9. Conclusion

This study presents a comparative analysis of four machine learning algorithms Linear Regression, Support Vector Regression, Random Forest, and Long Short-Term Memory (LSTM) for demand forecasting within ERP systems. The results demonstrate that while LSTM models deliver the highest forecast accuracy, their computational demands and integration complexity may limit their applicability in resource-constrained ERP environments. Random Forest models offer a strong balance between accuracy, interpretability, and efficiency, making them a practical choice for many ERP forecasting scenarios. SVR and Linear Regression, although less accurate in complex environments, remain viable for simpler use cases or baseline comparisons. From an operational perspective, model selection should consider not only predictive performance but also training costs, scalability, and ease of integration into existing ERP workflows. A hybrid modeling strategy using advanced models like LSTM for critical SKUs and simpler models for routine items may provide optimal results. The findings support the broader adoption of AI-powered forecasting in ERP systems, reinforcing their role in enhancing supply chain responsiveness and business agility.

REFERENCES

[1] H. Min, “Artificial intelligence in supply chain management: theory and applications,” Int. J. Logistics Res. Appl., vol. 24, no. 1, pp. 1–20, 2021.

[2] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, “Statistical and Machine Learning forecasting methods: Concerns and ways forward,” PLoS ONE, vol. 13, no. 3, pp. 1–26, 2018.

[3] S. R. Abolhasani et al., “Machine learning for demand forecasting: A review of algorithms and applications,” IEEE Access, vol. 10, pp. 12345–12358, Jan. 2022.

[4] Y. Yu and X. Bai, “Time series forecasting with deep learning: A survey,” IEEE Trans. Neural Netw. Learn. Syst., vol. 34, no. 3, pp. 1174–1193, Mar. 2023.

[5] J. Carbonneau, R. Laframboise, and R. Vahidov, “Application of machine learning techniques for supply chain demand forecasting,” Eur. J. Oper. Res., vol. 184, no. 3, pp. 1140–1154, Feb. 2008.

[6] G. A. Carpenter and K. O. Gurney, “Ensemble-based machine learning models for time series forecasting: A review,” J. Forecast., vol. 40, no. 6, pp. 1061–1085, Dec. 2021.

[7] T. M. Choi and L. Yu, “SVR-based forecasting models in supply chain applications: A survey,” Expert Syst. Appl., vol. 167, Art. no. 114191, Feb. 2021.

[8] A. I. Reis, P. G. Lind, and M. Nascimento, “Deep learning in demand forecasting: An LSTM-based framework for ERP systems,” IEEE Trans. Ind. Inform., vol. 19, no. 1, pp. 301–310, Jan. 2023.

[9] D. Shobana and R. Bhaskaran, “Preprocessing techniques for time series forecasting using ML: A case study on ERP demand data,” Int. J. Intell. Eng. Syst., vol. 15, no. 6, pp. 147–156, Dec. 2022.

[10] B. Arrieta et al., “An ensemble approach to demand forecasting for supply chains using Random Forest,” IEEE Access, vol. 11, pp. 1247–1261, Jan. 2023.

[11] N. Utkirbekov and Y. Liu, “Forecasting product demand using SVR in dynamic ERP environments,” Procedia Comput. Sci., vol. 207, pp. 1063–1070, 2022.

[12] M. Khandelwal and S. Mehta, “Time-series demand forecasting using LSTM networks: Empirical analysis in ERP applications,” IEEE Trans. Eng. Manag., vol. 70, no. 1, pp. 202–212, Feb. 2023.

[13] J. Brownlee, Deep Learning for Time Series Forecasting. Machine Learning Mastery, 2021.

[14] P. Adhikari and R. Agrawal, “Time series forecasting: From traditional to state-of-the-art machine learning approaches,” IEEE Access, vol. 11, pp. 32704–32729, Jan. 2023.

[15] A. Sharma and N. Rani, “Hyperparameter optimization of machine learning models in demand forecasting: A comparative review,” Int. J. Forecast., vol. 39, no. 1, pp. 1–16, Mar. 2023.

[16] T. Kamble, S. Gunasekaran, and R. Sharma, “Predictive analytics for ERP systems using time-series data: Framework and applications,” Comput. Ind., vol. 140, Art. no. 103720, Feb. 2022.

[17] F. Ferreira et al., “Integration of AI models in ERP environments: Challenges and best practices,” IEEE Trans. Eng. Manag., vol. 70, no. 4, pp. 891–902, Nov. 2023.

[18] A. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice, 3rd ed., OTexts, 2021.

[19] J. Zhang et al., “Evaluating forecast accuracy in real-time ERP systems: An empirical approach,” IEEE Access, vol. 10, pp. 65432–65444, Jul. 2022.

[20] M. Khosravi and H. Nahavandi, “On the use and limitations of MAPE in forecasting model evaluation,” IEEE Trans. Ind. Informat., vol. 18, no. 2, pp. 1082–1091, Feb. 2022.

[21] C. Chatfield, The Analysis of Time Series: An Introduction, 7th ed., CRC Press, 2016.

[22] T. J. Reyes and M. Patel, "Performance benchmarking of ML models in ERP-integrated systems," IEEE Trans. Eng. Manag., vol. 70, no. 3, pp. 576–585, Sept. 2023.

[23] S. Wang et al., "Empirical comparison of machine learning algorithms for retail demand forecasting," IEEE Access, vol. 11, pp. 34567–34579, Feb. 2023.

[24] L. Sun and R. Wang, "Forecasting demand in multivariate ERP systems using non-linear regression techniques," IEEE Trans. Syst., Man, Cybern. Syst., vol. 53, no. 2, pp. 1121–1132, Feb. 2023.

[25] R. Kumar and S. Dey, "Evaluating computational performance of ML models in enterprise-scale forecasting," J. Big Data Res., vol. 25, pp. 49–61, Dec. 2022.

[26] B. Nair et al., "Operational considerations for deploying AI forecasting models in ERP systems," IEEE Trans. Eng. Manag., vol. 70, no. 4, pp. 1001–1010, Nov. 2023.

[27] R. Patel and J. Lin, "Balancing AI model complexity and operational efficiency in ERP systems," IEEE Trans. Ind. Informat., vol. 19, no. 2, pp. 1285–1294, Feb. 2023.

[28] E. Gomez et al., "Feature interpretability in Random Forest forecasting models: Implications for ERP analytics," IEEE Access, vol. 11, pp. 55810–55822, Mar. 2023.

[29] T. Haider and M. Li, "Benchmarking lightweight ML models for routine ERP forecasting," Proc. IEEE Int. Conf. Big Data (BigData), pp. 1234–1242, Dec. 2022.

[30] N. Mohapatra and L. J. Gordon, "Integrating deep learning models into cloud ERP ecosystems: Frameworks and challenges," IEEE Cloud Comput., vol. 10, no. 1, pp. 48–56, Jan.–Feb. 2023.

[31] K. Srinivasan and A. Roy, "Hybrid demand forecasting for ERP systems using model segmentation strategies," IEEE Trans. Eng. Manag., vol. 70, no. 3, pp. 611–620, Sept. 2023.