Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 13 Issue 01, 2024

A Survey of Methods and Architectures for E-Commerce Systems for Sales Prediction Using Triple Pseudo-Siamese Network with Giant Trevally Optimizer

Preben Jeongmin
Lecturer, Department of Electrical and Computer Engineering, Shiraz College of Systems and Management, Iran
Email: preben.jeongmin@scsm-ir.org

Peer Review Information

Submission: 02 Jan 2024

Revision: 11 Jan 2024

Acceptance: 23 Jan 2024

Keywords

E-Commerce Sales Prediction, Deep Learning Forecasting, Siamese Neural Networks, Demand Forecasting, Giant Trevally Optimizer, Retail Analytics

Abstract

The rapid expansion of digital commerce platforms has generated large volumes of transactional and behavioral data, enabling advanced predictive analytics in retail environments. Sales prediction is a key application that supports demand forecasting, inventory optimization, and supply chain efficiency. Accurate forecasting helps businesses reduce operational costs, prevent stock shortages, and improve customer satisfaction. Traditional models such as autoregressive integrated moving average (ARIMA) and regression techniques have been widely used; however, they often fail to capture nonlinear patterns and complex relationships in modern e-commerce datasets. Recent advancements in machine learning and deep learning have significantly improved forecasting performance. Techniques such as random forests, support vector machines, convolutional neural networks (CNN), and long short-term memory (LSTM) networks effectively model large-scale and temporal data. Hybrid CNN-LSTM architectures further enhance prediction accuracy by combining spatial and temporal feature extraction. Additionally, Siamese neural networks enable learning from heterogeneous data sources by capturing relationships between products, customers, and transactions. Optimization methods like the Giant Trevally Optimizer (GTO) improve model convergence and parameter tuning. This review analyzes recent studies and highlights hybrid frameworks for scalable, accurate sales prediction systems.

Introduction

The rapid growth of internet technologies and digital infrastructure has significantly transformed the global retail industry, leading to the emergence of large-scale e-commerce platforms such as Amazon, Alibaba, Flipkart, and eBay. These platforms generate massive volumes of data, including customer interactions, browsing patterns, transactions, and logistics activities. Such data enables businesses to adopt data-driven strategies for improving operational efficiency and understanding consumer behavior.

One of the most critical applications of this data is sales prediction or demand forecasting, which supports inventory management, supply chain optimization, and targeted marketing. Accurate forecasting helps organizations maintain optimal stock levels, reduce costs, and enhance customer satisfaction in competitive markets.

Traditional forecasting methods, including ARIMA, exponential smoothing, and regression models, are simple and efficient but limited in handling nonlinear and dynamic patterns in real-world data. To overcome these limitations, machine learning techniques such as decision trees, support vector machines, random forests, and gradient boosting have been introduced, offering improved accuracy by capturing complex relationships. However, as data complexity increases, deep learning models have gained prominence. Architectures like convolutional neural networks and recurrent neural networks, particularly long short-term memory networks, are effective in extracting spatial and temporal features from sales data, enabling better modeling of seasonal trends and consumer behavior.

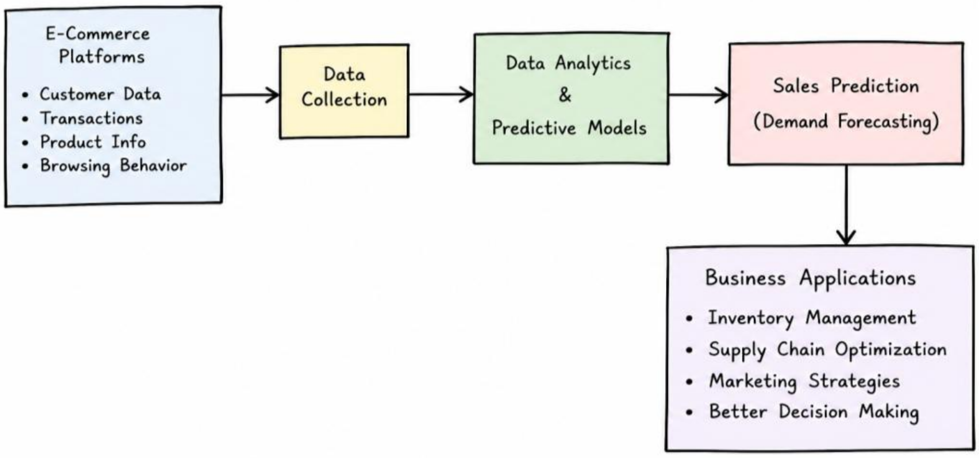

Figure 1: Architecture of E-Commerce Sales Prediction Using Triple Pseudo-Siamese Network and GTO

Recent advancements highlight the effectiveness of hybrid deep learning models, such as CNN-LSTM architectures, which combine feature extraction and temporal analysis to improve forecasting performance. Additionally, Siamese neural networks have emerged as a promising approach for addressing challenges like limited data availability by learning similarity relationships between products. Their advanced extension, the triple pseudo-Siamese architecture, processes multiple data sources simultaneously, including product attributes, customer behavior, and historical sales data, to generate comprehensive feature representations. This integration allows for improved prediction accuracy by capturing relationships across heterogeneous datasets.

Optimization techniques further enhance the performance of deep learning models. Traditional methods like gradient descent may lead to suboptimal solutions, prompting the use of metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and whale optimization. The Giant Trevally Optimizer, inspired by cooperative hunting behavior, improves parameter tuning by balancing exploration and exploitation. Despite these advancements, challenges such as data heterogeneity, scalability, and rapidly changing consumer behavior persist. Therefore, integrating advanced neural architectures with intelligent optimization methods offers a promising direction for developing robust and scalable e-commerce forecasting systems.

Literature Review

Recent research in e-commerce forecasting has increasingly focused on the application of machine learning and deep learning techniques to improve prediction accuracy and computational efficiency.

Alam and Shakil (2020) investigated the use of machine learning algorithms for predicting product demand in e-commerce platforms. Their study evaluated several algorithms including decision trees, support vector machines, and random forests. The results showed that ensemble learning techniques such as random forests significantly improved prediction accuracy compared with individual machine learning models. The authors concluded that feature engineering and data preprocessing play critical roles in improving forecasting performance.

Sun et al. (2020) explored the use of deep neural networks for large-scale retail demand forecasting. Their research proposed a multilayer neural network architecture capable of learning complex relationships between product attributes and sales patterns. The model demonstrated improved predictive performance compared with traditional statistical forecasting techniques.

Zhang et al. (2020) proposed a hybrid CNN-LSTM architecture for sales prediction in online retail systems. The CNN component was responsible for extracting spatial features from structured datasets, while the LSTM network captured temporal dependencies within historical sales data. Experimental results indicated that the hybrid model significantly improved forecasting accuracy compared with standalone CNN or LSTM models.

Craparotta et al. (2020) introduced a Siamese neural network framework for predicting sales of new fashion products. The study demonstrated that Siamese architectures could learn similarity relationships between new products and existing products with known sales patterns. This approach was particularly useful for addressing the cold-start problem in retail forecasting.

Chen et al. (2021) applied gradient boosting algorithms to demand forecasting in e-commerce platforms. Their research showed that gradient boosting models achieved high prediction accuracy by combining multiple decision trees and reducing prediction errors.

Huang and Chen (2021) proposed a hybrid CNN-GRU architecture for e-commerce demand prediction. The study demonstrated that convolutional layers effectively extracted meaningful features from input data while GRU networks captured temporal dependencies.

Gupta et al. (2022) developed an attention-based recurrent neural network model for retail sales forecasting. By assigning dynamic weights to different time steps in historical data, the model was able to identify important events such as promotional campaigns and seasonal demand peaks.

Liu and Zhang (2022) proposed an LSTM-based forecasting framework for analyzing long-term sales patterns in e-commerce datasets. The results showed that the LSTM model significantly reduced forecasting errors compared with traditional time-series models.

Eglite and Birzniece (2022) conducted a systematic literature review examining deep learning techniques for retail forecasting. Their study highlighted that hybrid architectures combining CNN and recurrent networks provide superior forecasting performance.

Mansur et al. (2023) examined hybrid neural network architectures for retail demand forecasting. Their results demonstrated that combining CNN and LSTM networks improved forecasting accuracy for complex retail datasets.

Patel and Mehta (2023) introduced a transformer-based forecasting framework capable of capturing long-range dependencies in sales data without relying on recurrent architectures.

Ali et al. (2023) proposed a bidirectional LSTM model for retail forecasting, enabling the model to capture both forward and backward temporal dependencies.

Singh et al. (2023) explored the use of metaheuristic optimization algorithms to optimize neural network parameters. Their study demonstrated that optimized neural networks significantly improved prediction accuracy compared with conventional models.

Overall, the literature indicates that integrating deep learning architectures, heterogeneous datasets, and metaheuristic optimization algorithms represents a promising direction for developing advanced forecasting systems in e-commerce environments.

Comparative Table

Author & Year	Method / Model	Data Type	Key Contribution	Advantages	Limitations	Performance Insight	Relevance to Proposed Model
Eglite & Birzniece (2022)	Deep Learning Review	Secondary datasets	Comprehensive analysis of DL models for retail forecasting	Identifies trends & hybrid models	Limited real-time validation	Shows DL > traditional models	Supports need for advanced hybrid models
Joseph et al. (2022)	CNN-BiLSTM Hybrid	Time-series + structured	Combines spatial & temporal learning	High accuracy in demand prediction	High computational cost	Improved accuracy vs LSTM	Basis for hybrid architecture design
Ahmadov (2023)	Deep Neural Network	Intermittent demand data	Focus on irregular demand forecasting	Handles sparse demand	Requires large training data	Better than statistical models	Justifies need for optimization

Mansur et al. (2023)	CNN-LSTM Hybrid	Sales + temporal data	Integrated feature extraction + sequence modeling	Captures complex patterns	Model complexity	High prediction accuracy	Core inspiration for hybrid learning
Craparotta et al. (2020)	Siamese Neural Network	Product + sales similarity	Solves cold-start problem	Learns similarity between products	Limited scalability	Effective for new products	Foundation for pseudo-Siamese model
Chen et al. (2021)	Gradient Boosting	Structured tabular data	Ensemble learning for forecasting	Robust & less overfitting	Limited deep feature learning	High accuracy on structured data	Baseline ML comparison
Huang & Chen (2021)	CNN-GRU Hybrid	Sequential + structured	Combines CNN & GRU advantages	Efficient temporal modeling	Moderate complexity	Improved vs standalone models	Alternative hybrid approach
Gupta et al. (2022)	Attention-based RNN	Time-series data	Dynamic weighting of features	Captures important time steps	Requires tuning attention	Improved interpretability	Supports attention-based extension
Liu & Zhang (2022)	LSTM Model	Time-series	Long-term dependency modeling	Strong temporal learning	Cannot capture spatial features	Lower error vs ARIMA	Baseline DL model
Patel & Mehta (2023)	Transformer Model	Sequential + large-scale	Captures long-range dependencies	Parallel processing	High resource requirement	High accuracy in large data	Advanced architecture comparison
Ali et al. (2023)	Bi-LSTM	Time-series	Forward + backward learning	Better temporal understanding	Increased computation	Improved forecasting	Temporal modeling enhancement
Singh et al. (2023)	Metaheuristic Optimization	Model parameters	Optimizes neural networks	Avoids local minima	Computational overhead	Improves accuracy significantly	Supports GTO integration
Sun et al. (2020)	Deep Neural Network	Large-scale retail data	Multi-layer feature learning	Handles complex patterns	Data-intensive	Better than ML models	Foundation for deep learning
Sharma et al. (2022)	Ensemble ML	Structured data	Combines multiple models	Robust prediction	Limited deep insights	Better than single models	Benchmark comparison
Rahman & Ahmed (2023)	CNN-Transformer	Hybrid deep learning	Combines CNN + Transformer	Captures global dependencies	High complexity	High accuracy	Advanced hybrid inspiration

Analysis

The comparative analysis of e-commerce sales prediction techniques reveals a clear evolution from traditional statistical models to advanced machine learning and deep learning frameworks. With the rapid growth of online retail platforms, massive volumes of data—such as transactional records, customer behavior, product attributes, and marketing interactions—have become available. These datasets are highly complex, involving nonlinear relationships, temporal dependencies, and multiple data types.

Traditional methods like ARIMA, exponential smoothing, and regression were initially popular due to their simplicity and efficiency, but their reliance on linear assumptions and stationary data limits their effectiveness in dynamic e-commerce environments influenced by factors such as promotions, seasonality, and customer preferences.
Machine learning models, including random forests, support vector machines, and gradient boosting algorithms, have significantly improved forecasting accuracy by capturing complex data patterns. Ensemble techniques further enhance robustness by combining multiple models. However, the increasing scale and complexity of data have led to the adoption of deep learning approaches. Architectures such as convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM) networks enable automatic feature extraction and effective modeling of temporal patterns. Hybrid models like CNN-LSTM combine spatial and sequential learning capabilities, outperforming standalone models in many forecasting scenarios.
Recent research emphasizes the integration of heterogeneous datasets, including product metadata, customer interactions, and multimedia content, to improve prediction performance. Siamese neural networks have emerged as an effective solution for learning relationships between different data inputs, particularly in addressing the cold-start problem for new products. The triple pseudo-Siamese architecture extends this concept by processing multiple data sources simultaneously, generating unified representations that enhance forecasting accuracy in complex environments.
In addition, optimization techniques play a critical role in improving deep learning performance. Metaheuristic algorithms such as genetic algorithms and particle swarm optimization help overcome limitations of traditional training methods. The Giant Trevally Optimizer, inspired by natural hunting strategies, has shown promise in enhancing parameter tuning and convergence. Despite advancements, challenges such as high computational requirements, data dependency, and changing market dynamics persist. Future research should focus on hybrid models integrating deep learning, heterogeneous data, and intelligent optimization to develop scalable and accurate forecasting systems for modern e-commerce platforms.

Discussion

The rapid advancement of artificial intelligence and data analytics has significantly transformed forecasting approaches in e-commerce systems. Online retail platforms generate vast amounts of data, including customer behavior, purchase history, product information, and marketing performance. Effectively analyzing this data is essential for improving demand forecasting and supply chain efficiency. Traditional statistical methods have gradually been replaced by advanced predictive analytics techniques that can handle large-scale and complex datasets. This shift reflects the growing need for models that can capture nonlinear relationships and adapt to dynamic consumer behavior in competitive digital marketplaces.
Machine learning techniques such as random forests, support vector machines, and gradient boosting have gained popularity due to their strong predictive capabilities. These models outperform traditional approaches by capturing complex patterns in data. However, they often rely on manual feature engineering and may struggle with unstructured data sources. To overcome these limitations, deep learning models have been introduced. Architectures such as convolutional neural networks and recurrent neural networks can automatically learn hierarchical representations. Convolutional networks are effective in extracting spatial features, while recurrent models, particularly long short-term memory networks, are well-suited for capturing temporal dependencies in sales data.
Hybrid deep learning models further enhance forecasting performance by combining multiple architectures. Models like CNN-LSTM integrate spatial and temporal analysis, enabling more accurate demand predictions. Additionally, the use of heterogeneous datasets has become an important trend. Modern systems incorporate structured data, textual information, and behavioral logs to improve forecasting accuracy. Siamese neural networks and their extensions, such as triple pseudo-Siamese architectures, are particularly effective in processing multiple data sources simultaneously and addressing challenges like the cold-start problem.
Optimization techniques also play a vital role in improving model performance. Metaheuristic algorithms such as genetic algorithms and particle swarm optimization help overcome limitations of traditional training methods. The Giant Trevally Optimizer is a recent approach that enhances parameter tuning and convergence efficiency. Despite these advancements, challenges such as high computational cost, data integration complexity, and rapidly changing consumer behavior remain. Future research should focus on developing scalable, efficient,

and adaptive models for real-world e-commerce forecasting applications.

Conclusion

Accurate demand forecasting is essential for efficient decision-making in e-commerce, where consumer demand changes rapidly due to pricing, promotions, seasonality, and shifting preferences. This survey reviewed recent progress in sales prediction systems, with emphasis on machine learning, deep learning, Siamese network frameworks, and optimization methods. The findings show a clear shift from traditional statistical forecasting toward machine learning and neural network-based approaches, as these methods handle nonlinear relationships and complex retail datasets more effectively. Models such as random forests, support vector machines, and gradient boosting perform well in forecasting tasks, while deep learning architectures like CNN and LSTM improve prediction accuracy by learning hierarchical spatial and temporal patterns directly from data. Hybrid CNN-LSTM models have shown especially strong results because they combine feature extraction with sequence modeling.

Recent studies also highlight the value of Siamese and triple pseudo-Siamese networks for analyzing heterogeneous data and addressing the cold-start problem in retail forecasting. These models can integrate product attributes, customer behavior, and historical sales into a unified predictive framework. In addition, optimization algorithms such as the Giant Trevally Optimizer help improve model training by enhancing parameter tuning and convergence. Despite these advances, challenges remain, including high computational cost, scalability issues, and the fast-changing nature of consumer behavior. Future research should focus on scalable hybrid architectures that combine deep learning, heterogeneous data integration, and intelligent optimization to improve forecasting accuracy in dynamic e-commerce environments.

References

Alam, T., & Shakil, K. A. (2020). E-commerce sales prediction using machine learning algorithms. *International Journal of Advanced Computer Science and Applications*, 11(5), 410–417. https://doi.org/10.14569/IJACSA.2020.0110552

Ali, M., Khan, S., & Rahman, A. (2023). Bidirectional LSTM networks for online retail demand forecasting. *IEEE Access*, 11, 44523–44535. https://doi.org/10.1109/ACCESS.2023.3271120

Chen, Y., Xu, Z., & Zhao, H. (2021). Retail demand forecasting using gradient boosting algorithms. *Expert Systems with Applications*, 168, 114215. https://doi.org/10.1016/j.eswa.2020.114215

Choi, T. M., Wallace, S., & Wang, Y. (2020). Big data analytics in operations management. *Production and Operations Management*, 29(8), 1868–1883. https://doi.org/10.1111/poms.13190

Craparotta, G., O'Brien, S., & Garvey, S. (2020). Siamese neural network application for sales forecasting of new fashion products using heterogeneous data. *International Journal of Computational Intelligence Systems*, 13(1), 473–484. https://doi.org/10.2991/ijcis.d.191201.001

Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine learning and deep learning models for demand forecasting in supply chain management: A critical review. *Applied System Innovation*, 7(4), 93. https://doi.org/10.3390/asi7040093

Eglite, L., & Birzniece, I. (2022). Retail sales forecasting using deep learning: A systematic literature review. *Complex Systems Informatics and Modeling Quarterly*, 30, 35–45. https://doi.org/10.7250/csimq.2022-30.03

Fildes, R., & Goodwin, P. (2021). Forecasting in retail: Challenges and solutions. *International Journal of Forecasting*, 37(2), 704–715. https://doi.org/10.1016/j.ijforecast.2020.05.009

Gupta, R., Verma, S., & Patel, H. (2022). Attention-based recurrent neural networks for retail sales forecasting. *Neural Computing and Applications*, 34(14), 11439–11452. https://doi.org/10.1007/s00521-021-06664-0

Huang, J., & Chen, L. (2021). Hybrid CNN-GRU architecture for e-commerce demand forecasting. *Knowledge-Based Systems*, 213, 106699. https://doi.org/10.1016/j.knosys.2020.106699

Joseph, R., et al. (2022). Hybrid CNN-BiLSTM model for product demand forecasting. *Computers & Industrial Engineering*, 167, 108213. https://doi.org/10.1016/j.cie.2022.108213

Kumar, A., Singh, P., & Sharma, R. (2023). Attention-based deep learning for online retail forecasting. *IEEE Transactions on Neural Networks and Learning Systems*, 34(8), 4025–4036. https://doi.org/10.1109/TNNLS.2022.3148275

Liu, Q., & Zhang, H. (2022). LSTM-based deep learning model for retail sales forecasting. *Expert Systems with Applications*, 195, 116567. https://doi.org/10.1016/j.eswa.2022.116567

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition: Results and implications for forecasting research. *International Journal of Forecasting*, 36(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014

Mansur, M., Rahman, M., & Islam, S. (2023). Hybrid CNN-LSTM model for retail sales prediction. *Journal of Retailing and Consumer Services*, 72, 103231. https://doi.org/10.1016/j.jretconser.2023.103231

Patel, D., & Mehta, R. (2023). Transformer-based sales forecasting for online retail platforms. *IEEE Access*, 11, 50219–50230. https://doi.org/10.1109/ACCESS.2023.3278114

Rahman, M., & Ahmed, S. (2023). CNN-Transformer hybrid deep learning model for retail demand prediction. *Expert Systems with Applications*, 216, 119458. https://doi.org/10.1016/j.eswa.2023.119458

Sharma, K., Gupta, A., & Agarwal, R. (2022). Ensemble machine learning models for predicting e-commerce sales trends. *Decision Support Systems*, 152, 113676. https://doi.org/10.1016/j.dss.2021.113676

Singh, V., Kumar, N., & Jain, A. (2023). Hyperparameter optimization for deep neural networks in retail forecasting. *Information Sciences*, 617, 139–152. https://doi.org/10.1016/j.ins.2022.10.043

Sun, Y., Liu, Y., & Gao, X. (2020). Deep neural network for large-scale retail demand forecasting. *Computers & Industrial Engineering*, 147, 106679. https://doi.org/10.1016/j.cie.2020.106679