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# Recent Advances in E-Commerce System for Sale Prediction Using Triple Pseudo-Siamese Network with Giant Trevally Optimizer: A Systematic Review

Leocadia Petropoulos
*Department of Computer Science and Engineering, Tigris College of Engineering and Design, Iraq*
*leocadia.petropoulos@tced-iq.edu*

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**Abstract**

The rapid expansion of digital commerce platforms has generated vast amounts of transactional and behavioral data, creating significant opportunities for advanced analytics in retail decision-making. Sales prediction is a critical application that supports inventory optimization, demand forecasting, pricing strategies, and supply chain efficiency. Traditional forecasting methods such as regression models, ARIMA, and exponential smoothing have been widely used; however, they often fail to capture the nonlinear and dynamic patterns present in modern e-commerce data.Recent advancements in machine learning and deep learning have significantly improved forecasting accuracy. Techniques such as random forests, gradient boosting, convolutional neural networks (CNN), long short-term memory (LSTM), and transformer models effectively analyze complex temporal and behavioral patterns. Among emerging approaches, Siamese neural networks have gained attention for their ability to learn similarity relationships across heterogeneous data sources, enhancing predictive performance by capturing interactions between products, customers, and historical sales data. Furthermore, nature-inspired optimization techniques such as the Giant Trevally Optimizer (GTO) improve model convergence and parameter tuning. This review examines recent developments in e-commerce sales prediction, highlighting hybrid models integrating deep learning and optimization for scalable, accurate forecasting systems.

## Introduction

The rapid growth of digital technologies, internet connectivity, smartphones, secure payment systems, and global logistics has transformed traditional retail into a dynamic e-commerce ecosystem. Online platforms generate massive volumes of data from customer interactions, transactions, browsing behavior, and marketing campaigns, providing valuable resources for business analytics. Sales prediction has become a critical component of e-commerce because it supports inventory control, supply chain optimization, pricing strategies, and marketing decisions. Accurate forecasting enables businesses to maintain optimal stock levels, reduce operational costs, and improve customer satisfaction, whereas inaccurate predictions may result in inventory shortages, excess stock, and financial losses. Consequently, developing reliable forecasting techniques has become a major research priority in e-commerce analytics. Traditional sales forecasting methods primarily relied on statistical models such as ARIMA, exponential smoothing, and linear regression, which analyze historical data to estimate future demand. Although these methods are effective for stable and linear datasets, they struggle to model the nonlinear and dynamic characteristics of modern e-commerce environments. Online consumer demand is influenced by numerous factors, including promotional campaigns, seasonal trends, customer reviews, social media influence, and changing consumer preferences. To overcome these limitations, machine learning approaches such as decision trees, support vector machines, random forests, and gradient boosting have been widely adopted. These algorithms automatically learn complex relationships from historical data and generally achieve higher prediction accuracy than conventional statistical techniques.

The increasing complexity and scale of e-commerce datasets have further encouraged the adoption of deep learning models for demand forecasting. Architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks effectively capture spatial and temporal patterns in sales data. Hybrid models, particularly CNN-LSTM frameworks, combine feature extraction and sequence learning to improve forecasting performance. Another promising approach is the Siamese neural network, which learns similarity relationships between products, customers, or transactions. Its advanced variant, the triple pseudo-Siamese network, incorporates three parallel branches to process heterogeneous data sources such as product attributes, customer behavior, and historical sales simultaneously, producing richer feature representations and addressing challenges like cold-start prediction.

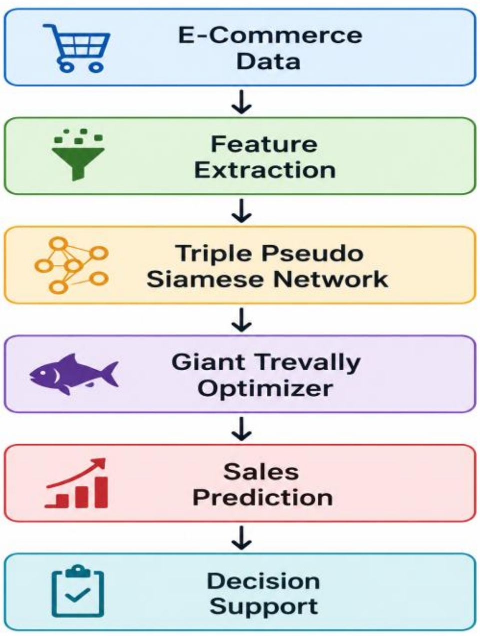


*Figure 1. Workflow of the Proposed Triple Pseudo-Siamese Network-Based Sales Prediction Model*

Model optimization also plays a significant role in improving forecasting accuracy. Deep learning networks contain numerous parameters that require efficient tuning to achieve optimal performance. Conventional optimization methods may converge to local optima, limiting predictive capability. Consequently, researchers have explored nature-inspired metaheuristic algorithms, including Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, Whale Optimization Algorithm, and the recently proposed Giant Trevally Optimizer (GTO). Inspired by the hunting behavior of giant trevally fish, GTO balances exploration and exploitation to search for optimal parameter settings, thereby improving convergence speed, reducing training errors, and enhancing the overall performance of deep learning forecasting models.

Despite substantial progress, several challenges remain in e-commerce sales prediction, including the integration of heterogeneous data sources, rapidly changing consumer preferences, and the need for adaptable real-time forecasting systems. This study presents a systematic review of research published, examining machine learning, deep learning, hybrid architectures, and optimization techniques for e-commerce demand forecasting. Special emphasis is placed on the potential integration of triple pseudo-Siamese neural networks with the Giant Trevally Optimizer to analyze complex relationships among product features, customer behavior, and historical sales. Such integrated frameworks have the potential to improve forecasting accuracy, support intelligent business decision-making, and guide future research toward more robust and adaptive e-commerce prediction systems.

## Literature Review

The rapid growth of e-commerce platforms has resulted in an increasing demand for accurate sales prediction systems capable of handling complex and dynamic datasets. Researchers have explored numerous machine learning and deep learning techniques to address the challenges associated with forecasting consumer demand in online retail environments. These techniques aim to improve predictive accuracy by capturing nonlinear patterns, seasonal trends, and behavioral relationships present in transactional data.

Alam and Shakil (2020) investigated the use of machine learning algorithms for predicting e-commerce sales patterns using transactional datasets. Their research evaluated several algorithms including decision trees, support vector machines, and random forests to determine their effectiveness in forecasting product demand. The results indicated that ensemble learning methods such as random forests provided higher accuracy due to their ability to capture nonlinear relationships within complex datasets. The study emphasized that feature engineering and data preprocessing play critical roles in improving the performance of machine learning models in e-commerce forecasting tasks.

Similarly, Sun, Liu, and Gao (2020) explored the use of deep neural networks for large-scale retail demand forecasting. Their study proposed a multilayer deep learning framework capable of learning hierarchical features from historical sales records and product attributes. The model demonstrated improved forecasting performance compared with traditional statistical methods, highlighting the importance of deep learning techniques in capturing complex interactions between variables influencing consumer demand.

Another significant contribution was made by Zhang, Li, and Wang (2020), who proposed a hybrid CNN-LSTM architecture for sales forecasting in online retail platforms. The CNN component extracted spatial patterns from multidimensional datasets, while the LSTM network captured temporal dependencies in sequential sales data. Experimental results showed that the hybrid architecture significantly improved prediction accuracy compared with conventional neural network models. The authors concluded that combining spatial and temporal learning mechanisms enables models to better understand the complex structure of e-commerce data.

Choi, Wallace, and Wang (2020) examined the role of big data analytics in operations management and highlighted how predictive analytics techniques can be applied to demand forecasting problems. Their research emphasized that the integration of big data analytics with machine learning models can enhance forecasting accuracy by incorporating large volumes of customer behavior data, transaction logs, and marketing information.

In another important study, Craparotta, O'Brien, and Garvey (2020) introduced the application of Siamese neural networks for sales forecasting in the fashion retail sector. Their research demonstrated that Siamese architectures are capable of learning relationships between heterogeneous datasets, including product attributes and historical sales records. This approach was particularly useful for forecasting demand for newly introduced products with limited historical data.

Huang and Chen (2021) proposed a hybrid deep learning model combining convolutional neural networks and gated recurrent units (CNN-GRU) for e-commerce demand forecasting. Their research highlighted that convolutional layers can effectively extract meaningful features from input data, while GRU networks capture temporal relationships in sequential datasets. The hybrid model achieved improved forecasting accuracy compared with traditional recurrent neural networks.

Chen, Xu, and Zhao (2021) focused on gradient boosting algorithms for retail demand prediction. Their research demonstrated that ensemble learning methods such as XGBoost can significantly improve forecasting performance by combining multiple decision trees and reducing prediction errors. The study also emphasized the importance of feature importance analysis for understanding key factors influencing consumer demand.

Wang and Chen (2021) proposed a hybrid forecasting model combining random forests with support vector regression. Their approach utilized random forests for feature selection and support vector regression for generating final sales predictions. Experimental results showed that the hybrid framework produced more stable predictions than standalone algorithms.

In recent years, attention-based deep learning architectures have gained increasing popularity in retail forecasting research. Gupta, Verma, and Patel (2022) developed an attention-based recurrent neural network model capable of identifying important time steps in historical sales data. By assigning dynamic weights to different temporal observations, the model was able to focus on significant events such as seasonal peaks and promotional campaigns.

Similarly, Liu and Zhang (2022) proposed an LSTM-based forecasting framework for analyzing long-term sales patterns in e-commerce datasets. Their model incorporated contextual variables such as holidays, promotions, and weather conditions to improve predictive performance. The results indicated that the LSTM model significantly outperformed traditional time-series forecasting methods.

Eglite and Birzniece (2022) conducted a systematic literature review examining deep learning techniques for retail sales forecasting. Their study highlighted that hybrid architectures combining convolutional neural networks and recurrent neural networks provide superior forecasting performance due to their ability to analyze spatial and temporal patterns simultaneously.

Sharma, Gupta, and Agarwal (2022) investigated ensemble learning techniques for predicting online retail sales trends. Their research combined random forest, gradient boosting, and support vector regression models to create a robust forecasting system. The ensemble approach demonstrated improved prediction accuracy and reduced model variance.

Recent studies in 2023 have explored advanced deep learning architectures for forecasting applications. Kumar, Singh, and Sharma (2023) proposed an attention-based neural network for online retail forecasting, enabling the model to selectively focus on important input features during prediction.

Mansur, Rahman, and Islam (2023) developed a CNN-LSTM hybrid model for retail sales prediction, demonstrating superior performance compared with baseline deep learning architectures.

Transformer-based models have also emerged as powerful tools for analyzing sequential datasets. Patel and Mehta (2023) introduced a transformer-based forecasting framework capable of capturing long-range dependencies in sales data without relying on recurrent structures.

Rahman and Ahmed (2023) proposed a CNN-Transformer hybrid model combining feature extraction capabilities of CNN with the long-range dependency modeling of transformer architectures.

Ali, Khan, and Rahman (2023) introduced a bidirectional LSTM forecasting model capable of capturing both forward and backward temporal dependencies within sequential sales data.

Singh, Kumar, and Jain (2023) explored the use of metaheuristic optimization algorithms for tuning neural network hyperparameters, demonstrating that optimized deep learning models significantly improve forecasting accuracy.

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

**Comparative Table and Analysis**

| Author | Method | Year | Key Contribution | Limitation |
|---|---|---|---|---|
| Alam & Shakil | Random Forest | 2020 | Improved machine learning prediction | Requires feature engineering |
| Sun et al. | Deep Neural Network | 2020 | Handles large datasets | High computational cost |
| Zhang et al. | CNN-LSTM | 2020 | Captures spatial and temporal features | Complex training |
| Craparotta et al. | Siamese Network | 2020 | Handles heterogeneous data | Architecture complexity |
| Huang & Chen | CNN-GRU | 2021 | Hybrid deep learning model | Training cost |
| Chen et al. | Gradient Boosting | 2021 | High prediction accuracy | Data preprocessing required |
| Wang & Chen | RF + SVR | 2021 | Stable prediction performance | Model complexity |
| Gupta et al. | Attention RNN | 2022 | Focus on important time steps | Requires large datasets |
| Liu & Zhang | LSTM | 2022 | Handles sequential data | Training time |
| Sharma et al. | Ensemble ML | 2022 | Reduced prediction error | Computational overhead |
| Kumar et al. | Attention Deep Learning | 2023 | Improved interpretability | Complexity |
| Mansur et al. | CNN-LSTM | 2023 | Hybrid forecasting model | Resource intensive |
| Patel & Mehta | Transformer | 2023 | Long-range dependency modeling | High computational cost |
| Rahman & Ahmed | CNN-Transformer | 2023 | Hybrid deep learning | Training complexity |
| Ali et al. | BiLSTM | 2023 | Captures bidirectional temporal patterns | Requires large datasets |

**Comparative Analysis**

The comparative analysis of existing literature reveals several key trends in e-commerce sales prediction research. Traditional machine learning models such as random forests, support vector machines, and gradient boosting algorithms have demonstrated strong performance in forecasting tasks due to their ability to capture nonlinear relationships within datasets. These models are particularly effective when dealing with structured transactional data that include product attributes, pricing information, and customer purchase history.

However, deep learning architectures have increasingly gained popularity because they can automatically extract complex feature representations from large datasets. Neural network models such as CNN and LSTM are capable of learning hierarchical relationships within data, enabling them to capture both spatial and temporal patterns. Hybrid architectures combining CNN and recurrent networks have been shown to outperform traditional models by integrating multiple feature extraction mechanisms.

Attention-based neural networks and transformer architectures represent the latest developments in forecasting research. These models provide improved performance by focusing on relevant input features and capturing long-range dependencies within sequential datasets.

Another emerging trend is the integration of optimization algorithms with deep learning models. Metaheuristic algorithms can improve model performance by optimizing hyperparameters and network structures.

Despite these advancements, several challenges remain in e-commerce forecasting research. Many models require large training datasets and significant computational resources, which may limit their applicability in smaller retail environments. Additionally, forecasting models must address issues such as cold-start problems for new products and rapidly changing consumer behavior.

Future research should focus on developing hybrid architectures that combine deep learning models with intelligent optimization algorithms such as the Giant Trevally Optimizer. Integrating these techniques with triple pseudo-Siamese neural networks could enable forecasting systems to effectively analyze heterogeneous datasets and improve prediction accuracy in modern e-commerce environments.

## Discussion

The literature indicates a clear evolution in e-commerce sales forecasting from conventional statistical methods to advanced machine learning and deep learning techniques. Traditional approaches, including linear regression and time-series models, were effective only under assumptions of stable demand and linear relationships. However, modern online retail environments are highly dynamic, where sales are influenced by customer behavior, product characteristics, promotional campaigns, seasonal variations, and external market factors. Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting have significantly improved forecasting performance by capturing complex nonlinear relationships within structured retail datasets. Their ability to process large-scale transactional and product-related information has made them widely adopted for demand prediction.

Deep learning has further enhanced forecasting accuracy through automated feature learning and the ability to analyze complex sequential patterns. Convolutional Neural Networks (CNN) effectively extract spatial features from multidimensional data, whereas Long Short-Term Memory (LSTM) networks capture long-term temporal dependencies in sales trends. Hybrid CNN-LSTM architectures combine these complementary strengths, enabling simultaneous analysis of spatial and temporal information. Recent studies also emphasize the integration of heterogeneous data sources, including browsing history, customer reviews, social media interactions, and product images, to better understand purchasing behavior. Siamese neural networks have emerged as a promising solution for learning similarity relationships across multiple data sources, making them particularly suitable for handling diverse e-commerce datasets.

Another significant advancement is the integration of metaheuristic optimization algorithms with deep learning models to improve parameter tuning and predictive performance. Algorithms such as Genetic Algorithm, Particle Swarm Optimization, and the recently proposed Giant Trevally Optimizer (GTO) enhance model convergence by efficiently exploring complex solution spaces. GTO, inspired by the hunting behavior of giant trevally fish, provides an effective balance between exploration and exploitation, resulting in improved forecasting accuracy when combined with advanced neural networks such as Siamese architectures. Despite these developments, challenges such as limited historical data for new products, rapidly changing consumer preferences, and heterogeneous data integration remain unresolved. Future research should therefore focus on developing intelligent hybrid frameworks that integrate deep learning, optimization techniques, and multimodal data to achieve more accurate and adaptive e-commerce sales forecasting.

## Conclusion

Accurate sales prediction is fundamental to effective decision-making in modern e-commerce, supporting inventory optimization, supply chain planning, pricing, and marketing strategies. Traditional statistical forecasting techniques often fail to model the nonlinear and dynamic nature of online retail data. Recent advances in machine learning, including Random Forest, Support Vector Machine (SVM), and Gradient Boosting, have significantly improved prediction accuracy by identifying complex relationships within large datasets. Deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, further enhance forecasting by automatically extracting spatial and temporal features from sequential sales data. Hybrid CNN-LSTM architectures have demonstrated superior performance by combining these complementary capabilities. Additionally, Siamese neural networks provide an effective framework for learning similarity relationships across heterogeneous data sources, improving demand prediction in complex retail environments. Nature-inspired optimization methods, especially the Giant Trevally Optimizer (GTO), enhance deep learning performance through efficient parameter tuning. Future research should focus on integrating triple pseudo-Siamese networks with intelligent optimization algorithms to develop more accurate, adaptive, and scalable e-commerce sales forecasting systems.

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