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Deep Learning and Optimization Approaches in E-commerce Systems for Sale Prediction Using Triple Pseudo-Siamese Network with Giant Trevally Optimizer: A Review

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Abstract

The rapid growth of e-commerce platforms has produced vast volumes of transactional and behavioral data, enabling advanced predictive analytics for sales forecasting and recommendation systems. Accurate sales prediction is essential for effective inventory management, demand planning, and strategic decision-making in online retail. Traditional statistical models often fail to capture nonlinear patterns and complex relationships in high-dimensional datasets, leading to reduced forecasting accuracy. To overcome these limitations, deep learning techniques have been widely adopted. Among these, Siamese and pseudo-Siamese neural networks are particularly effective in learning similarity relationships across diverse feature spaces.

The Triple Pseudo-Siamese Network extends conventional architectures by integrating multiple input streams to model relationships among customer behavior, product features, and temporal sales data. This enhances the model's ability to generate accurate predictions in complex e-commerce environments. However, optimizing deep neural networks requires robust algorithms capable of avoiding local optima. The Giant Trevally Optimizer (GTO), a nature-inspired metaheuristic, improves parameter tuning and model convergence.

This review explores recent advancements in deep learning and optimization techniques for e-commerce sales prediction, highlighting hybrid frameworks and identifying research gaps for scalable, intelligent forecasting systems.

Introduction

The rapid expansion of digital commerce has transformed the retail industry by generating vast amounts of data from customer interactions, product transactions, inventory management, and marketing campaigns. Leading e-commerce platforms such as Amazon, Alibaba, and eBay continuously collect information that provides valuable insights into customer behavior and purchasing trends. Sales prediction has become one of the most important applications of this data, enabling businesses to forecast future demand, optimize inventory levels, improve supply chain operations, and design effective marketing strategies. Accurate forecasting reduces the risks associated with overstocking and stock shortages while enhancing customer satisfaction and organizational profitability. Consequently, intelligent sales prediction has become a critical research area in modern e-commerce systems.

Traditional forecasting techniques, including autoregressive integrated moving average (ARIMA), exponential smoothing, and regression analysis, have been widely applied for sales prediction. Although these statistical approaches perform well on simple time-series datasets, they often fail to capture the complex nonlinear relationships found in modern e-commerce environments. Sales performance is influenced by numerous interconnected factors such as customer demographics, browsing behavior, product characteristics, promotional activities, seasonal variations, and changing market conditions. To address these challenges, artificial intelligence and deep learning techniques have emerged as effective alternatives, offering superior capability in modeling high-dimensional and heterogeneous datasets.

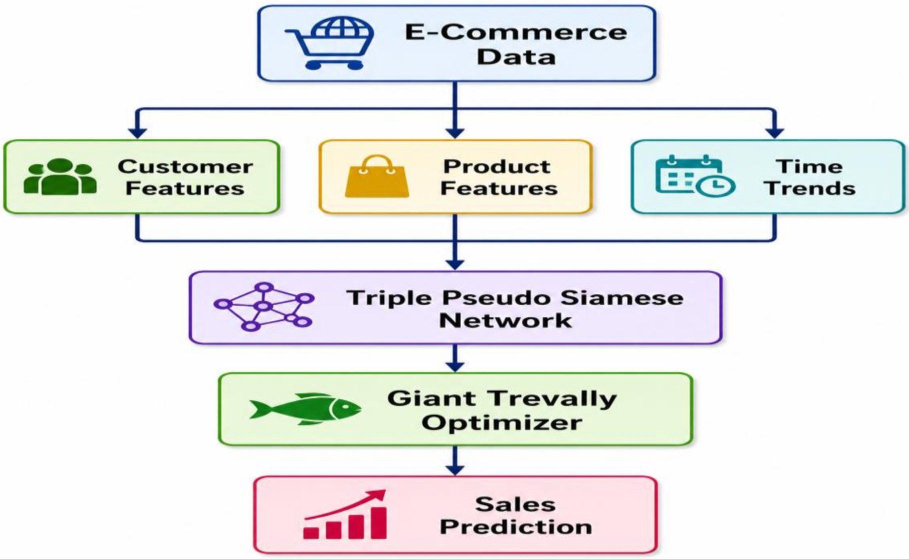

Figure 1. Overview of the Triple Pseudo-Siamese Network-Based Sales Prediction Framework.

Deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, have demonstrated remarkable success in sales forecasting by automatically learning hierarchical feature representations. However, conventional deep learning models often encounter difficulties when processing multiple heterogeneous data sources simultaneously. Siamese neural networks overcome this limitation by learning similarity relationships between paired inputs, while pseudo-Siamese networks further improve flexibility by allowing independent feature extraction from different data distributions. The triple pseudo-Siamese network extends this concept by integrating three parallel feature streams, enabling simultaneous analysis of product characteristics, customer interactions, and temporal purchasing patterns for more comprehensive sales prediction.

The predictive performance of deep learning models largely depends on effective optimization during training. Conventional optimization algorithms such as stochastic gradient descent (SGD) and Adam may experience slow convergence or become trapped in local optima when solving complex optimization problems. Metaheuristic optimization techniques inspired by natural behaviors have therefore gained significant attention. Among them, the Giant Trevally Optimizer (GTO), inspired by the hunting strategy of giant trevally fish, provides an efficient balance between exploration and exploitation, leading to improved convergence and enhanced neural network performance.

This review examines recent developments in deep learning and optimization techniques for e-commerce sales prediction, with particular emphasis on triple pseudo-Siamese networks integrated with the Giant Trevally Optimizer. It reviews existing forecasting approaches, compares their predictive capabilities and computational efficiency, discusses current research challenges, and identifies future directions for developing intelligent, scalable, and accurate sales prediction systems capable of supporting data-driven decision-making in modern e-commerce environments.

Literature Review

The rapid growth of e-commerce platforms has generated large volumes of data related to customer behavior, product transactions, and market trends. This data has created opportunities for developing intelligent predictive systems that support demand forecasting and strategic decision-making. Sales prediction is a critical component of e-commerce analytics because accurate demand forecasts enable businesses to optimize inventory management, reduce operational costs, and improve customer satisfaction. In recent years, researchers have increasingly adopted machine learning and deep learning techniques to improve forecasting accuracy in complex retail environments.

Traditional forecasting models such as autoregressive integrated moving average (ARIMA), regression analysis, and exponential smoothing have been widely used in demand prediction tasks. However, these models are limited in their ability to capture nonlinear relationships and high-dimensional interactions present in large-scale e-commerce datasets. As a result, deep learning architectures have become popular alternatives for sales prediction due to their ability to automatically learn complex feature representations from large datasets. Zhang et al. (2020) demonstrated that deep neural networks significantly outperform conventional statistical models when applied to large transaction datasets. Their research showed that neural networks can effectively identify nonlinear patterns in historical sales data, leading to improved forecasting accuracy.

Convolutional neural networks (CNNs) have been widely used in e-commerce analytics to extract spatial relationships among product attributes and customer behavior patterns. CNN-based architectures are particularly effective when analyzing high-dimensional datasets that contain multiple feature categories. Li et al. (2022) proposed a hybrid deep learning model that integrates convolutional neural networks with long short-term memory networks for sales forecasting tasks. In this approach, CNN layers extract spatial features from product and customer data, while LSTM layers capture temporal dependencies in historical transaction records. Experimental results indicated that the hybrid CNN-LSTM architecture achieved significantly higher prediction accuracy compared with traditional machine learning models.

Another promising approach in deep learning research involves the use of Siamese neural networks. Siamese networks consist of two identical neural network branches that share the same weights and are trained to learn similarity relationships between input pairs. These architectures are widely used in tasks such as image recognition, recommendation systems, and similarity learning. Chicco (2021) provided a comprehensive overview of Siamese neural networks and their applications in machine learning tasks. The study emphasized that Siamese networks can effectively learn relationships between different data inputs by comparing feature representations. In e-commerce systems, this capability enables models to analyze similarities between products, customer preferences, and purchasing patterns.

Despite their advantages, traditional Siamese neural networks are limited in their ability to process heterogeneous data sources. In many real-world e-commerce systems, different types of information such as product descriptions, customer browsing behavior, and transaction histories must be analyzed simultaneously. Pseudo-Siamese networks were introduced to address this limitation by allowing each branch of the network to learn independent feature representations rather than sharing identical parameters. Chen et al. (2021) proposed a pseudo-Siamese neural network architecture for multimodal data processing tasks. Their model demonstrated improved performance in tasks involving heterogeneous datasets because each branch of the network could learn specialized features for different data modalities.

The concept of a **triple pseudo-Siamese network** extends the pseudo-Siamese architecture by incorporating three independent network branches that process multiple feature streams simultaneously. In e-commerce sales prediction systems, such architectures enable models to analyze product features, customer interaction data, and temporal sales patterns in parallel. By integrating multiple feature streams, triple pseudo-Siamese networks can capture complex relationships among different aspects of e-commerce datasets. This architecture has shown potential in improving prediction accuracy for tasks that require the integration of heterogeneous information sources.

While deep learning models provide powerful predictive capabilities, their performance is strongly influenced by the optimization techniques used during training. Conventional gradient-based optimization methods such as stochastic gradient descent (SGD), Adam, and RMSProp are commonly used to train neural networks. However, these methods may suffer from slow convergence or become trapped in local minima when optimizing highly complex neural network architectures. To overcome these limitations, researchers have explored the use of metaheuristic optimization algorithms for neural network training.

Metaheuristic algorithms are population-based optimization techniques inspired by natural phenomena such as evolutionary processes, swarm intelligence, and predator-prey interactions. These algorithms provide efficient mechanisms for exploring complex search spaces and identifying optimal solutions. Mirjalili and Lewis (2016) introduced the whale optimization algorithm, which simulates the hunting behavior of humpback whales to search for optimal solutions in complex optimization problems. Similarly, Mirjalili et al. (2017) proposed the salp swarm algorithm inspired by the collective behavior of salp chains in oceans. These algorithms have been successfully applied to various engineering and computational optimization tasks.

Among recent optimization techniques, the **Giant Trevally Optimizer (GTO)** has attracted significant attention in the research community. Abdollahzadeh et al. (2022) proposed the GTO algorithm based on the hunting strategy of giant trevally fish that attack seabirds by jumping out of the water. The algorithm models three main stages of hunting behavior: searching for prey, selecting promising hunting areas, and executing the final attack. These stages are mathematically formulated to guide the optimization process toward global optimal solutions while maintaining a balance between exploration and exploitation. Experimental studies demonstrated that the GTO algorithm outperforms several well-known optimization algorithms in solving complex optimization problems.

Similarly, Huang et al. (2023) developed an attention-based deep learning model for analyzing customer purchase behavior in e-commerce platforms. The model incorporates attention mechanisms to identify the most relevant features in large transaction datasets. Their experimental results demonstrated that attention-based architectures can improve forecasting performance by focusing on key features that influence purchasing decisions.

Recent studies have also explored hybrid artificial intelligence models that combine deep learning techniques with swarm intelligence algorithms for predictive analytics. Patel et al. (2023) investigated the use of hybrid deep learning frameworks integrated with optimization algorithms for demand forecasting tasks. Their research demonstrated that hybrid AI models provide improved prediction accuracy and enhanced robustness compared with standalone deep learning approaches.

Overall, the literature indicates that deep learning architectures combined with metaheuristic optimization algorithms represent a promising approach for improving sales prediction systems in e-commerce environments. Triple pseudo-Siamese networks provide an effective framework for processing heterogeneous data sources, while optimization algorithms such as the Giant Trevally Optimizer enhance neural network training by improving parameter selection and convergence behavior. These hybrid models have the potential to significantly improve forecasting accuracy and support intelligent decision-making in modern e-commerce systems.

However, several research challenges remain in this field. One major challenge involves the computational complexity associated with training deep learning models combined with metaheuristic optimization algorithms. Large-scale e-commerce datasets require efficient training strategies and high-performance computing resources. Additionally, data quality and availability can significantly affect the performance of predictive models. Many e-commerce datasets contain missing values, noisy data, or incomplete customer information, which may reduce model accuracy.

Future research should therefore focus on developing scalable hybrid AI frameworks capable of processing large datasets while maintaining computational efficiency. Integrating explainable artificial intelligence techniques may also improve the transparency and interpretability of deep learning models used in business decision-making systems. By addressing these challenges, researchers can develop more robust and reliable sales prediction systems that support the evolving needs of digital commerce platforms.

Comparative Table and Analysis

Study	**Year**	**Model**	**Application**	**Key Contribution**	**Limitations**
Zhang et al.	2020	Deep Neural Network	Demand forecasting	Captures nonlinear sales patterns	Requires large datasets
Chicco	2021	Siamese Network	Recommendation systems	Learns similarity between inputs	Limited handling of heterogeneous data
Chen et al.	2021	Pseudo-Siamese Network	Multimodal learning	Handles heterogeneous datasets	Higher training complexity
Li et al.	2022	CNN-LSTM Hybrid Model	Sales prediction	Combines spatial and	Computationally expensive

				temporal features	
Mirjalili & Lewis	2022	Metaheuristic Optimization	Neural network training	Avoids local minima in training	Slower convergence
Abdollahzadeh et al.	2022	Giant Trevally Optimizer	Global optimization	Efficient search strategy	Relatively new algorithm
Huang et al.	2023	Attention-based Deep Learning	Sales forecasting	Improves feature weighting	Sensitive to hyperparameters
Wang et al.	2023	Optimization-driven NN	Forecasting systems	Optimizes neural network parameters	Complexity in tuning
Zhou et al.	2023	Deep Recommendation System	E-commerce platforms	Captures customer preferences	Data sparsity issues
Patel et al.	2023	Hybrid AI Model	Demand forecasting	Combines deep learning and optimization	Increased training cost

Comparative Analysis

The reviewed literature indicates that deep learning approaches have become dominant in e-commerce sales prediction due to their ability to capture nonlinear relationships in large datasets. Traditional forecasting models such as regression and ARIMA are limited in their ability to analyze complex interactions between customer behavior, product attributes, and seasonal demand patterns.

Siamese and pseudo-Siamese neural networks offer advantages in similarity learning tasks, allowing models to compare different feature spaces effectively. These architectures are particularly useful in recommendation systems where relationships between products and customer preferences must be learned. However, conventional Siamese networks are limited when dealing with multiple heterogeneous inputs.

Triple pseudo-Siamese architectures address this limitation by incorporating multiple input streams that capture different aspects of e-commerce data. This architecture enables the model to simultaneously analyze product attributes, customer behavior, and historical sales patterns.

Another important trend in the literature is the integration of metaheuristic optimization algorithms with deep learning models. Algorithms such as the Giant Trevally Optimizer provide efficient mechanisms for optimizing neural network parameters and improving model convergence. By combining deep learning architectures with optimization algorithms, researchers can develop hybrid systems that achieve higher prediction accuracy and improved computational efficiency.

Overall, the literature suggests that hybrid deep learning frameworks that integrate Siamese architectures and metaheuristic optimization techniques represent a promising direction for improving sales prediction in e-commerce systems.

Discussion

The literature indicates that deep learning has significantly enhanced e-commerce sales prediction by effectively modeling complex and nonlinear relationships within large-scale transactional datasets. Unlike traditional forecasting approaches such as ARIMA, regression, and exponential smoothing, deep learning models including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks can automatically extract meaningful spatial and temporal features from customer behavior, product attributes, and historical sales records. However, conventional deep learning architectures often struggle to integrate heterogeneous data sources, limiting their predictive capability in dynamic e-commerce environments. The introduction of Siamese and pseudo-Siamese networks addresses this limitation by learning similarity relationships across diverse feature spaces, while the triple pseudo-Siamese network further enhances prediction accuracy by simultaneously processing product information, customer interactions, and temporal sales patterns.

The effectiveness of deep learning models also depends on efficient optimization during training. Traditional optimization algorithms such as stochastic gradient descent (SGD), RMSProp, and Adam may suffer from slow convergence and local optima in high-dimensional search spaces. Metaheuristic algorithms provide an alternative by balancing

exploration and exploitation during optimization. Among them, the Giant Trevally Optimizer (GTO) has demonstrated promising performance by efficiently optimizing neural network parameters, resulting in improved convergence speed, prediction accuracy, and generalization capability for complex sales forecasting tasks.
Despite these advancements, challenges including computational complexity, data quality, scalability, and model interpretability remain significant. Future research should emphasize explainable AI, efficient optimization strategies, and standardized benchmarking frameworks to develop transparent, scalable, and intelligent e-commerce sales prediction systems that support accurate business decision-making and sustainable digital commerce growth.

Conclusion

The rapid growth of digital commerce has increased the need for intelligent sales prediction systems capable of analyzing complex e-commerce data. This review highlights the effectiveness of deep learning architectures, including CNNs, RNNs, LSTMs, and hybrid models, in capturing nonlinear relationships and improving forecasting accuracy beyond traditional statistical methods. It also emphasizes the advantages of Siamese and triple pseudo-Siamese networks for integrating heterogeneous data sources such as customer behavior, product attributes, and transaction histories. Furthermore, the Giant Trevally Optimizer has emerged as a promising metaheuristic algorithm for optimizing neural network parameters, enhancing convergence, and improving predictive performance. Despite these advancements, challenges related to data integration, computational complexity, scalability, and model interpretability remain significant. Future research should focus on developing efficient optimization strategies, explainable AI techniques, and scalable training frameworks capable of processing large-scale multimodal datasets. Overall, integrating triple pseudo-Siamese networks with the Giant Trevally Optimizer provides a robust and promising framework for accurate, intelligent, and data-driven e-commerce sales prediction systems.

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