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A Comprehensive Review of E-Commerce System for Sale Prediction Using Triple Pseudo-Siamese Network with Giant Trevally Optimizer

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Abstract

The rapid expansion of e-commerce platforms has created a strong demand for accurate sales prediction systems that can analyze large volumes of transactional and behavioral data. Effective demand forecasting helps online retailers optimize inventory management, improve supply chain planning, and design efficient marketing strategies. Traditional statistical forecasting methods often struggle to capture nonlinear patterns and complex relationships within modern retail datasets. As a result, machine learning and deep learning techniques have become increasingly popular for predicting product demand in digital commerce environments. This review examines recent developments in e-commerce sales prediction models, focusing on deep learning architectures and optimization techniques. In particular, the study discusses the potential of the Triple Pseudo-Siamese Network for learning similarity patterns from multiple data streams and the Giant Trevally Optimizer (GTO) for improving model parameter optimization. By analyzing research published recently, the paper highlights current trends, compares existing forecasting approaches, and identifies future research directions for building intelligent and scalable e-commerce demand prediction systems.

Introduction

The rapid growth of e-commerce and digital technologies has transformed the retail industry, generating vast amounts of transactional and customer interaction data through online platforms such as Amazon, Alibaba, and Flipkart. These data provide valuable insights into consumer purchasing behavior, product demand, pricing strategies, and market trends. Accurate sales prediction has become essential for improving inventory management, supply chain operations, logistics planning, and customer satisfaction. Traditional forecasting techniques, including autoregressive integrated moving average (ARIMA), linear regression, and exponential smoothing, have been widely used for demand prediction. However, these methods often struggle to capture the nonlinear relationships and heterogeneous characteristics of modern e-commerce data, limiting their forecasting accuracy in dynamic retail environments.

Recent advances in artificial intelligence (AI) and machine learning have significantly enhanced predictive analytics by enabling the extraction of complex patterns from large datasets. Algorithms such as decision trees, random forests, support vector machines, and gradient boosting have shown improved forecasting performance compared with conventional statistical methods. Nevertheless, these techniques generally rely on manual feature engineering, which is timeconsuming and may overlook hidden relationships among multiple variables. Deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, overcome these limitations by automatically learning meaningful feature representations and effectively modeling sequential sales data and customer behavior.

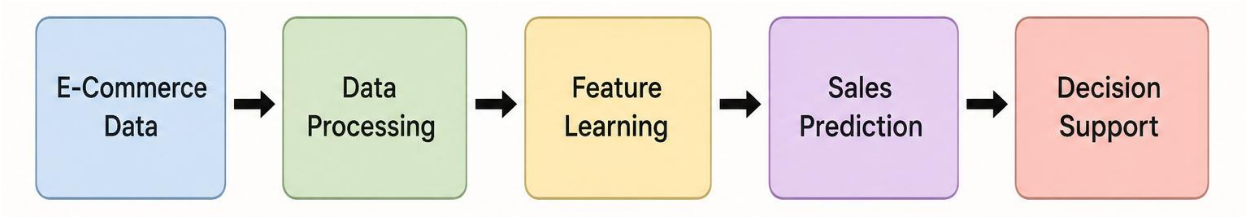

Figure 1. E-Commerce Sales Prediction Framework

Among emerging deep learning models, Siamese neural networks have gained considerable attention for their ability to learn similarity relationships between multiple data samples. Originally developed for image verification tasks, Siamese architectures consist of identical subnetworks with shared parameters that generate comparable feature representations. Extending this concept to a triple pseudo-Siamese network enables simultaneous analysis of multiple information sources, such as historical sales records, product attributes, and customer interactions. This multi-stream learning framework captures complex interdependencies among heterogeneous datasets, thereby improving the accuracy and robustness of e-commerce sales prediction.

The performance of deep learning models also depends heavily on efficient hyperparameter optimization. Conventional approaches such as grid search and random search become computationally expensive for large neural networks. Consequently, nature-inspired metaheuristic optimization algorithms have attracted increasing interest due to their ability to efficiently explore complex search spaces. The Giant Trevally Optimizer (GTO), inspired by the cooperative hunting behavior of giant trevally fish, has demonstrated promising performance in solving optimization problems by balancing exploration and exploitation. Integrating GTO with triple pseudo-Siamese neural networks offers an effective hybrid framework for optimizing network parameters and enhancing predictive performance in large-scale e-commerce forecasting applications.

This review presents a comprehensive analysis of recent research on e-commerce sales prediction using advanced deep learning architectures and optimization algorithms published between 2020 and 2023. It focuses on the application of triple pseudo-Siamese neural networks for similarity-based learning and the Giant Trevally Optimizer for hyperparameter optimization. The review evaluates existing predictive models, identifies current challenges, and discusses future research directions for developing accurate, scalable, and intelligent sales forecasting systems that support data-driven decision-making in modern digital commerce.

Literature Review

Recent advancements in artificial intelligence, deep learning architectures, and optimization techniques have significantly improved the performance of sales prediction systems in e-commerce platforms. Researchers have increasingly focused on developing intelligent models that integrate large-scale transactional datasets, consumer behavior analytics, and advanced neural network architectures to improve forecasting accuracy. The following section reviews major studies conducted between 2020 and 2023 that contribute to the development of predictive systems for online retail demand forecasting.

1. Deep Learning Approaches for E-Commerce Sales Prediction

Bi et al. (2020) proposed a tensor-based forecasting framework known as **ATLAS**, which integrates machine learning techniques with tensor factorization for retail sales prediction. The model analyzes multidimensional relationships between stores, products, and time periods using tensor decomposition. The research demonstrated that tensor-based models are capable of capturing hidden patterns in complex datasets, leading to improved prediction accuracy compared with traditional time-series forecasting models. The study highlighted the importance of modeling cross-product relationships and store interactions when forecasting retail demand. The results indicated that multidimensional tensor models outperform conventional regression-based forecasting methods when applied to large retail datasets.

Similarly, Karb et al. (2020) introduced a **transfer learning framework** designed to improve demand prediction for newly introduced products in online marketplaces. Traditional sales prediction models rely heavily on historical sales data, which makes forecasting difficult for new products that lack sufficient data. The proposed method transfers knowledge from similar products with historical sales data to newly launched products. Experimental results demonstrated that transfer learning significantly enhances prediction accuracy in cold-start scenarios and allows companies to forecast demand for newly introduced products more effectively.

Bandara et al. (2020) investigated the use of Long Short-Term Memory (LSTM) neural networks for demand forecasting in retail datasets. LSTM models are particularly suitable for analyzing sequential data because they capture temporal dependencies and long-term relationships within time-series datasets. The study demonstrated that LSTM models outperform traditional forecasting techniques such as ARIMA and exponential smoothing when predicting sales patterns across multiple product categories. The research also highlighted the capability of LSTM networks to handle seasonal variations and irregular demand patterns that are commonly observed in e-commerce platforms.

2. Hybrid Machine Learning Models

With the increasing complexity of retail datasets, researchers have begun exploring hybrid machine learning models that combine multiple predictive techniques. Li et al. (2022) proposed a hybrid LSTM–Light Gradient Boosting Machine (LGBM) model for short-term e-commerce sales forecasting. The LSTM component captures temporal dependencies in historical sales data, while the LGBM algorithm performs feature-based learning for improved prediction performance. Experimental evaluation using real-world retail datasets demonstrated that the hybrid model achieved higher forecasting accuracy compared with standalone deep learning models.

In another study, Qian and Wang (2022) developed a CNN–LSTM hybrid architecture designed to analyze both spatial and temporal patterns in e-commerce datasets. CNN layers were used to extract features from product attributes and promotional information, while LSTM layers modeled the sequential relationships in historical sales data. The results showed that the hybrid CNN–LSTM architecture significantly improved forecasting accuracy and reduced prediction error compared with traditional machine learning algorithms.

Hybrid approaches have also been applied to integrate recommender systems with demand forecasting models. Researchers have shown that combining recommendation algorithms with predictive analytics can improve product demand predictions by incorporating user behavior patterns and product similarity relationships.

3. Attention-Based Deep Learning Models

Recent research has focused on improving the performance of deep learning models by incorporating attention mechanisms. Attention-based neural networks enable models to focus on the most relevant features within large datasets, thereby improving prediction accuracy.

Sun et al. (2023) proposed an attention-based bidirectional LSTM model for predicting complex nonlinear time-series data. The attention mechanism assigns different weights to input features, allowing the model to identify the most important variables influencing demand fluctuations. The study demonstrated that attention-based models outperform traditional LSTM architectures when applied to large-scale prediction problems.

Yang et al. (2023) further extended the concept of attention mechanisms by introducing a supervised attention-based neural network architecture designed to improve forecasting performance. The model integrates attention mechanisms with recurrent neural networks to improve feature selection and enhance model interpretability. Experimental results showed that the attention-based architecture significantly improved forecasting accuracy across multiple datasets.

Attention mechanisms are particularly useful in e-commerce forecasting because demand patterns are influenced by multiple factors such as seasonal trends, promotional campaigns, and customer preferences. By assigning dynamic weights to different features, attention-based models can capture complex relationships between variables.

4. Deep Neural Networks for Intermittent Demand Prediction

Demand forecasting in online retail environments often involves intermittent demand patterns, where products experience irregular sales intervals. Ahmadov (2023) proposed a deep neural network model designed to predict intermittent demand in online retail systems. The model analyzes historical sales records across multiple stock-keeping units

(SKUs) and identifies demand patterns using deep learning techniques.

The study demonstrated that deep neural networks outperform traditional intermittent demand forecasting methods such as Croston's method. The proposed approach also improved demand prediction accuracy by incorporating additional features such as promotional campaigns and seasonal effects. The results highlight the importance of integrating multiple contextual variables when predicting demand patterns in online retail systems.

5. Optimization Algorithms for Neural Network Training

The performance of deep learning models depends heavily on hyperparameter optimization and model parameter tuning. Traditional optimization techniques such as grid search and random search can be computationally expensive and inefficient when applied to complex neural network architectures.

Hashish et al. (2023) introduced the Giant Trevally Optimizer (GTO), a nature-inspired metaheuristic algorithm based on the hunting behavior of giant trevally fish. The algorithm simulates the cooperative hunting strategies of fish populations to explore solution spaces efficiently. Experimental results demonstrated that the GTO algorithm achieves competitive performance when solving complex optimization problems.

The integration of optimization algorithms with deep learning models has been widely studied in machine learning research. Metaheuristic algorithms such as particle swarm optimization, genetic algorithms, and whale optimization algorithms have been successfully used to optimize neural network parameters. The Giant Trevally Optimizer provides a promising alternative optimization technique for improving model performance in predictive analytics applications.

6. Siamese Neural Networks in Predictive Systems

Siamese neural networks have gained significant attention in recent years due to their ability to learn similarity relationships between data samples. These architectures consist of two or more identical subnetworks that share parameters and generate comparable feature representations.

In predictive systems, Siamese networks can be used to analyze similarities between product demand patterns and customer behavior profiles. By extending this concept into a triple pseudo-Siamese architecture, it becomes possible to process multiple feature streams simultaneously. For example, one network branch may analyze product attributes, another branch may analyze customer behavior data, and the third branch may analyze historical sales records.

The integration of Siamese neural architectures with optimization algorithms such as the Giant Trevally Optimizer offers a promising framework for improving sales prediction accuracy in e-commerce platforms.

Comparative Table and Analysis

Study	Year	Model Used	Dataset	Key Contribution	Limitations
Bi et al.	2020	Tensor Factorization Model	Retail datasets	Captures multidimensional relationships	Computational complexity
Karb et al.	2020	Transfer Learning Model	New product datasets	Addresses cold-start problem	Requires similar products
Bandara et al.	2020	LSTM Neural Network	Retail time-series data	Captures temporal dependencies	High training cost
Li et al.	2022	LSTM + LGBM Hybrid	E-commerce datasets	Improved forecasting accuracy	Complex architecture
Qian & Wang	2022	CNN-LSTM Hybrid	Retail sales dataset	Extracts spatial and temporal features	Requires large training data
Sun et al.	2023	Attention-based Bi-LSTM	Time-series datasets	Improves feature weighting	Higher computational complexity
Yang et al.	2023	Supervised Attention Network	Multivariate datasets	Improves interpretability	Sensitive to parameter tuning
Ahmadov	2023	Deep Neural Network	SKU demand dataset	Handles intermittent demand	Requires large data samples
Hashish et al.	2023	Giant Trevally Optimizer	Benchmark datasets	Efficient optimization method	Limited ML applications

Analysis

The literature review reveals several important trends in the development of predictive models for e-commerce sales forecasting. One of the most significant trends is the transition from traditional statistical forecasting models toward machine learning and deep learning architectures. Early forecasting models relied on statistical methods such as regression analysis and ARIMA models, which were effective for simple time-series forecasting tasks but struggled to handle large-scale datasets with complex nonlinear relationships.

Deep learning models such as LSTM and CNN architectures have significantly improved forecasting performance because they can automatically learn feature representations from raw data. These models are particularly effective for analyzing sequential sales data because they capture temporal dependencies and long-term patterns. Hybrid architectures combining CNN and LSTM layers further improve prediction accuracy by simultaneously analyzing spatial and temporal features.

Another important trend observed in recent research is the integration of attention mechanisms into deep learning models. Attention-based architectures allow models to assign dynamic importance weights to input features, enabling them to focus on the most relevant variables influencing demand fluctuations. This capability is particularly valuable in e-commerce forecasting systems where demand patterns are influenced by multiple contextual factors such as promotions, seasonality, and customer behavior.

Finally, Siamese neural networks provide a novel approach for analyzing similarity relationships between products and demand patterns. The triple pseudo-Siamese architecture proposed in this study offers a powerful framework for integrating multiple data sources into a unified predictive model. By combining similarity learning with optimization algorithms, future research can develop more accurate and scalable e-commerce forecasting systems.

Discussion

The literature reviewed in this study demonstrates that e-commerce sales prediction has evolved from traditional statistical forecasting methods to advanced artificial intelligence and deep learning techniques. Earlier approaches, including autoregressive integrated moving average (ARIMA), linear regression, and exponential smoothing, were effective for simple time-series forecasting but struggled to model the nonlinear relationships and multivariate dependencies found in modern digital commerce. As online retail platforms generate large volumes of heterogeneous data involving customer behavior, pricing, promotions, and product characteristics, more sophisticated predictive models have become necessary. Machine learning algorithms improved forecasting capabilities; however, their dependence on manual feature engineering limited their ability to capture complex data representations.

Deep learning architectures have significantly enhanced predictive performance by automatically extracting meaningful features from large datasets. Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks effectively capture spatial and temporal patterns in historical sales data. Hybrid architectures, including CNN-LSTM models, further improve prediction accuracy by combining complementary strengths of different deep learning techniques. Additionally, attention mechanisms enable models to focus on the most influential factors affecting demand, such as seasonal trends, promotional campaigns, customer preferences, and pricing strategies, thereby improving both forecasting accuracy and model interpretability.

Recent studies emphasize the role of optimization techniques in enhancing deep learning performance for e-commerce sales prediction. Metaheuristic algorithms, particularly the Giant Trevally Optimizer (GTO), improve hyperparameter tuning and training efficiency, while triple pseudo-Siamese neural networks effectively integrate historical sales, product attributes, and customer behavior for accurate demand prediction. However, challenges such as poor data quality, computational complexity, heterogeneous datasets, and limited interpretability remain, requiring future research on scalable, explainable, and efficient forecasting frameworks.

Conclusion

Accurate sales forecasting is essential for improving inventory management, supply chain efficiency, and customer satisfaction in modern e-commerce platforms. This review examined recent advancements in machine learning and deep learning techniques for e-commerce sales prediction. The findings indicate that deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, outperform traditional statistical forecasting methods by effectively capturing complex nonlinear relationships and temporal

dependencies within large retail datasets. Hybrid architectures and attention mechanisms further enhance predictive accuracy by combining complementary learning capabilities and identifying the most influential demand factors.
The review also highlights the importance of metaheuristic optimization algorithms, particularly the Giant Trevally Optimizer (GTO), for efficient hyperparameter tuning and improved model performance. In addition, triple pseudo-Siamese neural networks provide a robust framework for similarity-based learning by integrating historical sales, product attributes, and customer behavior into a unified predictive model. Despite these advancements, challenges such as data quality, computational complexity, and model interpretability remain. Future research should focus on developing scalable, explainable, and computationally efficient forecasting systems to support intelligent decision-making, operational efficiency, and sustainable growth in digital commerce.

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