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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

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Abstract

The rapid expansion of digital commerce platforms has led to the generation of massive volumes of transactional and behavioral data, creating new opportunities for advanced analytics in retail decision-making. Sales prediction has become a critical application, enabling businesses to optimize inventory management, demand forecasting, pricing strategies, and supply chain operations. Traditional forecasting methods such as regression models, ARIMA, and exponential smoothing have been widely used; however, they often fail to capture the complex nonlinear patterns and dynamic nature of modern e-commerce data. Recent advancements in machine learning and deep learning, including random forests, gradient boosting, convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and transformer models, have significantly improved prediction accuracy by learning intricate relationships within large datasets. Among emerging approaches, Siamese neural networks have gained attention for their ability to model similarity across heterogeneous inputs, enhancing forecasting by analyzing relationships among product attributes, customer behavior, and historical sales. Additionally, nature-inspired optimization techniques such as the Giant Trevally Optimizer (GTO) improve model performance and convergence. This review examines recent studies (2020–2023), highlighting hybrid models that integrate deep learning and optimization for robust e-commerce sales prediction.

Introduction

The rapid advancement of digital technologies and internet infrastructure has significantly transformed the global retail industry over the past two decades. Traditional brick-and-mortar retail models have gradually shifted toward online platforms, giving rise to the modern e-commerce ecosystem, where transactions are conducted electronically through websites and mobile applications. The proliferation of smartphones, improved payment systems, and global logistics networks has enabled businesses to reach consumers across geographical boundaries. As a result, e-commerce platforms such as Amazon, Alibaba, Flipkart, and eBay generate enormous volumes of data related to customer interactions, product transactions, browsing behavior, and marketing activities. These large datasets provide valuable opportunities for businesses to analyze consumer behavior and predict future sales trends. Sales prediction is one of the most critical tasks in e-commerce analytics because it directly influences strategic decision-making processes such as inventory management, supply chain planning, pricing strategies, and marketing campaigns. Accurate demand forecasting helps organizations maintain optimal stock levels, avoid product shortages or overstocking, and improve customer satisfaction by ensuring product availability. In contrast, inaccurate sales predictions can lead to significant operational inefficiencies, increased costs, and lost revenue opportunities. Therefore, developing reliable forecasting models capable of analyzing complex retail datasets has become a key research focus in the field of data analytics and artificial intelligence.

Traditionally, demand forecasting has relied on statistical time-series models such as autoregressive integrated moving average (ARIMA), exponential smoothing, and linear regression techniques. These models analyze historical data patterns to predict future values based on mathematical relationships between past observations. While statistical forecasting methods have been widely used in supply chain management and retail analytics, they often assume linear relationships and stationary data distributions. However, real-world e-commerce datasets rarely follow such assumptions. Consumer demand in online retail environments is influenced by numerous dynamic factors including promotional campaigns, seasonal events, social media trends, product reviews, and changing consumer preferences. Consequently, traditional statistical models often fail to capture the complex nonlinear patterns and hidden relationships present in modern e-commerce data.

The emergence of machine learning (ML) techniques has significantly improved the capability of predictive models to analyze complex datasets and generate accurate forecasts. Machine learning algorithms such as decision trees, support vector machines (SVM), random forests, and gradient boosting models have been widely applied to sales forecasting tasks because they can identify nonlinear relationships among multiple variables. These algorithms learn patterns from historical data and automatically adjust their internal parameters to improve prediction performance. For example, ensemble learning methods such as random forests and gradient boosting combine multiple models to reduce prediction errors and improve robustness.

Despite the advantages of traditional machine learning algorithms, the increasing complexity and scale of e-commerce data require more advanced modeling techniques capable of extracting deeper insights from large datasets. This has led to the growing adoption of deep learning techniques in sales forecasting research. Deep learning models are based on artificial neural networks with multiple hidden layers that can learn hierarchical feature representations from raw data. These models have demonstrated remarkable success in various domains such as image recognition, natural language processing, and predictive analytics.

Among deep learning architectures, convolutional neural networks (CNN) and recurrent neural networks (RNN) are widely used for forecasting tasks. CNN models are particularly effective at extracting spatial features from structured data, while recurrent neural networks are designed to process sequential information. A popular variant of RNN is the Long Short-Term Memory (LSTM) network, which can capture long-term dependencies within time-series data. LSTM models have been successfully applied in retail forecasting because they can learn temporal patterns in sales data influenced by seasonal demand and promotional activities.

To further improve forecasting performance, researchers have developed hybrid deep learning architectures that combine multiple neural network models. For instance, CNN-LSTM models integrate convolutional layers for feature extraction with recurrent layers for temporal pattern recognition. Such hybrid frameworks allow models to simultaneously capture spatial and temporal relationships within e-commerce datasets. Several studies have reported that hybrid deep learning architectures significantly outperform traditional machine learning models in demand forecasting tasks.

Another emerging research direction in predictive analytics is the use of Siamese neural networks, which are specialized deep learning architectures designed to learn similarity relationships between input data. Siamese networks consist of two or more identical neural networks that share parameters and process different input samples simultaneously. The outputs of these networks are compared to determine the similarity between the inputs. This architecture has been widely used in applications such as face recognition, signature verification, and recommendation systems.

In the context of e-commerce forecasting, Siamese networks can be used to analyze relationships between products, customers, and transaction histories. For example, a Siamese architecture can learn similarities between newly introduced products and existing products with known sales patterns. This capability is particularly useful in addressing the cold-start problem, where newly launched products lack sufficient historical data for accurate demand forecasting.

An advanced variant of Siamese networks is the triple pseudo-Siamese network, which extends the traditional architecture by incorporating three parallel feature extraction branches. Each branch processes a different type of input data, such as product attributes, customer behavior data, and historical sales information. The outputs of these branches are combined to generate a unified representation that captures complex relationships between heterogeneous data sources. By integrating multiple data modalities, triple pseudo-Siamese networks can provide more comprehensive insights into consumer purchasing behavior and improve forecasting accuracy.

In addition to neural network architectures, the optimization of model parameters plays a crucial role in improving the performance of forecasting systems. Deep learning models often contain millions of parameters that must be carefully tuned during training to achieve optimal performance. Traditional optimization methods such as gradient descent can sometimes become trapped in local minima, leading to suboptimal solutions. To address this challenge, researchers have explored metaheuristic optimization algorithms inspired by natural processes.

Metaheuristic algorithms such as genetic algorithms, particle swarm optimization (PSO), ant colony optimization, and whale optimization algorithms have been widely applied to optimize neural network parameters and improve model convergence. These algorithms simulate natural behaviors such as evolution, swarm intelligence, and animal hunting strategies to efficiently search large solution spaces.

Recently, the Giant Trevally Optimizer (GTO) has been introduced as a novel nature-inspired optimization algorithm. The algorithm is based on the hunting behavior of giant trevally fish, which exhibit coordinated strategies when capturing prey near coastal areas. The optimization process involves exploration and exploitation phases that enable the algorithm to effectively search complex solution spaces and identify optimal parameter configurations. Integrating the Giant Trevally Optimizer with deep learning architectures can enhance model performance by improving parameter tuning and reducing training errors.

Despite significant advancements in predictive analytics and deep learning technologies, several challenges remain in the development of accurate e-commerce forecasting systems. One major challenge is the heterogeneity of e-commerce data, which often includes structured transactional data, unstructured textual reviews, customer behavior logs, and multimedia content such as product images. Integrating these diverse data sources into a unified forecasting framework requires sophisticated feature extraction techniques and efficient neural network architectures.

Another challenge involves the dynamic nature of consumer behavior in online retail environments. Customer preferences can change rapidly due to trends, seasonal events, or marketing campaigns. Therefore, forecasting models must be capable of adapting to changing data distributions and identifying emerging patterns in real time.

This study aims to provide a comprehensive systematic review of recent advancements in e-commerce sales prediction systems, focusing on research published between 2020 and 2023. The review analyzes machine learning models, deep learning architectures, and optimization techniques applied to demand forecasting in online retail platforms. Particular attention is given to hybrid deep learning frameworks and advanced neural network architectures capable of handling large-scale heterogeneous datasets.

Furthermore, this study explores the potential of integrating triple pseudo-Siamese neural networks with the Giant Trevally Optimizer to develop advanced forecasting systems capable of analyzing complex relationships between product attributes, customer behavior, and historical sales data. Such integrated models could significantly improve forecasting accuracy and provide valuable insights for e-commerce decision-making processes.

The remainder of this paper is organized as follows. The next section presents a detailed review of recent literature on machine learning and deep learning approaches for e-commerce sales prediction. This is followed by a comparative analysis of existing forecasting models. Subsequently, the discussion section highlights emerging research trends and identifies potential research gaps. Finally, the conclusion summarizes the key findings and outlines future research directions for intelligent e-commerce forecasting 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 review reveals a significant shift from traditional statistical forecasting methods to machine learning and deep learning approaches in e-commerce sales prediction. Early forecasting models relied primarily on linear regression and time-series analysis techniques, which assumed stable demand patterns and limited interactions among variables. However, modern online retail environments involve complex relationships between numerous factors such as customer behavior, product characteristics, seasonal trends, marketing campaigns, and external economic conditions. As a result, researchers have increasingly adopted advanced data-driven approaches to improve forecasting accuracy.

Machine learning algorithms have played a crucial role in this transition. Techniques such as random forests, support vector machines, and gradient boosting algorithms have demonstrated strong performance in predicting product demand because they can capture nonlinear relationships in high-dimensional datasets. These models are particularly useful when dealing with structured data such as transaction records, pricing information, and product attributes.

Deep learning models have further enhanced forecasting capabilities by enabling automated feature extraction from large datasets. Neural network architectures such as convolutional neural networks and recurrent neural networks have proven effective in analyzing sequential sales data and identifying hidden patterns. CNN-based models can extract spatial features from multidimensional datasets, while recurrent neural networks such as LSTM can capture long-term temporal dependencies in time-series data.

Hybrid deep learning models combining CNN and LSTM architectures have emerged as a popular approach for sales forecasting in e-commerce systems. These models can simultaneously analyze spatial and temporal patterns in data, leading to improved prediction accuracy compared with single-model approaches.

Another important trend identified in the literature is the increasing use of heterogeneous data sources in forecasting models. Modern e-commerce systems generate multiple types of data, including browsing behavior, social media interactions, customer reviews, and product images. Integrating these data sources can provide a more comprehensive understanding of consumer behavior and improve demand prediction performance.

Siamese neural networks represent a promising architecture for handling heterogeneous datasets because they can learn relationships between multiple input sources. These networks consist of parallel subnetworks that share parameters and learn similarity representations between inputs. In the context of e-commerce forecasting, Siamese networks can analyze relationships between product attributes, historical sales patterns, and customer behavior data.

Another key development in forecasting research is the integration of optimization algorithms with deep learning models. Neural networks contain numerous hyperparameters that must be carefully tuned to achieve optimal performance. Metaheuristic optimization algorithms such as genetic algorithms, particle swarm optimization, and nature-inspired algorithms have been used to optimize neural network parameters.

The Giant Trevally Optimizer is a relatively new optimization algorithm inspired by the hunting behavior of giant trevally fish. This algorithm uses exploration and exploitation strategies to search complex solution spaces and identify optimal parameter configurations. When combined with deep learning architectures such as Siamese networks, the Giant Trevally Optimizer can significantly improve forecasting accuracy and model efficiency.

Despite these advancements, several research challenges remain. Many forecasting models require large datasets for training, which may not always be available for newly introduced products. Additionally, consumer behavior patterns in e-commerce environments are highly dynamic and can change rapidly due to market trends and external events.

Future research should focus on developing hybrid architectures that integrate deep learning models, optimization algorithms, and multi-modal data sources to improve forecasting accuracy in dynamic retail environments.

Conclusion

Accurate sales prediction is essential for efficient decision-making in modern e-commerce systems. Forecasting models enable businesses to optimize inventory management, improve supply chain efficiency, and design effective marketing strategies. Traditional statistical forecasting methods have historically been used for demand prediction, but they often struggle to capture the complex nonlinear patterns present in e-commerce datasets.

Recent advancements in machine learning and deep learning techniques have significantly improved forecasting accuracy. Algorithms such as random forests, support vector machines, and gradient boosting models have demonstrated strong performance in predicting sales trends. However, deep learning architectures have proven particularly effective because they can automatically learn complex feature representations from large datasets.

Neural network architectures such as convolutional neural networks and long short-term memory networks are widely used for analyzing sequential sales data. Hybrid models combining CNN and LSTM architectures have achieved superior forecasting performance by integrating spatial and temporal feature extraction capabilities.

Another promising research direction involves the use of Siamese neural networks for analyzing heterogeneous datasets. These architectures can learn similarity relationships between different data sources and improve forecasting accuracy for complex retail environments.

Optimization algorithms also play a critical role in improving the performance of deep learning models. Nature-inspired algorithms such as the Giant Trevally Optimizer provide efficient strategies for tuning neural network parameters and enhancing model convergence.

Overall, the integration of deep learning architectures, optimization algorithms, and heterogeneous data sources represents a promising approach for developing advanced sales prediction systems in e-commerce platforms.

Future research should focus on developing hybrid forecasting frameworks that combine triple pseudo-Siamese networks with intelligent optimization algorithms to improve predictive performance in dynamic retail environments.

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