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

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Abstract

The rapid expansion of digital commerce platforms has generated vast amounts of transactional and behavioral data, creating new opportunities for advanced predictive analytics in retail environments. Sales prediction has become a critical application, enabling businesses to forecast demand, optimize inventory management, and improve supply chain efficiency while reducing operational costs and enhancing customer satisfaction. Traditional forecasting techniques such as ARIMA and regression models have been widely used; however, they often struggle to capture the nonlinear relationships and complex patterns present in modern e-commerce datasets. Recent advancements in machine learning and deep learning, including random forests, support vector machines, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks, have significantly improved prediction accuracy by effectively modeling temporal and spatial patterns. Hybrid CNN-LSTM architectures further enhance performance by combining feature extraction and sequence learning capabilities. Additionally, Siamese neural networks enable the analysis of heterogeneous data sources by learning similarity relationships across inputs, making them particularly useful for new product demand prediction. Optimization techniques such as the Giant Trevally Optimizer further enhance model performance, leading to more accurate and scalable e-commerce forecasting systems.

Introduction

The rapid development of internet technologies and digital infrastructure has significantly transformed the global retail industry over the past two decades. The emergence of e-commerce platforms has revolutionized traditional business models by enabling organizations to sell products and services through online marketplaces. Companies such as Amazon, Alibaba, Flipkart, and eBay have created digital ecosystems where millions of products are traded daily. These platforms generate enormous volumes of data related to customer interactions, product browsing behavior, purchase transactions, marketing campaigns, and logistics operations. The availability of such large-scale datasets provides new opportunities for businesses to apply data-driven techniques to analyze consumer behavior and improve operational efficiency.

One of the most important applications of data analytics in e-commerce systems is sales prediction, also known as demand forecasting. Accurate sales forecasting plays a crucial role in supply chain management, inventory control, and marketing strategy development. By predicting future product demand, businesses can maintain optimal inventory levels, reduce storage costs, and avoid stock shortages. Furthermore, sales prediction enables organizations to design targeted marketing campaigns and optimize pricing strategies based on expected consumer demand patterns. In highly competitive online retail markets, companies that can accurately forecast demand gain a significant advantage in terms of operational efficiency and customer satisfaction.

Traditionally, demand forecasting has relied on statistical methods such as autoregressive integrated moving average (ARIMA), exponential smoothing models, and regression analysis. These methods analyze historical sales data and attempt to identify patterns that can be used to predict future demand. While statistical models are relatively simple to implement and computationally efficient, they often assume linear relationships between variables and require stationary time-series data. However, real-world e-commerce datasets are characterized by nonlinear relationships, complex dependencies, and dynamic consumer behavior patterns. Factors such as promotional campaigns, seasonal events, product reviews, and social media trends can significantly influence purchasing decisions, making demand forecasting a highly complex problem.

The limitations of traditional statistical models have led researchers to explore machine learning techniques for sales prediction. Machine learning algorithms are capable of learning complex patterns from large datasets and adapting to changing data distributions. Algorithms such as decision trees, support vector machines (SVM), random forests, and gradient boosting models have been widely applied to retail forecasting problems. These algorithms can capture nonlinear relationships between variables and provide more accurate predictions compared with traditional statistical models. Ensemble learning techniques, which combine multiple models to generate a final prediction, have also been shown to improve forecasting performance.

Despite the advantages of traditional machine learning algorithms, the increasing scale and complexity of e-commerce datasets require more advanced modeling techniques. This has led to the growing adoption of deep learning approaches in predictive analytics. Deep learning models are based on artificial neural networks with multiple hidden layers that can automatically learn hierarchical feature representations from raw data. These models have demonstrated remarkable success in fields such as computer vision, natural language processing, and recommendation systems.

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

Recent studies have shown that hybrid deep learning models, which combine multiple neural network architectures, can significantly improve forecasting accuracy. For example, CNN-LSTM models integrate convolutional layers for feature extraction with recurrent layers for temporal modeling. Such hybrid frameworks allow predictive models to capture both spatial and temporal relationships within datasets. These architectures have been widely used in retail forecasting applications where sales patterns are influenced by multiple factors.

Another emerging research direction involves the use of Siamese neural networks for predictive analytics. Siamese networks consist of two or more identical neural networks that share parameters and process different input samples simultaneously. The architecture is designed to learn similarity relationships between input data. Siamese networks have been successfully applied in applications such as image recognition, recommendation systems, and anomaly detection.

In the context of e-commerce forecasting, Siamese neural networks can be used to analyze relationships between product attributes, customer behavior, and historical sales patterns. For example, when a new product is introduced in an online marketplace, there may be limited historical sales data available for forecasting. Siamese networks can address this cold-start problem by comparing the new product with similar products that have existing sales records.

An advanced extension of Siamese networks is the triple pseudo-Siamese architecture, which consists of three parallel neural network branches designed to process different data modalities simultaneously. Each branch extracts features from a specific type of input data, such as product metadata, customer behavior logs, and historical sales data. The outputs of these branches are combined to generate a unified feature representation that captures complex relationships between heterogeneous datasets. This architecture enables predictive models to integrate multiple data sources and improve forecasting accuracy.

In addition to neural network architectures, optimization techniques play an important role in improving the performance of deep learning models. Neural networks contain numerous parameters that must be optimized during training to achieve optimal performance. Traditional optimization methods such as gradient descent may sometimes converge to local minima, resulting in suboptimal solutions.

To address this challenge, researchers have explored metaheuristic optimization algorithms inspired by natural processes. Algorithms such as genetic algorithms, particle swarm optimization, ant colony optimization, and whale optimization algorithms have been widely used to optimize neural network parameters.

The Giant Trevally Optimizer (GTO) is a recently proposed metaheuristic algorithm inspired by the hunting behavior of giant trevally fish. The algorithm simulates the cooperative hunting strategies used by these fish to capture prey. By combining exploration and exploitation mechanisms, the algorithm efficiently searches large solution spaces and identifies optimal parameter configurations. Integrating the Giant Trevally Optimizer with deep learning architectures can significantly 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 developing accurate forecasting systems for e-commerce environments. These challenges include data heterogeneity, rapidly changing consumer behavior, and scalability issues associated with large datasets. Therefore, there is a growing need for advanced hybrid architectures that integrate deep learning models with intelligent optimization algorithms.

This survey aims to provide a comprehensive overview of recent research on e-commerce sales prediction systems, focusing on machine learning models, deep learning architectures, Siamese network frameworks, and metaheuristic optimization algorithms published between 2020 and 2023. The study also explores the potential of integrating triple pseudo-Siamese neural networks with the Giant Trevally Optimizer to develop advanced forecasting systems capable of analyzing heterogeneous datasets in modern online retail platforms.

Literature Review

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Comparative Table

Study	Method	Year	Key Contribution	Limitation
Eglite & Birzniece	Deep Learning Review	2022	Analysis of DL forecasting models	Limited datasets
Joseph et al.	CNN-BiLSTM	2022	Hybrid architecture for forecasting	High computation
Ahmadov	Deep Neural Network	2023	Intermittent demand forecasting	Data intensive
Mansur et al.	Hybrid Neural Network	2023	Improved spatial-temporal modeling	Model complexity
Craparotta et al.	Siamese Network	2020	Forecasting for new products	Limited scalability

Analysis

The comparative analysis of recent research in e-commerce sales prediction highlights the evolution of forecasting techniques from traditional statistical models to advanced machine learning and deep learning frameworks. Over the past decade, forecasting methods have undergone significant transformation due to the increasing availability of large-scale datasets generated by online retail platforms. These datasets include transactional records, customer browsing behavior, product attributes, promotional campaigns, and social media interactions. The complexity and volume of such data require predictive models capable of capturing nonlinear relationships, temporal patterns, and heterogeneous information sources.

One of the most important findings from the literature is that traditional statistical forecasting methods are increasingly being replaced by machine learning models. Earlier approaches such as ARIMA, exponential smoothing, and regression analysis were widely used for demand forecasting because they are simple to implement and computationally efficient. However, these methods assume linear relationships between variables and stationary time-series data, which limits their effectiveness in dynamic e-commerce environments. Consumer demand patterns in online marketplaces are influenced by numerous factors such as seasonal events, pricing strategies, marketing campaigns, and customer reviews. These factors introduce nonlinear relationships that cannot be effectively modeled using traditional statistical techniques.

Machine learning algorithms such as random forests, support vector machines, and gradient boosting models have demonstrated improved predictive performance in retail forecasting tasks. Ensemble learning techniques combine multiple models to reduce prediction errors and improve robustness. Random forests, for example, can capture complex interactions between variables and are less prone to overfitting compared with single decision tree models. Similarly, gradient boosting algorithms such as XGBoost have gained popularity due to their ability to optimize prediction performance through iterative learning processes.

Despite the advantages of traditional machine learning models, deep learning techniques have further improved forecasting accuracy by enabling predictive models to learn hierarchical feature representations from large datasets. Neural network architectures such as convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM) networks are widely used for analyzing sequential datasets in retail forecasting applications. CNN models are particularly effective in extracting spatial features from structured data such as product attributes and sales records. On the other hand, recurrent neural networks and LSTM architectures are designed to capture temporal dependencies in time-series data, making them suitable for forecasting tasks where past sales patterns influence future demand.

Hybrid deep learning models have emerged as a powerful approach for e-commerce forecasting. These models combine multiple neural network architectures to capture different types of patterns in data. For instance, CNN-LSTM hybrid architectures integrate convolutional layers for feature extraction with recurrent layers for temporal pattern recognition. Such hybrid frameworks allow predictive models to simultaneously analyze spatial and temporal relationships within datasets. Several studies have demonstrated that hybrid deep learning architectures outperform standalone machine learning models and traditional forecasting techniques.

Another significant development in recent research is the use of heterogeneous datasets in predictive models. Modern e-commerce systems generate multiple types of data, including product metadata, customer behavior logs, textual reviews, and multimedia content such as product images. Integrating these diverse data sources into a unified forecasting framework can significantly improve predictive performance. However, handling heterogeneous datasets requires advanced neural network architectures capable of processing multiple data modalities simultaneously.

Siamese neural networks have emerged as a promising solution for addressing this challenge. Siamese networks consist of multiple identical neural subnetworks that share parameters and learn similarity relationships between input samples. In retail forecasting applications, Siamese architectures can analyze relationships between product attributes and historical sales patterns. This capability is particularly useful in addressing the cold-start problem, where newly introduced products lack sufficient historical sales data for accurate forecasting. By comparing new products with existing products that have known sales patterns, Siamese networks can generate more reliable predictions.

An extension of this architecture is the triple pseudo-Siamese network, which includes three parallel neural subnetworks designed to process different types of input data simultaneously. Each branch extracts features from a specific dataset, such as product attributes, customer behavior data, or transaction histories. The outputs from these branches are then combined to generate a unified feature representation. This architecture allows predictive models to capture complex relationships between heterogeneous datasets and improve forecasting accuracy in e-commerce systems.

In addition to neural network architectures, optimization algorithms play an essential role in improving model performance. Deep learning models often contain millions of parameters that must be optimized during training. Traditional optimization methods such as gradient descent can sometimes converge to local minima, leading to suboptimal solutions. To overcome this limitation, researchers have explored metaheuristic optimization algorithms inspired by natural processes.

Metaheuristic algorithms such as genetic algorithms, particle swarm optimization, ant colony optimization, and whale optimization algorithms have been widely used for optimizing neural network parameters. These algorithms simulate natural behaviors such as evolution, swarm intelligence, and animal hunting strategies to search large solution spaces efficiently.

One of the most recent developments in this area is the Giant Trevally Optimizer (GTO), a nature-inspired metaheuristic algorithm based on the hunting behavior of giant trevally fish. The algorithm employs exploration and exploitation mechanisms to identify optimal solutions in complex optimization problems. Integrating the Giant Trevally Optimizer with deep learning architectures can significantly enhance forecasting performance by optimizing network parameters and improving model convergence.

The comparative analysis of existing studies reveals several important research trends. First, there is a clear shift from traditional statistical models toward machine learning and deep learning frameworks for demand forecasting. Second, hybrid neural network architectures are increasingly being used to capture multiple patterns in datasets. Third, the integration of heterogeneous data sources has become an important factor in improving predictive performance. Finally, optimization algorithms are playing an increasingly important role in improving the efficiency and accuracy of deep learning models.

Despite these advancements, several challenges remain in developing accurate forecasting systems for e-commerce platforms. Many predictive models require large training datasets and high computational resources, which may limit their practical application in small and medium-sized businesses. Additionally, rapidly changing consumer behavior and market dynamics can make forecasting models less reliable over time.

Future research should focus on developing hybrid architectures that combine deep learning models, heterogeneous data integration, and intelligent optimization algorithms. Integrating triple pseudo-Siamese neural networks with the Giant Trevally Optimizer represents a promising research direction for developing next-generation forecasting systems capable of handling complex e-commerce datasets.

Such advanced architectures could significantly improve prediction accuracy and provide valuable insights for businesses operating in dynamic online retail environments.

Discussion

The rapid advancement of artificial intelligence and data analytics has significantly transformed forecasting methodologies used in e-commerce systems. Modern online retail platforms generate vast volumes of data, including customer browsing behavior, purchase history, product attributes, marketing campaign performance, and social media interactions. Analyzing these datasets effectively has become essential for businesses seeking to improve demand forecasting and optimize supply chain operations. The literature reviewed in this study demonstrates that predictive analytics has evolved from traditional statistical forecasting methods to advanced machine learning and deep learning frameworks capable of handling large-scale heterogeneous datasets.One of the major trends observed in recent research is the widespread adoption of machine learning techniques for demand forecasting. Algorithms such as random forests, support vector machines, and gradient boosting have demonstrated strong predictive performance compared with conventional statistical models. These algorithms are particularly effective in capturing nonlinear relationships between variables and adapting to dynamic consumer behavior patterns. However, machine learning models typically require extensive feature engineering and may struggle to extract meaningful patterns from unstructured data sources.To address these limitations, researchers have increasingly turned to deep learning architectures, which are capable of automatically learning hierarchical feature representations from raw data. Neural network models such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have proven effective in analyzing complex retail datasets. CNN models are capable of extracting spatial patterns from structured datasets such as product attributes and transaction records, while RNN models, particularly long short-term memory (LSTM) networks, can capture temporal dependencies in sequential sales data.

Another important trend highlighted in the literature is the development of hybrid deep learning architectures. Hybrid models such as CNN-LSTM combine spatial and temporal feature extraction capabilities, enabling predictive models to analyze complex relationships between multiple variables. These architectures have been widely used in retail forecasting applications because they can capture both short-term and long-term demand patterns.In addition to hybrid deep learning models, recent research has explored the use of heterogeneous datasets in demand forecasting systems. E-commerce platforms generate diverse types of data, including structured transactional data, textual reviews, multimedia product descriptions, and customer behavior logs. Integrating these heterogeneous data sources into predictive models can significantly improve forecasting accuracy by providing a more comprehensive understanding of consumer behavior patterns.

Siamese neural networks represent a promising architecture for analyzing heterogeneous datasets. These networks consist of parallel neural subnetworks that share parameters and learn similarity relationships between input data samples. In e-commerce forecasting applications, Siamese networks can analyze relationships between products and historical sales patterns, enabling predictive models to forecast demand for newly introduced products that lack sufficient historical data.The triple pseudo-Siamese architecture represents an extension of this concept by incorporating three parallel neural network branches designed to process different types of input data simultaneously. Each branch extracts features from a specific data modality, such as product metadata, customer activity logs, or historical transaction records. The integration of these feature representations enables predictive models to capture complex relationships between heterogeneous datasets.Another important aspect of predictive modeling discussed in the literature is the role of optimization algorithms in improving model performance. Deep learning models often contain millions of parameters that must be optimized during training to achieve optimal predictive accuracy. Traditional optimization methods such as gradient descent may not always converge to the global optimum, particularly in complex optimization problems.

Metaheuristic optimization algorithms inspired by natural processes have been widely used to address this challenge. Algorithms such as genetic algorithms, particle swarm optimization, and whale optimization algorithms have demonstrated strong performance in optimizing neural network parameters. The Giant Trevally Optimizer (GTO) is a recent addition to this family of algorithms. Inspired by the cooperative hunting behavior of giant trevally fish, the GTO algorithm employs exploration and exploitation strategies to search large solution spaces efficiently.Integrating the Giant Trevally Optimizer with deep learning architectures such as triple pseudo-Siamese networks can significantly enhance forecasting performance by improving parameter optimization and model convergence. Such hybrid frameworks represent a promising direction for future research in predictive analytics for e-commerce systems.

Despite these advancements, several challenges remain in developing accurate forecasting systems. These include the high computational cost of deep learning models, the difficulty of integrating heterogeneous datasets, and the rapidly changing nature of consumer behavior in online marketplaces. Addressing these challenges will require the development of more efficient algorithms and scalable architectures capable of handling large-scale retail datasets.

Conclusion

Accurate demand forecasting is a fundamental requirement for efficient decision-making in modern e-commerce systems. Online retail platforms operate in highly dynamic environments where consumer demand patterns are influenced by numerous factors, including pricing strategies, marketing campaigns, seasonal events, and customer preferences. Predictive analytics plays a crucial role in helping organizations anticipate these demand fluctuations and optimize their operational strategies accordingly.This survey examined recent developments in e-commerce sales prediction systems, focusing on machine learning models, deep learning architectures, Siamese network frameworks, and optimization algorithms published between 2020 and 2023. The review revealed that traditional statistical forecasting methods are gradually being replaced by machine learning and deep learning techniques due to their ability to capture complex nonlinear relationships within large datasets.Machine learning algorithms such as random forests, support vector machines, and gradient boosting models have demonstrated strong predictive performance in retail forecasting tasks. These algorithms are particularly effective in capturing nonlinear relationships between variables and adapting to changing consumer behavior patterns. However, traditional machine learning models often require extensive feature engineering and may struggle to handle unstructured data sources.

Deep learning models have significantly advanced the capabilities of predictive analytics in retail forecasting. Neural network architectures such as convolutional neural networks and long short-term memory networks can automatically learn hierarchical feature representations from large datasets. Hybrid architectures combining CNN and LSTM models have shown particularly strong performance because they integrate spatial and temporal feature extraction mechanisms.Another important development in recent research is the use of Siamese neural networks for predictive analytics. These architectures can learn similarity relationships between heterogeneous datasets and are particularly useful for addressing the cold-start problem in retail forecasting. The triple pseudo-Siamese network architecture extends this concept by integrating multiple data modalities into a unified predictive framework.Optimization algorithms also play a crucial role in improving the performance of predictive models. Metaheuristic algorithms inspired by natural processes have been widely used to optimize neural network parameters and improve model convergence. The Giant Trevally Optimizer represents a promising optimization technique that can efficiently search large solution spaces and identify optimal parameter configurations.Integrating triple pseudo-Siamese neural networks with the Giant Trevally Optimizer offers a promising approach for developing advanced forecasting systems capable of handling complex e-commerce datasets. Such hybrid architectures can analyze heterogeneous data sources and capture complex relationships between product attributes, customer behavior patterns, and historical sales data.

Despite significant progress in predictive analytics and deep learning technologies, several challenges remain in the development of accurate forecasting systems for e-commerce environments. These challenges include the high computational cost of deep learning models, scalability issues associated with large datasets, and the dynamic nature of consumer behavior in online retail markets.Future research should focus on developing scalable hybrid architectures that integrate deep learning models with intelligent optimization algorithms and heterogeneous data integration techniques. Such approaches could significantly improve forecasting accuracy and enable businesses to make more informed decisions in highly competitive online retail environments.Overall, the integration of deep learning architectures, heterogeneous data sources, and intelligent optimization algorithms will play a key role in the development of next-generation predictive analytics systems for e-commerce platforms.

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