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Predicting Customer Purchase Patterns in Online Retail Using a CNN-Based Deep Learning Model

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ABSTRACT

Accurately predicting customer purchase patterns in online retail enables personalized recommendations, targeted marketing, and improved business decision-making. However, challenges such as high-dimensional transactional data, class imbalance, and the limitations of traditional Machine Learning (ML) models often hinder predictive performance. In this study, a Convolutional Neural Network (CNN) based model was designed to predict customer purchase behavior from online retail transaction data. CNNs are particularly effective at learning complex patterns and feature relationships, making them well-suited for structured data representation. The experiment was conducted on an online retail dataset comprising customer purchase patterns obtained from the University of California, Irvine repository, one of the most widely used benchmark datasets for evaluating ML algorithms. The performance of the CNN model was evaluated using accuracy, precision, recall, F1-score, and the Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC), achieving 93.6% accuracy, 100.0% precision, 91.1% recall, 95.4% F1-score, and an AUC-ROC of 0.98. These results demonstrate that deep learning can effectively model customer purchasing behavior, offering valuable insights for online retail platforms aiming to anticipate customer actions and optimize engagement strategies.

INTRODUCTION

Understanding consumer behavior patterns is crucial to a business's success. Gaining insights into consumer preferences, purchasing patterns, and emerging trends is essential for enhancing sales, improving customer engagement, and maintaining a competitive edge (Fernando *et al*, 2023; Yosheswari, 2024). Consumer behavior patterns refer to the consistent habits, preferences, and decision-making processes that individuals or groups display when purchasing or using products and services (Oke *et al*, 2016). With the rise of e-commerce, online shopping has become the dominant mode of purchasing due to its convenience, time-saving benefits, and cost-effectiveness (Sikder and Rolfe, 2023).

In recent years, predicting consumer behavior has become increasingly crucial, especially for personalized marketing and strategic decision-making. By understanding customer purchase patterns, particularly repeat purchases, businesses can improve customer retention, boost profitability, and refine marketing strategies (Jain *et al.*, 2023). The widespread adoption of digital technologies and the growth of online retail have generated massive volumes of consumer data, which organizations can leverage to make data-driven decisions (Camilleri, 2020; Rosário and Dias, 2023). These decisions depend on online and offline consumer data, essentially for the optimizing marketing campaigns and product recommendations. However, accurately predicting customer repeat purchases remains a complex challenge due to the unpredictable nature of purchasing decisions, which are influenced by various psychological, social, and contextual factors (Van Chau and He, 2024).

Traditional machine learning (ML) techniques, such as decision trees, k-nearest neighbors, linear regression, logistic regression, naive Bayes, support vector machines, and statistical models, have been employed to predict customer behavior Chaubey (Chaubey *et al*., 2023; Dani and Ginting, 2023; Sabbeh, 2018). While these models provide valuable insights, they often struggle to manage large-scale datasets and fail to capture the intricate, non-linear relationships that characterize customer purchasing patterns (Tufail *et al*., 2023). There is a growing need for more sophisticated models that can effectively handle high-dimensional data and deliver accurate predictions, particularly in predicting repeat purchases, such as deep learning.

Deep learning, a subfield of artificial intelligence, has shown considerable potential in addressing these challenges (Sarker, 2021; Wilson and Anwar, 2024). Among deep learning architectures, Convolutional Neural Networks (CNNs) stand out due to the ability to recognize intricate patterns and model spatial relationships within data (Khan *et al*., 2020). Researchers initially developed CNNs for image-processing tasks and have since applied them successfully in various domains, including natural language processing and time-series analysis. The ability of CNNs to detect hierarchical features in data such as customer preferences, purchase sequences, and behavioral trends makes them particularly well-suited for modeling repeat customer purchases in e-commerce (Al-Ebrahim *et al*., 2023).

Unlike traditional models, CNNs can automatically learn important features from raw data, removing the need for manual feature engineering (Liu *et al*., 2021). This ability makes them especially useful for processing different forms of customer data, such as transactional histories, product reviews, and browsing behavior (Alzubaidi *et al*., 2021). Furthermore, CNNs offer advantages in scalability, generalization, and robustness when applied to large datasets.

By leveraging CNNs, businesses can gain deeper insights into customer purchase behavior, enabling more accurate forecasting of future repeat purchases and developing personalized marketing strategies. For example, CNNs can analyze demographic information alongside historical transaction data and browsing patterns to predict repeat purchases and tailor offerings accordingly. This capability gives companies a competitive edge in today's fast-evolving digital marketplace (Theodorakopoulos and Theodoropoulou, 2024).

Therefore, this study proposes a CNN-based model for predicting customer repeat purchase behavior using transactional data from an online retail store. The objective is to evaluate the effectiveness of CNN in capturing complex behavioral patterns and compare its performance with that of traditional ML models. The study aims to contribute to developing a more reliable and scalable predictive model for online retail, offering actionable insights to improve customer retention, sales forecasting, and overall business performance.

RELATED WORKS

In the e-commerce industry, ML and deep learning techniques have been applied to predict customer purchase patterns and enhance decision-making in personalized recommendations, demand forecasting, and sales optimization. These techniques help businesses identify what products customers are likely to buy, when they are likely to make purchases, and how purchasing trends evolve. While some studies have relied on a single predictive approach to uncover these insights, others have explored and compared multiple models to improve prediction accuracy and capture the complexities of consumer purchase behavior more effectively.

Ali-Hakami and Mahmoud (2022) introduced a deep learning-based ensemble model for predicting consumer behavior from social media activities, addressing the limitations of traditional ML models in handling complex behavior patterns. The proposed model integrates VGG19 and DenseNet201 pre-trained deep learning algorithms in an optimized ensemble framework, improving classification accuracy. Experimental results show that the ensemble model achieves 98.78% accuracy on the Facemg database, outperforming conventional consumer behavior detection models by over 8%.

Zhang *et al*. (2022) explored the application of deep learning models in consumer behavior prediction, focusing on developing and evaluating Deep Neural Networks (DNNs). The study introduced two enhanced models, Recurrent Deep Neural Network (rDNN) and K-means Deep Neural Network (KmDNN), which improve prediction accuracy by refining the structure and learning capabilities of standard DNNs. Using AUC and F-score as evaluation metrics, rDNN outperforms KmDNN (AUC of 0.8322 versus 0.8064) and the baseline DNN (0.7893), thus demonstrating the potential of advanced deep neural networks in improving consumer purchase behavior analysis.

Kaewkiriya and Wisaeng (2023) proposed a customer predictive model for investment that utilizes ensemble learning techniques to recommend suitable funds based on an investor's profile. The study explored the limitations of traditional ML models in predicting optimal investment choices and demonstrated that combining multiple methods through voting ensemble learning improves forecasting accuracy. Testing various preprocessing approaches, such as date range clustering (62.24% accuracy) and K-means clustering (69.21% accuracy), the ensemble model achieves high accuracy (92.38%) in predicting fund risk and category, with neural networks achieving the highest accuracy (93.43%) among the tested algorithms. Findings from the study suggested that ensemble learning enhances investment recommendation systems, offering more personalized, data-driven investment guidance.

Sharma and Waoo (2023) presented ML-based techniques for predicting consumer behavior, focusing on customer ratings and feedback analysis. The work specifically utilized Naïve Bayes and Logistic Regression to classify consumer sentiments to assess the impact of reviews on purchasing decisions. The experimental results indicated that Logistic Regression outperforms Naïve Bayes (96.62% versus 93.41%), achieving higher accuracy, recall, and F1-scores in sentiment classification.

Liu (2024) investigated the application of deep learning techniques in predicting online marketplace user purchase behavior, specifically focusing on Recurrent Neural Networks (RNNs). The research highlighted how RNNs effectively capture temporal dependencies in user behavior data, significantly improving prediction accuracy. Experimental results showed that the RNN model achieved an accuracy of 89.2% and an F1-score of

0.883, outperforming other models in handling consumer behavior patterns' dynamic and complex nature.

Modak *et al*. (2024) explored the impact of Convolutional Neural Networks (CNNs) on digital marketing strategies within the banking sector. The study evaluated various CNN architectures, including VGG16, ResNet50, and InceptionV3, demonstrating their ability to analyze complex customer behavior data and enhance customer segmentation, campaign optimization, and personalized experiences. Comparative analyses revealed that ResNet50 achieved the highest accuracy of 89% and an F1-score of 88%, significantly outperforming traditional models like Random Forest (65.08%) and Logistic Regression (74%), thus highlighting the superiority of CNNs in uncovering intricate consumer preference patterns.

DESCRIPTION OF THE FRAMEWORK

The description of the framework utilized is as follows:

Data Description

The dataset used for the experiment was obtained from the University of California, Irvine (UCI) ML Repository. The UCI is a well-known repository containing datasets, domain theories, and data generators widely used by the ML community for empirical algorithm analysis. The dataset focuses on consumer behavior in e-commerce, specifically repeated purchases. It contains eight features: *InvoiceNo*, *StockCode*, *Description*, *Quantity*, *InvoiceDate*, *UnitPrice*, *CustomerID*, *and Country* with 541,909 instances. The dataset includes transactional data from a UK-based, non-store online retailer that primarily sells unique, all-occasion gifts. Many of the company’s customers are wholesalers.

Data Pre-processing

The following data pre-processing techniques were applied to prepare the dataset for customer purchase pattern prediction:

1. **Missing Value Treatment** – Records with missing values were identified and either imputed using mean/mode (for numerical/categorical variables respectively) or removed, depending on the extent of missingness.
2. **Data Normalization** – Data normalization ensures that all instances in the features are standardized and scaled between 0 and 1, thereby enhancing the performance and training stability of the model. The Min-Max normalization technique was used to normalize the data in the customer churn dataset.
3. **Categorical Encoding** – Categorical variables were transformed into numerical format using One-Hot Encoding.

Synthetic Minority Over-sampling Technique

Synthetic Minority Over-sampling Technique (SMOTE) is one of the popular techniques used in ML to deal with imbalanced datasets, where one class (typically the minority class) has far fewer instances than the other(s) (Elreedy and Atiya, 2019). Data imbalance occurs when there is a huge difference between classes of data within the target variable. This study used SMOTE to generate synthetic samples by selecting instances of the minority class (i.e., no repeated purchase, labeled as 0), identifying their *k*-nearest neighbors, and creating new synthetic instances along the line segments connecting the selected instance to its neighbors.

In this study, SMOTE was applied after preprocessing and before model training to improve the classifier's sensitivity to the minority class. We used k=5 for nearest neighbors and increased the minority class size by 100%, resulting in a balanced dataset.

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning architecture commonly used for analyzing spatial and structured data (Namatēvs, 2017). While traditionally employed in image and video recognition tasks, CNNs have also shown promising performance in non-visual domains, including e-commerce and customer behavior prediction (Nagrath *et al*., 2021). The CNN model learns meaningful patterns from structured customer activity data to enhance behavior prediction accuracy.

Unlike fully connected networks such as Multi-Layer Perceptrons, CNNs apply convolutional operations to local regions of the input data, enabling the network to detect localized and hierarchical patterns (Khan *et al*., 2020). This makes CNNs highly effective in learning temporal or spatial dependencies that may exist in structured transaction or clickstream data.

The structure of a CNN typically includes convolutional layers, activation functions, pooling layers, and fully connected layers (Purwono *et al*., 2022). The convolutional layers apply filters (kernels) that move across the input matrix to extract relevant features (Namatēvs, 2017). These filters can learn specific patterns representing customer behaviors, such as purchase frequency, browsing patterns, or session durations. The activation function (e.g., ReLU) introduces non-linearity into the model, allowing it to learn complex patterns (Dubey *et al*., 2022). Pooling layers are used to reduce the dimensionality of feature maps, control overfitting, and improve computational efficiency. Finally, the output is passed through one or more fully connected layers for classification or regression tasks.

Given a structured input vector $\mathrm{x} \in \mathbb{R}^{\mathrm{H} \times \mathrm{W} \times \mathrm{C}}$, where H *and* W denote the height and width of the input matrix (e.g., time steps and features), and C represents the number of channels, the CNN performs a convolutional operation defined as in Equation 1:

$$f(x) = \Phi\ (_{i,j,k} w_{i,j,k} \cdot x_{i,j,k} + \mathrm{b}) \qquad (1)$$

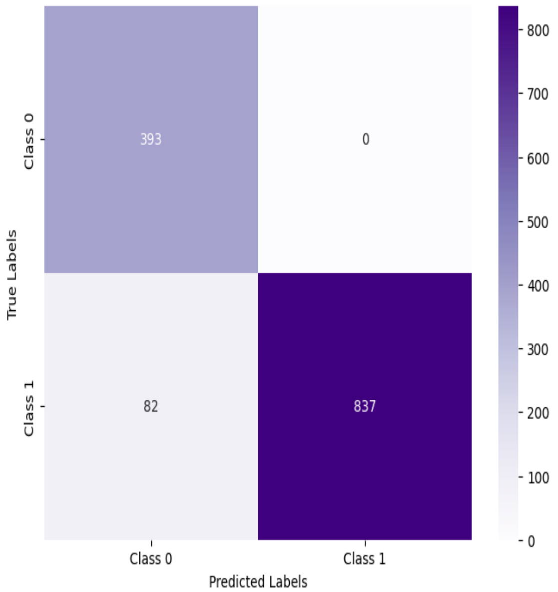

Figure 1: Confusion Matrix Generated by the CNN Model

Figure 1 shows that out of the 393 single-transaction customers in the test set, the model correctly identified all 393 as single-transaction customers, with none misclassified as multiple-transaction customers. This demonstrates that the model exhibited sensitivity (recall) of approximately 100% in identifying single-transaction customers. Similarly, out of the 919 multiple-transaction customers, 837 were correctly identified as multiple-transaction customers, while 82 were incorrectly classified as single-transaction customers. This implies a sensitivity of approximately 91.19% in recognizing multiple-transaction customers.

Table 1: Result of CNN Model Evaluation

Metrics	**Value (%)**

Accuracy	93.6
Recall	91.1
Precision	100.0
F-measure	95.4
ROC/AUC Score	98.0

As shown in Table 1, the model achieved an accuracy of 93.6%, indicating that it correctly classified most customers in the test set. The precision was 100.0%, demonstrating the model's ability to minimize FP predictions; every customer identified as a multiple-transaction customer was indeed one, ensuring that resources are directed only toward genuinely repeat customers. The recall was 91.1%, highlighting the model's strong capacity to correctly identify multiple-transaction customers, thereby reducing the likelihood of missed opportunities for engagement with these valuable customers. The F1 score, which balances precision and recall, was 95.4%, reflecting the model's overall reliability and effectiveness in handling the classification task.

These results demonstrate the potential of the ML model to automate and optimize customer transaction classification. By accurately predicting multiple-transaction customers with minimal false positives and false negatives, the model offers a valuable tool for improving customer relationship management strategies. Moreover, the high recall ensures the timely identification of multiple transaction customers, enabling prompt and targeted marketing efforts, while the model's high precision minimizes unnecessary interventions. These findings align with previous research advocating the use of ML for customer behavior prediction and highlight the scalability of such approaches for broader business applications. Similarly, the ROC AUC score of the CNN model is presented in Figure 2.

The ROC-AUC score of 0.98, as shown in Figure 2, demonstrates the outstanding classification performance of the proposed CNN-based model. The high AUC value indicates the CNN model's strong ability to distinguish between customers who are likely to make repeat purchases and those who are not. A ROC AUC value close to 1.0 in predictive modeling signifies excellent discriminative power, reflecting a model that correctly ranks positive instances (repeat purchasers) above negative ones (single-transaction customers) across a range of classification thresholds.

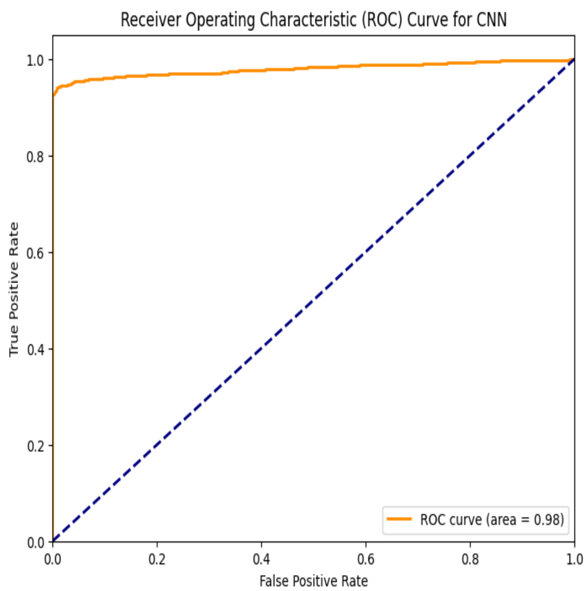

Figure 2: The ROC-AUC Score for the CNN Model

This result is particularly significant in online retail, where reliably identifying repeat customers can drive effective marketing, personalized engagement, and customer retention strategies. A high ROC AUC validates the model's effectiveness and implies robustness and generalisability, even when operating under different decision thresholds.

Performance Comparison with Existing Systems

The performance comparison between the proposed model and three existing systems in terms of classification accuracy is presented in Table 2. The comparison is based on existing works with the same dataset but different methods.

The results of the proposed model outperformed those of the systems developed by Quynh *et al.* (2021), Paranavithana *et al.* (2023), and Deniz and Bülbül (2024). This suggests that the proposed approach is more effective in achieving the desired outcomes.

Table 2: Comparative Analysis with Existing Systems

Authors	**Model**	**Accuracy (%)**
Quynh *et al.*, (2021)	Random Forest	76.0
Paranavithana et al.(2023)	Naive Bayes	79.0
Deniz and Bülbül (2024)	SVM	92.0
Proposed Model	**CNN**	**93.6**

CONCLUSIONS AND FUTURE WORK

This study evaluated the effectiveness of a CNN model for customer behavior prediction in e-commerce. Based on the results of the comparative analysis with existing systems, CNN outperformed across all performance metrics. The superior performance of CNN highlights its ability to capture intricate patterns in customer behavior data, making it a robust and effective approach for predictive analytics in e-commerce.

These findings emphasize the potential of deep learning in enhancing customer behavior prediction, thereby enabling more accurate recommendations, targeted marketing, and improved user experiences.

However, several limitations must be acknowledged. First, the dataset used may not adequately capture the diversity of real-world e-commerce environments, which could limit the model's generalisability. Furthermore, although the model demonstrates strong performance, it lacks interpretability, an inherent limitation of deep learning that may hinder trust and reduce explainability in high-stakes applications such as targeted marketing or fraud detection.

Future work will explore the integration of advanced deep learning architectures, such as hybrid CNN-RNN models, to further improve predictive performance. Additionally, incorporating attention mechanisms and transfer learning techniques could help refine feature extraction, enhance model generalization, and improve the interpretability of predictions. Expanding the dataset to include multimodal customer interaction data, such as text and clickstream analysis, could provide deeper insights into purchasing patterns and decision-making behaviors. Further research will also focus on systematic hyperparameter optimization (e.g., using Bayesian or grid search methods) and model interpretability techniques such as SHAP or LIME.

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