Enhancing Customer Purchasing Behaviour Prediction in E-Commerce: A Deep Learning Perspective

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Abstract: Digital retailers are experiencing a growing volume of online transactions with consumers, which is driven by consumers' ability to buy products through E commerce platforms. Such interactions tend to form complex behavioural constructs that are extractable to assist companies in comprehending consumer requirements. One of the most important applications is the correct determination of the behavior of consumers in the e commerce domain. For selling any sort of product over the Internet or in the other words in order to achieve high profit in an e-commerce business, the interplay between a customer and a merchandise is quite very critical. Moreover, a lot of e commerce websites and services proliferate and competition has become just a mouse-click away. Therefore the need to stay in the business, and enhance profitability measures purchases in a more advanced way predicting desirability and allowing companies to customize services for customers based on their indees. To help forecast behavioral patterns the research will incorporate foam Developing Learning approaches. Also, narrative data from the dataset would be drawn through exploratory data analysis (EDA). The dataset used in this research encompasses of different attributes, such as kind of visitors, that is whether they made a purchase or not and many other variables. In this research, Deep Learning techniques aptly suited for Multi-Level Data due to its robust capacity of modeling and accurate categorization are employed. In addition to the insights gained from each particular set of data within EDA, the results from the behavioural analysis prediction using any of the deep learning methods can add useful statistics to the e commerce companies. Understanding user behaviour Smart usability design engagement, site design optimization, personalisation and improvements in user experience..

1 INTRODUCTION

In the dynamic realm of digital commerce, the rapid shift toward online platforms has significantly reshaped consumer behavior, necessitating that e-commerce businesses stay ahead by accurately understanding and predicting purchasing patterns. (Sarkar, Mia, et al. , 2023) This evolution has emocratized shopping and created an environment where every user interaction generates valuable data that can reveal deep insights into consumer preferences and trends. This paper presents a comprehensive study that leverages advanced data analytics, particularly focusing on Logistic Regression, Neural Networks, and XGBoost, to predict the accuracy of reorder behaviors in e commerce. The foundation of this research is built on meticulous Exploratory Data Analysis (EDA) of a diverse dataset that includes customer demographics, browsing history, purchase frequencies, and past interactions with promotional offers. By uncovering hidden patterns through EDA, we aim to enhance our understanding of the factors influencing consumer decisions in online shopping. Notably, we achieved an accuracy of 90.13% using Artificial Neural Networks, demonstrating the effectiveness of this technique in predicting reorder behaviors.

Deep Learning and machine learning techniques, such as Neural Networks and XGBoost, are pivotal in this study, enabling us to process large volumes of data and extract complex patterns that traditional statistical methods might overlook. By integrating these techniques, the study seeks to develop robust predictive models capable of forecasting key consumer behaviors, such as the likelihood of reordering and product preferences. The implications of these predictive models are profound, offering e-commerce businesses a competitive edge through data-driven decision-making. (Kumar, Margala, et al. , 2023) Accurate behavioral

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predictions facilitate the creation of personalized marketing campaigns, optimized user experiences, and targeted strategies that resonate with specific customer segments. The ultimate goal of this research is to equip companies with the knowledge and skills necessary to successfully negotiate the complex terrain of consumer behavior, promote innovation in customer service, and maintain development in the fiercely competitive e-commerce sector. There are six sections in this study. The arrangement is as follows: Section 2 examines pertinent scholarly works. A thorough explanation of the research technique is given in Section 3. Section 4 discusses the results analysis and accuracy validation using different evaluation criteria. The paper's conclusion, found in Section 5, reviews the goals in light of the data and considers potential future approaches for the study of consumer purchasing behavior. Lastly, Section 6 contains a list of references.

2 LITERATURE SURVEY

The literature review reveals a range of approaches employed in predicting customer purchasing behavior, each utilizing various supervised classification techniques. These include Logistic Regression, Decision Trees, K-Nearest Neighbors, Naïve Bayes, Support Vector Machines (SVM), Random Forests, and Stochastic Gradient Descent, which, after thorough feature optimization, achieved a remarkable accuracy rate of 88%. (Sarkar, Mia, et al. , 2023) To reduce dataset complexity and boost classifier performance, K-means clustering was introduced, which enhanced data homogeneity. This, combined with algorithms like C4.5, J48, CS-MC4, and Multinomial Logistic Regression, delivered superior prediction outcomes.

(Kumar, Margala, et al. , 2023) Moreover, a dynamic pricing strategy was developed to categorize customers based on behavioral patterns and optimize pricing in real-time, guided by historical data. This strategy aimed to maximize revenue while ensuring customer satisfaction. (Chaubey, Gavhane, et al. , 2014)SVM models also played a significant role in analyzing inventory and sales data, uncovering a critical insight that age is a major factor influencing online purchasing decisions. This discovery is crucial for developing more targeted e-commerce marketing strategies. (Vankhede, Kumar, et al. , 2024)Additionally, the Customer Behavior Mining Framework integrated K-means clustering and decision trees to anticipate customer actions, demonstrating moderate accuracy. However, the study suggests that the framework's performance could be enhanced by leveraging more sophisticated algorithms. Lastly, web usage mining was used to gather valuable insights by analyzing client, server, and agent logs. This approach offered a holistic view of customer behavior, examining both technical and interaction aspects within e-commerce platforms to provide deeper understanding and actionable insights.

3 DESIGN AND PRINCIPLE OF OPERATION

3.1 METHODOLOGY

The dataset utilized for this study is the Instacart Market Basket Analysis dataset, sourced from the public dataset repository, Kaggle. (Valecha, Varma, et al. , 2018) This dataset contains a comprehensive record of over 3 million grocery orders made by more than 200,000 users across multiple retailers. It includes detailed information on customer purchasing behavior, such as the products ordered, the sequence of orders, product categories, and reorder patterns. The procedure is carried out to perform the analysis effectively to gain the necessary insights for in E-commerce. The whole methodology is divided into the following steps as shown in Fig. 1:

- Data Collection
- Data Preprocessing
- Feature Engineering
- Model Selection
- Model Design
- Training
- Evaluation
- Hyper Parameter Tuning
- Re-Evaluation

Figure 1: Methodology.

3.1.1 Data Collection

The dataset utilized for this study is the Instacart Market Basket Analysis dataset, sourced from the public dataset repository, Kaggle. This dataset contains a comprehensive record of over 3 million grocery orders made by more than 200,000 users across multiple retailers. It includes detailed information on customer purchasing behavior, such as the products ordered, the sequence of orders, product categories, and reorder patterns. The procedure is carried out to perform the analysis effectively to gain the necessary insights for in E-commerce.

3.1.2 Data Preprocessing

Data preprocessing involved several critical steps to prepare the data for predictive modeling. Initially, missing values were identified and handled by either removing incomplete entries or imputing values, depending on the significance of the feature. Categorical variables such as product names and aisles were transformed using label encoding or one-hot encoding to convert them into numerical formats.

3.1.3 Feature Engineering

A primary focus was on feature engineering, where new variables were added to improve model accuracy, including reorder frequency, duration between orders, and product affinity ratings. These actions were essential for enhancing the dataset's quality and maximizing machine learning algorithms' performance.

3.1.4 Model Selection

Complex patterns and temporal relationships are captured by Deep Learning models like Artificial Neural Networks (ANNs) and classic Machine Learning methods like Logistic Regression, XGboost.

3.1.5 Model Design

The model design phase focuses on architecture, using layers and activation functions suited to the dataset. A specific model architecture, using a four-layer structure with a ReLU activation function, yielded superior accuracy.

3.1.6 Training

The dataset was separated into training and test sets in order to evaluate the model's performance. Some of the algorithms that were trained using features generated from product data, client orders, and reorder trends are XGboost, Artificial Neural Networks, and logistic regression.

3.1.7 Evaluation

Performance is evaluated using criteria like as accuracy, precision, recall, and F1-score. The efficacy of the model is further validated by comparative analysis. Businesses gain from the system by using it to make better decisions, target customers more effectively, and maximize marketing campaigns.

3.1.8 Hyper parameter Tuning

The act of adjusting a machine learning model's pre-training parameters—which are not determined by the data—is known as hyperparameter tuning. The performance of the model is greatly influenced by these variables, also known as hyperparameters. (Baderiya, Chawan, et al. , 2018) Two common tuning methods are Random Search and Grid Search. While Random Search selects random combinations of hyperparameters, Grid Search tests a preset set of values for each hyperparameter in detail.

3.1.9 Evaluation

The results are then re-evaluated after tuning the hyper parameters till the expected outcomes are obtained.

4 RESULTS AND ANALYSIS

We used XGBoost, Logistic Regression, and Artificial Neural Networks (ANN) to assess our system's performance. To ensure data quality and relevance to our analysis, these models were trained on a carefully preprocessed dataset that underwent intensive cleaning, normalization, and feature engineering. To accomplish the goals, exploratory data analysis is then carried out. The trained models are assessed using metrics including recall, F1-score, accuracy, precision, and ROC curves.

Accuracy: This is the proportion of accurately predicted instances to all instances in a dataset. It is a typical metric for assessing models of categorization. The calculation of accuracy is as:

$$\text{Accuracy} = \left(\frac{\text{Number of Correct Predictions}}{\text{Total number of Predictions}}\right) * 100$$

A model is considered to have a high accuracy score when its predictions closely match the actual outcomes. (Sabbeh, 2018) However, it's important to keep in mind that accuracy may not always be a reliable indicator for unbalanced datasets; in these

Precision: This calculates the percentage of accurate positive predictions among all the model's positive predictions

$$\text{Precision} = \frac{TP}{TP + FP}$$

F1-Score: The F1-score, which is the harmonic mean of recall and precision, is a single measure that strikes a balance between the two.

$$F1 - \text{ score } = 2 * \left(\frac{\text{Precision } * \text{ Recall}}{\text{Precision } + \text{ Recall}}\right)$$

Recall: Recall, or sensitivity, is the proportion of actual positive examples that the model correctly predicted situations, other metrics like precision, recall, or F1-score may provide greater insight into the model's performance

$$\text{Recall} = \frac{TP}{TP + FN}$$

4.1 Logistic Regression Classifier

Logistic regression is a widely used statistical technique for binary classification that predicts the likelihood of an outcome based on one or more predictor variables. (Saroja, Kannan, et al. , 2018) It makes use of the logistic function, which converts a linear feature combination into a likelihood score with a range of 0 to 1.

Through the establishment of a threshold of 0.5, the model divides the result into two categories. The accuracy evaluation yielded a value of 78%. Class 0.0 is more accurately predicted by the model than class 1.0, as seen by its higher precision and recall. Since class 1.0 has a lower recall, it is possible that there is a problem with the model's performance for this class or with class imbalance since the model is having a trouble identifying instance of a class.

Table 1 Logistic Regression Classification report.

Class	Precision	Recall	F1-score
0	0.80	0.96	0.87
1	0.66	0.26	0.37
Accuracy			0.78

4.2 XGBoost Results

The gradient boosting framework for classification and regression tasks is improved by the potent and effective machine learning algorithm known as XGBoost (Extreme Gradient Boosting). It works by creating a group of decision trees, with each new tree trying to fix the mistakes produced by the ones before it. (Yunshengi, Qianqian, et al. , 2018). Two important aspects of XGBoost are its parallel processing capability, which speeds up model training, and its regularization capabilities, which aid in preventing overfitting.

To maximize performance, the method makes use of sophisticated strategies like tree trimming, handling missing values, and integrated cross-validation. Large datasets and complicated issues are particularly well suited for XGBoost, which is why it is a popular choice for both real-world applications and data science contests.

Because of its adaptability, practitioners can achieve strong model performance and excellent predicted accuracy by customizing it through hyperparameter tuning. When evaluation the accuracy, the obtained result is 74%. In comparison to class 0.0, class 1.0 (the minority class) has a lower F1 score of 0.37, indicating that the model performed less well in class 1.0 prediction.

A lower score indicates difficulties with either precision, recall, or both for class 1.0. Recall and precision are combined into one measure, the F1 score. Based on its AUC score of 0.83, the model seems to have a reasonable ability to differentiate between the classes. While the general average F1 score of 0.60 indicates the overall performance across both classes, the weighted average F1 score of 0.79 accounts for the distribution of course.

Table.2 XG Boost Classification report.

Class	Precision	Recall	F1-score
0	0.97	0.74	0,84
1	0.24	0.77	0.37
Accuracay			0.74

The confusion matrix for the XGBoost model is as follows:

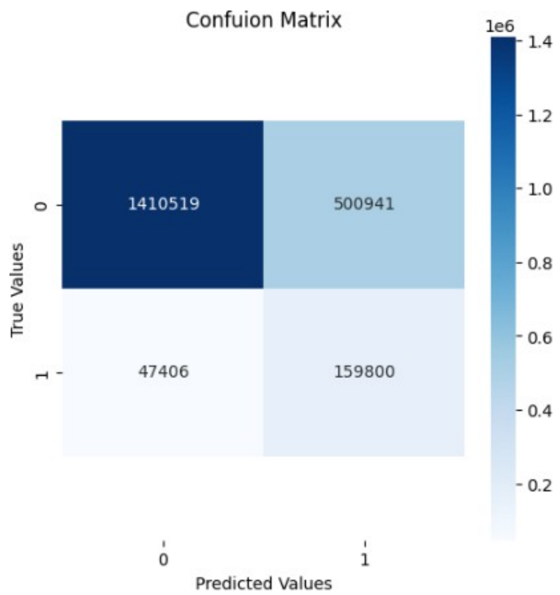

Figure 2: XGBoost Classification matrix.

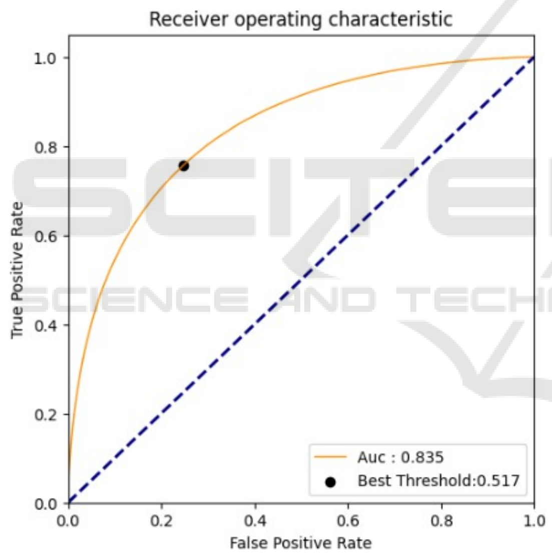

Figure 3: XGBoost ROC Curve.

4.3 Artificial Neural Network (ANN)

An Artificial neural network (ANN) classifier is a computational model that resonates the human brain and is designed to perform a range of classification tasks. ANNs are highly helpful for classification applications since they can learn complex and non-linear correlations in data. (Sharma, Vidyalakshmi, et al. , 2014) The network employs optimization techniques like gradient descent during the learning phase to minimize the discrepancy between the expected and actual results.

This method, called backpropagation, is applied to change wights. Backpropagation is the technique by which artificial neural networks (ANNs) train by modifying the weights of connections based on the prediction error. This high level of accuracy reflects the model's strong overall performance. With an F1 Score of 0.89, the model appears to be able to handle the majority class well, as evidenced by the balanced precision and recall over the whole dataset.

The model performs well in class discrimination, demonstrating a strong capacity to differentiate between the two classes with an AUC-ROC score of 0.81. Macro Average F1 Score: At 0.66, this metric provides an average performance measure across both classes without considering class imbalance. Weighted Average F1 Score: At 0.89, this metric accounts for class distribution, reflecting better performance when considering the number of instances in each class. In our comparative analysis, we benchmarked the performance of ANN model against other machine learning techniques commonly used in predictive analytics.

The following pictures shows the classification matrix and the ROC curves for the ANN model:

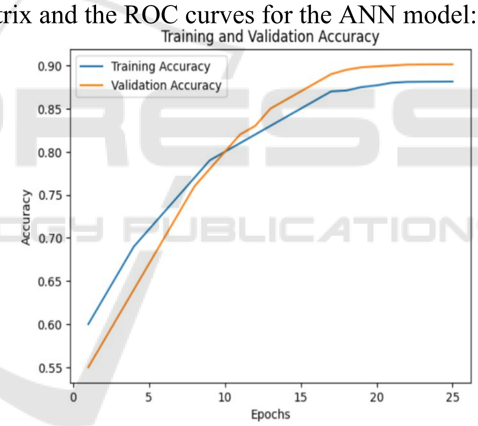

Figure 4: Training and Validation Accuracy graph.

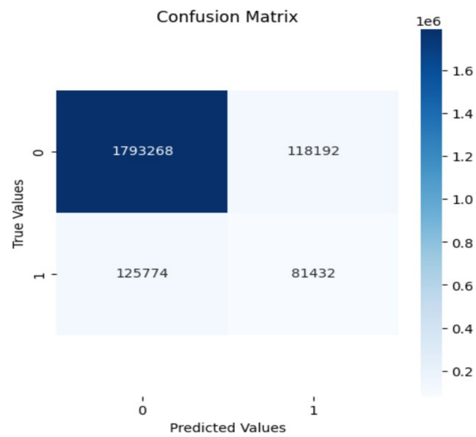

Figure 5: Classification matrix for ANN.

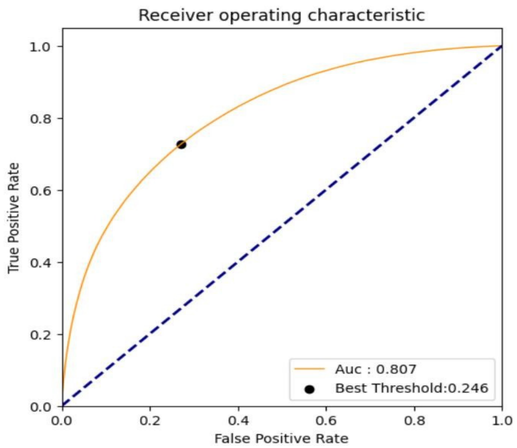

Figure 6 : ANN ROC Curve.

4.4 Comparison Table

The table below compares the F1-scores, recall, accuracy, and precision of the models Logistic Regression, XGBoost, and ANN

Table .3 Comparison Table.

Metrics/Model	Logistic Regression	XgBoost	ANN
Accuracy	0.78	0.74	0.9013
Precision	0.70	0.61	0.89
Recall	0.55	0.70	0.78
F1-Score	0.47	0.47	0.76

The four main metrics—accuracy, precision, recall, and F1- score—that are used to measure the efficacy of Logistic Regression, XGBoost, and Artificial Neural Networks (ANN) are compared in the table. ANN outperforms both XGBoost (74%) and Logistic Regression (78%) in terms of overall performance, with the maximum accuracy of 90.13%.

Comparison graph between the accuracies of the models Logistic Regression, XGBoost, ANN is shown as below:

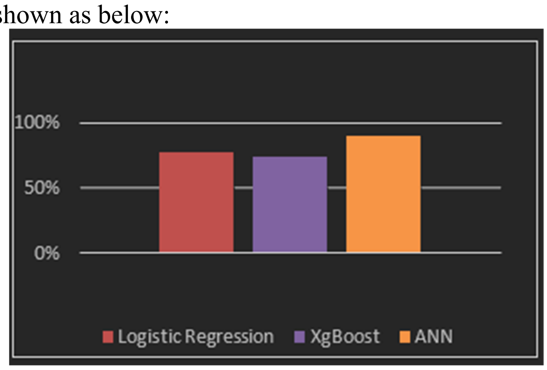

Figure 7 : Model comparison.

When comparing the models based on accuracy, the Artificial Neural Network (ANN) classifier demonstrates the highest performance, achieving an accuracy of 90.13%, significantly outperforming both Logistic Regression and XGBoost. Logistic Regression, with an accuracy of 78%, performs better than XGBoost, which scores 74%, but both fall short of the ANN's capability. The substantial difference in accuracy between ANN and the other models suggests that ANN is more effective at capturing complex patterns in the data, making it the most suitable model for tasks requiring high predictive performance.

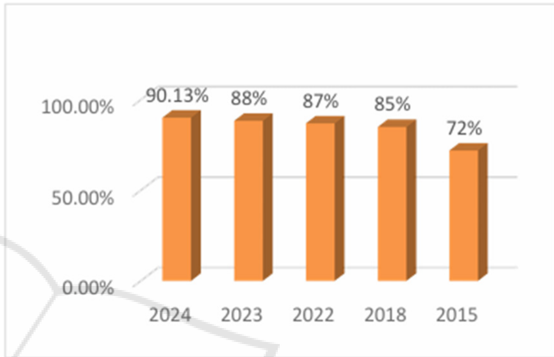

Figure 8: Accuracy comparision with other researchers.

The Fig.8 shows the improvement in model accuracy over time. In 2024, ANN achieved the highest accuracy at 90.13%, followed by ensemble stack algorithms in 2023 with 88%. In 2022, a combination of classifiers like C4.5 and MLR reached 87%. Earlier models, such as MLPNN and Naive Bayes in 2018, achieved 85%, while the Decision Tree in 2015 had the lowest accuracy at 72%. The trend highlights significant advancements in predictive accuracy, with ANN and ensemble methods at the forefront.

5 CONCLUSION

With an accuracy of 90.13%, our study shows how powerful advanced deep learning techniques—specifically, Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs)—can be in forecasting consumer purchase behavior in e-commerce. This demonstrates how the models can identify intricate patterns in data that traditional approaches frequently fail to pick up on. Thorough data pretreatment, hyperparameter tweaking, and cross-validation were essential to this accomplishment since they guaranteed clean, well structured data and optimized model performance. The models provide businesses with insightful information that helps them make data-driven decisions and customize marketing to increase sales and improve consumer engagement. Subsequent investigations could delve into sophisticated structures such as Transformer models to enhance performance, tackle scalability issues for real-time implementation, and integrate ensemble learning techniques. Predictive accuracy could be further increased by incorporating additional data sources and improving feature engineering.

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