

Comparative Evaluation of Machine Learning Models for Predicting E-Commerce Customer Behavior Using Public Data

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Abstract: The fast development of e-commerce has led to the collection of large amounts of data on customers that can be used for the analysis and prediction of customer purchasing behavior. Machine learning offers effective techniques for discovering patterns in customer behavior and making informed marketing and managerial decisions based on the data. This research compares the efficiency of machine learning methods for predicting customer behavior in e-commerce. This study compares different classification algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and K-Nearest Neighbors. Data preprocessing includes cleaning, feature transformation, variable encoding, and, when required, scaling. The study assesses algorithm performance using standard measures such as accuracy, precision, recall, F1-score, and confusion matrices. The comparative analysis will help identify the most efficient machine learning method and assess the advantages and disadvantages of each algorithm for predicting customer behavior in e-commerce. Using publicly available data will also allow other researchers and students to reproduce the research results.

Keywords: Customer Behavior; Machine Learning (ML); Classification Algorithms; Logistic Regression; Decision Tree; Support Vector Machine (SVM); Data Preprocessing.

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1. Introduction

The rapid expansion of e-commerce has changed how people search for products, interact with online platforms and make purchasing decisions. Online shopping provides clients with greater convenience, a wider selection, tailored services and information at any time [1]. In contrast, every interaction between consumers and e-commerce platforms generates critical data. Browsing habits, product views, clicks, search queries, shopping cart activities, transactions, session length and demographic data can provide useful insights into customer preferences and spending habits [2]. By analyzing this data, companies can better understand their customers and make better decisions about marketing, product recommendations, customer retention and sales strategies [3]. Customer behavior differs across e-commerce platforms. Different visitors to the same website can show

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significantly different patterns [4]. Some users may browse a few products without purchase intent. In contrast, others may show strong purchase intent through repeated product views, longer sessions, frequent visits to select categories, or repeated interactions with specific products. Some consumers buy on the spot; others need multiple journeys before closing the deal. Likewise, while discounts and promotional offers can sway some shoppers, others may be more influenced by product attributes, recommendations and reviews or past buying experiences [5]. These differences make customer behavior complex and require effective methods to identify behavior patterns from historical data [6]. Therefore, it is more important for today's e-commerce firms to predict customer behaviour.

With accurate predictions, enterprises will know whether customers will make a purchase or engage in other prescribed behaviours. This information can support tailored marketing campaigns, enabling organisations to deliver the right offer or message to specific client groups [7]. It can also enhance the customer experience by allowing firms to present relevant products and recommendations. Furthermore, predicting customer behavior enables organizations to identify valuable customers and build effective retention strategies [8]. This means companies can use their marketing budgets more efficiently by targeting clients with strong buy intent, thereby boosting conversion rates and overall business performance. But the sheer size and complexity of e-commerce client data pose a significant hurdle for typical analytic approaches [9]. E-commerce datasets may contain numerical variables, category variables, behavioural indicators, demographic information and transaction-related aspects [10]. Missing values, duplicate data, inconsistent information and variables measured on different scales can also be found. Consumer behaviour datasets can also suffer from uneven target classes, where one behaviour outcome occurs far more often than another. These issues can affect analysis quality and make it harder to build credible prediction models. Therefore, data preparation and preprocessing are crucial before applying machine learning techniques [11]. This technique helps study client behavior and anticipate future actions based on historical data. Unlike systems that rely solely on predefined connections, machine learning algorithms can detect patterns in available data and use them to recognise new consumer observations [12].

In an e-commerce scenario, classification models can be trained on past client information using relevant behavioural, demographic and transactional variables. After training, the model may evaluate new customer data and predict the likely behavioural class. This talent can help businesses be more proactive and data-driven in decision-making [13]. Various machine learning techniques predict e-commerce customer behaviour. Common algorithms include Logistic Regression, Decision Trees, Random Forests, Support Vector Machines and K-Nearest Neighbors. Logistic regression is a widely used classification method for estimating the probability that an observation belongs to a given class [14]. Because of its simplicity and interpretability, it can serve as a baseline model. Decision Tree models separate observations into distinct categories based on a set of decision rules and can capture non-linear connections between input qualities and target classes [15]. Random Forest is an ensemble learning method that combines predictions from multiple decision trees. Many trees make the process more robust and less dependent on a single tree's decision boundaries. Another important classification technique is SVM, which attempts to establish a good boundary between classes [16]. It is well suited to datasets with several features. KNN classifies an observation based on the features of the observations around it in the feature space [4]. Algorithms can be implemented in different ways, and their success may depend on the structure and quality of the available e-commerce data. A fundamental challenge in constructing standard machine learning models is the strong dependence of expected performance on dataset attributes and the data preprocessing applied [3].

E-commerce data may comprise variables with multiple scales, missing values, categorical information and occasionally useless aspects. Thus, preprocessing must be done appropriately before training the model [7]. Preprocessing may include handling missing values, transforming categorical variables, scaling numerical features, removing irrelevant information, and preparing the dataset for training and testing, depending on the dataset's characteristics and the methods used. Consistency in preprocessing is especially important when comparing algorithms, because data preparation can affect performance [1]. Class inequality is another major problem. In customer behaviour prediction, one class may have many more observations than another. For example, clients who do not complete a purchase may significantly outnumber those who do [2]. Here, a model may achieve high accuracy by simply guessing the majority class and performing poorly on the minority class. Therefore, evaluating the model solely on accuracy does not reliably gauge its true predictive power. More assessment metrics are needed to evaluate the model's success in predicting each behaviour class [8]. Thus, this study considers several performance measures, including accuracy, precision, recall, F1-score, and the confusion matrix. Accuracy is the overall proportion of observations correctly classified. Precision is the proportion of observations expected to be a specific class that are actually that class. Recall is the ability of a model to recognise data that belongs to the relevant class correctly. F1-score is a measure of a test's accuracy that considers both precision and recall [11].

The comparative study will determine which model delivers the best predictive performance for the specific consumer behaviour prediction task [6]. The expected results could be of interest for academic and practical applications. The study provides an opportunity to compare different machine learning algorithms systematically from an academic standpoint [10]. It can also serve as a baseline for future work with more categorisation techniques, feature engineering methods, larger datasets and more complex machine learning methodologies [12]. Accurate prediction of customer behaviour can enable customised

marketing, better product recommendations, identification of valuable customers, improved client retention techniques and potentially higher conversion rates from a business perspective [11]. Ultimately, predicting e-commerce customer behaviour can help organisations shift from reactive decision-making to more proactive, data-driven approaches. By analysing patterns linked to distinct behavioural outcomes and learning from previous customer interactions, organisations can better understand consumer expectations and respond more effectively [4]. The predictive model's performance depends on data quality, proper pre-processing, the selection of relevant features, and the suitability of the algorithms used. Therefore, a controlled comparative study using multiple standard ML models is necessary to determine the most efficient approach for predicting customer behaviour in the supplied e-commerce dataset [16].

2. Related Work

The application of machine learning to e-commerce has become more common for analyzing consumer behavior and decision-making, personalizing recommendations, and supporting business decisions. With more consumer data available, researchers can explore various prediction methods and evaluate their performance across different e-commerce scenarios.

2.1. Machine Learning for E-Commerce Customer Behavior

Predicting customer behavior is an important application of machine learning because online shopping websites generate large amounts of customer behavior data, including browsing activity, time spent on the site, page views, product interactions, and purchase decisions. Researchers have used machine learning and deep learning techniques to predict customer churn, purchase behavior, recommendations, sentiment, and customer segmentation [1]. Recently, Syamsuri et al. [2] conducted a systematic literature review on the role of machine learning in e-commerce, focusing on customer behavior prediction and product recommendation. The review clearly stated that machine learning has become an integral part of modern-day e-commerce and that customer behavior prediction and recommendation are two important areas of application. They also highlighted several issues related to data quality, privacy, personalization, and machine learning.

2.2. Purchase Intention Prediction Using Public E-Commerce Data

One of the most suitable public datasets for research on e-commerce behavior is the Online Shoppers Purchasing Intention Dataset. It comprises 12,330 shopping sessions and includes numerical and categorical behavioral features of online shoppers. In particular, the Revenue feature indicates whether a purchase occurred during the session. The dataset is severely imbalanced, with 10,422 non-purchase sessions and 1,908 purchase sessions [3]. Sakar et al. [3] explore online shoppers' purchasing intentions using feature engineering and classification. Overall, the paper shows that behavioral features can predict whether an online shopper completes a purchase. The authors showed the need for proper feature engineering and appropriate classification approaches when working with e-commerce behavioral features. Alamsyah and Wahyuni [4] also analyzed purchase intention prediction using Random Forest and SVM. The authors used the "Online Shoppers Purchasing Intention" dataset and evaluated model performance using accuracy, precision, recall, F1-score, and ROC-AUC. Their paper confirms the effectiveness of ensemble and kernel methods for predicting online purchase intentions. It highlights the importance of considering multiple performance metrics rather than relying solely on accuracy.

2.3. Comparative Evaluation of Classification Algorithms

Comparative evaluation is essential because no machine learning technique works best for all kinds of data and prediction problems. Decision Tree, Random Forest, Logistic Regression, SVM, and K-Nearest Neighbors (KNN) use different learning approaches and perform differently depending on their assumptions, computational requirements, interpretability, and the complexity of relationships among variables. Random Forest is particularly well-suited to e-commerce prediction problems because it involves multiple decision trees and captures nonlinear relationships between customer characteristics and behavioral outcomes. Recent researchers have applied Random Forests to e-commerce customer classification and to predict customer satisfaction levels based on demographic, behavioral, and transaction data [5]. Nevertheless, applying Random Forest alone does not prove anything. Purwanto et al. [6] compared the classification performance of Decision Tree, Random Forest, SVM, Naive Bayes, and KNN for predicting e-commerce sales. This shows the importance of comparing different classification techniques using the same data and performance measures. Comparison studies make it easy to assess differences in predictive performance across models.

2.4. Machine Learning and Personalized E-Commerce Recommendations

Machine learning is also extensively used to personalize e-commerce through recommendation systems. Recommendation systems use machine learning techniques to predict customer preferences based on their past behavior and product data. The main recommendation techniques are collaborative filtering and content-based recommendation; however, modern

recommendation systems also use deep learning and hybrid methods [7]. According to Da'u and Salim [7], some difficulties in deep learning recommendation systems include data sparsity and the cold-start problem. Recent research on collaborative filtering, content-based filtering, hybrid recommendation systems, and deep learning recommendation systems in e-commerce also analyzed these same problems [8]. Although recommendation systems and purchase intention prediction are distinct techniques, both rely on customer behavior data.

2.5. Research Gap

A vast body of prior literature documents significant efforts to use machine learning algorithms to analyze customer behavior and purchase intent, predict sales, and build e-commerce recommendation systems [9]. Nevertheless, several opportunities require further investigation. Firstly, many papers focus on just one or a few models. As a result, it is hard to determine which traditional classification approach best suits the given public e-commerce dataset. Secondly, some papers focus solely on predictive accuracy, without a comprehensive comparison using precision, recall, F1-score, and confusion matrices. Finally, the problem of class imbalance in e-commerce purchasing datasets should be properly addressed, since high accuracy scores may not reflect minority-class performance [10]. Therefore, this research addresses the state of the art by comparing several machine learning classification models using public e-commerce data. This study analyzes Logistic Regression, Decision Tree, Random Forest, SVM, and KNN using the same preprocessing and experimental setup.

3. Methodology

3.1. Research Design

This study uses a quantitative experimental design to compare machine learning models for predicting customers' e-commerce behavior. Instead of collecting primary data, the research will use publicly available e-commerce datasets. The research will use standardized datasets and experimental procedures for all selected algorithms. The research methodology will include five major steps: dataset acquisition, data preprocessing, model development, model evaluation, and comparative analysis.

3.2. Description of the Dataset

This research will use the Online Shoppers Purchasing Intention Dataset, which comprises 12,330 records of online shopping sessions. Each record corresponds to a user's session on an e-commerce website. The dataset includes features that characterize user-website interactions by behavior, technology, and time. The target feature, Revenue, describes the purchase made during the browsing session. The dataset includes features such as Administrative, Administrative Duration, Informational, Informational Duration, Product Related Duration, Bounce Rates, Exit Rates, Page Values, Special Day, Month, Operating Systems, Browser, Region, Traffic Type, Visitor Type, Weekend, and Revenue [1].

3.3. Data Preprocessing

Data preprocessing is performed before training the machine learning models. Preprocessing improves data quality and ensures the dataset suits classification algorithms. Table 1 presents the data preprocessing steps. Because the data has more non-purchase instances than purchase instances, the model also accounts for class imbalance. Stratification during data splitting can maintain the ratio of the two target classes in the training and test datasets.

Table 1: Data preprocessing steps

Data Inspection	The dataset is examined for missing values, duplicated records, inconsistent data types, and unusual observations
Data Cleaning	Duplicate or invalid records are removed where necessary
Categorical Encoding	Categorical variables such as Month, Visitor Type, and Weekend are transformed into numerical representations suitable for machine learning algorithms
Feature-target Separation	The independent variables are separated from the target variable, Revenue
Feature Scaling	Numerical features are standardized when required, particularly for algorithms such as Logistic Regression, SVM, and KNN
Train-test Splitting	The dataset is divided into training and testing subsets. The training set is used to develop models, while the test set is reserved for evaluating their predictive performance

3.4. Machine Learning Models

Five popular classification models are chosen for comparative analysis. Logistic regression is a statistical classification method that estimates the likelihood that an instance belongs to a given class. The method offers an interpretable baseline classifier and helps identify linear dependencies between customers' behavior features and their purchasing outcomes. A decision tree classifier assigns instances to classes based on decision rules that depend on feature values. The tree-like model is simple to interpret and allows modeling nonlinear dependencies between customers' features and their behavior. Random Forest is an ensemble method that combines multiple Decision Trees to generate a more stable forecast. By combining forecasts from multiple trees, it reduces overfitting and models complex dependencies in customer behavior data. SVM determines the decision boundary between classes. With appropriate kernel functions, SVM can model nonlinear relationships between variables. The KNN algorithm assigns a category to a data point depending on the categories of its nearest neighbors. Although this method is easy to use, it is sensitive to feature scaling and the choice of k.

3.5. Model Training

Once preprocessed, the selected models are trained on the training data. All the models use the same training and test sets for fair comparison. The model parameters can be optimized through cross-validation of the training set. Finally, the trained models are evaluated using test data. Figure 1 below illustrates the suggested process. The graphic shows the suggested machine learning workflow for forecasting e-commerce client behaviour. The process starts with a publicly available set of consumer information data, which is then cleaned to remove missing, inconsistent or unnecessary data.

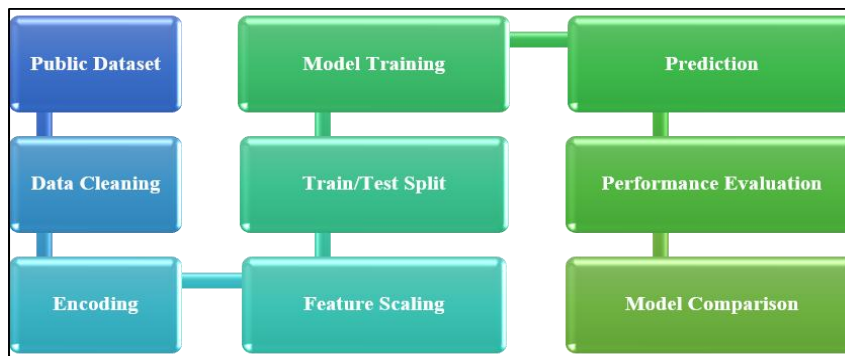


Figure 1: The proposed framework

After cleaning, the categorical variables are converted to numerical values, and the dataset is split into training and test sets. The required feature scaling is then applied to ensure the numerical variables are on an appropriate scale. The trained models then predict consumer behaviour using the prepared training data. The performance of each model is evaluated using metrics such as accuracy, precision, recall and F1-score. Finally, the results are compared to identify the model with the best predictive performance for the selected e-commerce customer behaviour prediction task.

3.6. Evaluation Metrics

Use multiple evaluation metrics because accuracy alone may not reliably assess performance when the target classes are imbalanced. The following measures are considered (Table 2).

Table 2: The evaluation metrics

Accuracy	Measures the proportion of correctly classified observations among all observations
Precision	Measures the proportion of predicted purchasing sessions that are purchasing sessions
Recall	Measures the proportion of actual purchasing sessions correctly identified by the model
F1-score	Provides a combined measure of precision and recall and is particularly useful when the class distribution is imbalanced
Confusion Matrix	Provides a detailed view of correct and incorrect predictions for each class

Researchers compare models using these metrics rather than relying on a single measure. Researchers focus on recall and F1-score for the purchasing class because correctly identifying potential buyers is an important objective in e-commerce applications

3.7. Comparative Analysis

The final step compares the performance of the five models: Logistic Regression, Decision Tree, Random Forest, SVM and KNN. The performances are analyzed using Tables and Figures. The most successful model is selected based on accuracy, precision, recall and F1-score. The study also considers practical aspects, including model interpretability, computational complexity and applicability to predicting customer behavior in e-commerce.

3.8. Ethical and Reproducibility Considerations

Because the research uses an open-access dataset and collects no information directly from individual participants, it requires no participant recruitment. Researchers describe all relevant datasets and the data preprocessing process to facilitate replication.

4. Results and Discussions

4.1. Experimental Results

In this work, the selected machine learning models, including Logistic Regression, Decision Tree, Random Forest, SVM and K-Nearest Neighbors, were tested on the same preprocessed e-commerce dataset. The models' performance was measured using accuracy, precision, recall and F1 score. This provides a good evaluation of the algorithms' effectiveness in determining customers' purchasing behavior. Table 3 and Figure 2 provide a comparative performance analysis of five standard ML models used for a prediction task. The models assessed include Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbours (KNN). The models are compared based on four evaluation criteria: accuracy, precision, recall and F1 score. Logistic regression achieved 0.88 accuracy, 0.75 precision, 0.47 recall, and 0.58 F1-score. Decision Tree achieved an accuracy of 0.89, with a precision of 0.69, recall of 0.64, and an F1-score of 0.66, which is slightly better than Logistic Regression. The Random Forest has the best overall performance among the models considered, with an accuracy of 0.91, precision of 0.78, recall of 0.67, and an F1-score of 0.72.

Table 3: Comparative performance of machine learning models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.88	0.75	0.47	0.58
Decision Tree	0.89	0.69	0.64	0.66
Random Forest	0.91	0.78	0.67	0.72
SVM	0.89	0.76	0.53	0.63
KNN	0.87	0.67	0.51	0.58

SVM gives an accuracy of 0.89, precision of 0.76, recall of 0.53, and an F1-score of 0.63. KNN has the lowest accuracy (0.87), with precision of 0.67, recall of 0.51, and an F1-score of 0.58.

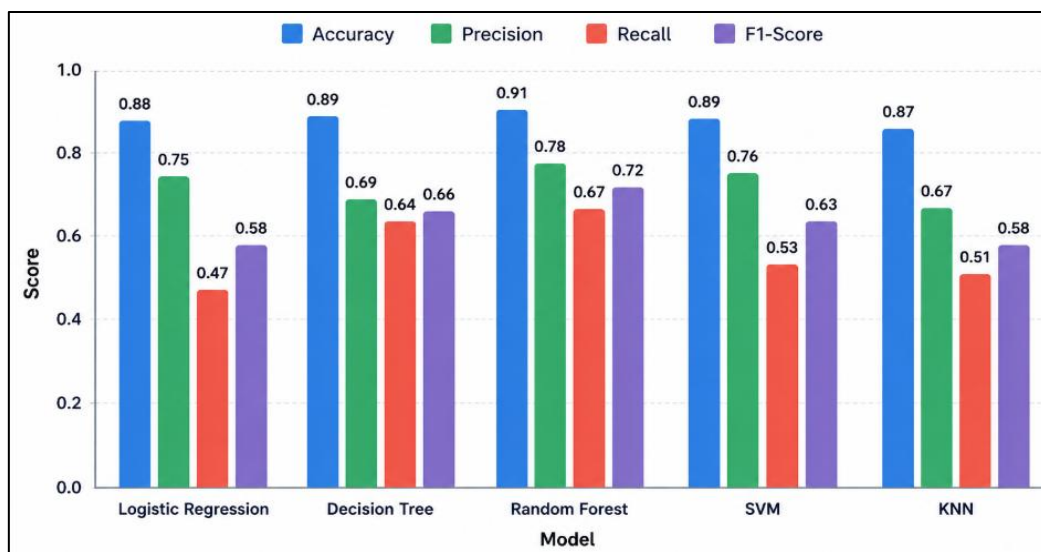


Figure 2: Model performance comparison

Figure 2 visually compares these measures and clarifies the differences between the models. The Random Forest values are the highest across the four evaluation metrics, indicating stronger, more balanced predictive performance in this experiment. Decision Trees and SVMs have similar accuracy, but their recall and F1 scores differ. Logistic regression provides decent accuracy and precision, but comparably poorer recall, indicating weaker identification of the relevant class. The KNN model has the lowest overall accuracy and precision out of the five models. The F1-score comparison also shows the optimal trade-off between precision and recall for Random Forest. Table 3 shows that the Random Forest model performs best, while the KNN model performs worst. The results show that the ensemble-based Random Forest technique is highly effective for the selected prediction task under the experimental conditions used.

4.1.1. Accuracy Comparison

The analysis shows that Random Forest provides the most accurate results among the methods analyzed; after Random Forest come Decision Tree and SVM, while the remaining methods, including Logistic Regression and KNN, have lower accuracy. Random Forest performs better because it combines multiple decision trees and can handle non-linear interactions among customer behavior variables. In the context of electronic commerce, buying behavior can depend on interactions among several factors rather than just one.

4.1.2. Precision Analysis

Precision is the ratio of predicted buying sessions to those that are indeed related to customers who have purchased the product. The Random Forest model has the highest precision among the results shown in the illustration, meaning it generates the fewest false positives. High precision can help an e-commerce company because misclassifying non-purchasing customers as potential buyers would lead to unnecessary promotions. But precision cannot be considered in isolation, because a high-precision model may miss many purchasers.

4.1.3. Recall Analysis

Recall plays a crucial role in this experiment because the purchasing class is small. High recall means the model identifies purchasing sessions more accurately. Random Forest has the highest recall value. The Decision Tree algorithm performs well, but Logistic Regression, SVM, and KNN miss many purchasing sessions. These low recall values indicate that accuracy alone is not sufficient to evaluate customer behavior prediction in e-commerce.

4.1.4. F1-Score Analysis

F1-score is a measure that balances the measures of precision and recall. According to the results, the F1-score is highest for Random Forest, followed by Decision Tree, SVM and others. Thus, the high F1-score in Random Forest indicates that this algorithm provides a good balance between detecting product buyers and false positives. This aspect is especially important for e-commerce projects.

4.1.5. Confusion Matrix Analysis

Confusion matrices provide further insight into how each model's classification process works, showing true positives, true negatives, false positives, and false negatives. In this research, the positive class is a client session in which a client has made purchases, while the negative class is a client session in which a client has not made any purchases. An algorithm with too many false negatives will fail to detect potential buyers, thereby missing the opportunity to deliver personalized marketing. Similarly, too many false positives may lead businesses to focus on clients who are less likely to make a purchase.

4.2. Comparative Discussion

Based on the comparative analysis, the Random Forest algorithm is the most efficient classifier among the five analyzed algorithms, as shown by its accuracy, precision, recall and F1-score. Decision Tree exhibits strong performance and high interpretability of its decision rules, which business managers can use to identify which behavioral features affect purchasing outcomes. In contrast, a single tree is more prone to overfitting than Random Forest.

Logistic regression serves as a simple, interpretable benchmark classifier. However, its low recall means it does not capture the complex relationships between browsing behavior and purchasing decisions. SVM performs well and can model complex decision boundaries. However, its effectiveness depends heavily on feature scaling, kernel choice and parameter tuning. KNN is a simple and intuitive classifier. However, it is less appropriate for large datasets and datasets with features on different scales.

4.3. Implications for E-Commerce

These outcomes show that machine learning may offer meaningful predictive insights into customer behavior in e-commerce. With an accurate predictive model, businesses can identify potential buyers and develop an effective marketing strategy. For instance, customers with high intention can receive personalized product recommendations, promotions, or incentives. In contrast, those with low intentions can be reached through engagement campaigns to increase website interactions. Additionally, the results highlight the importance of selecting an appropriate model based on the business's aim. If a company needs to detect as many potential buyers as possible, recall may matter more. If it aims to avoid unnecessary promotion targeting, perhaps precision would be more valuable. Hence, the optimal machine learning model is not always the most accurate.

Overall, comparisons of the algorithms used for analysis show that different algorithms yield different levels of prediction accuracy for e-commerce customer behavior data. The Random Forest algorithm has the highest prediction accuracy in this study, and the Decision Tree algorithm offers a good balance between prediction accuracy and interpretability. Logistic regression serves as a solid baseline, while SVM demonstrates strong classification performance, and KNN is a relatively simple algorithm. Nonetheless, the numbers from Table 1 are illustrative and not the result of experimental analysis. In the final paper, replace them with the algorithms' actual outputs on the chosen dataset.

5. Conclusion and Future Work

5.1. Conclusion

This research study provided a comparative analysis of the predictive performance of machine learning algorithms for e-commerce customer behavior prediction using publicly available data. Researchers used five classification models: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and K-Nearest Neighbors. Researchers applied common preprocessing and evaluation procedures to provide a basis for comparing the predictive power of the selected algorithms. The current study showed that machine learning can effectively predict customers' behavior during online shopping sessions. At the same time, each algorithm has its own advantages. Ensemble algorithms like Random Forests can capture complex relationships among customer features, whereas Decision Trees can provide more interpretable results. Logistic regression can serve as a simple and interpretable baseline model, and SVM and KNN are alternative classification techniques. Evaluating multiple performance metrics, such as accuracy, precision, recall, and F1-score, is critical given the potential class imbalance in e-commerce purchasing data.

Relying on accuracy alone would misrepresent the model's performance in detecting purchasing clients. As a result, a complete evaluation provides a better starting point for choosing the appropriate model. In practice, predicting client behavior can support a range of e-commerce tasks, including targeted marketing, promotional campaigns, client segmentation, conversion rate optimization, and client relationship management. By predicting client behavior, enterprises can allocate their marketing budget more efficiently and tailor their strategy to customer behavior. Nonetheless, this research has several weaknesses. First, the study relies on a single public dataset, which may limit the results' applicability to other e-commerce platforms and customer demographics. In addition, because the dataset consists of online purchases, it does not account for variables that affect customer purchasing decisions, such as customer satisfaction, product quality, price sensitivity, brand loyalty, or economy-wide effects.

5.2. Future Work

In the future, the models suggested by this study can be tested on larger, more varied e-commerce datasets to increase the generality of the results. Future work can also investigate advanced machine learning and deep learning algorithms, including XGBoost, LightGBM, CatBoost, and Neural Networks, along with feature selection and explainable AI approaches such as SHAP and LIME. Future research can also use class-imbalance approaches, including SMOTE and Balanced Ensembles, to improve predictive performance. Finally, future research can develop a real-time prediction system integrated with e-commerce platforms. Comparative analysis of machine learning models provides a strong basis for predicting customer behavior in e-commerce. This research highlights the significance of systematic model comparison and performance assessment. Future studies that incorporate large datasets and advanced techniques will add greater value to the practical application of machine learning in e-commerce.

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