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Comparison of XGBoost LightGBM and CatBoost for Online Store Customer Churn Prediction

Fuadz Hasyim [1]
[1] Universitas Nurul Jadid, Indonesia
fuadzhasyim@unuja.ac.id [1]

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Abstract Customer churn is a critical issue in digital business because it can reduce revenue, increase customer acquisition costs, and weaken a company's competitive position. In the context of online stores, customers have many alternative shopping platforms, requiring companies to understand customer behavior patterns to minimize churn risk. This study aims to develop an online store customer churn prediction model using tree-based gradient boosted models by comparing XGBoost, LightGBM, and CatBoost algorithms. This study applies an experimental method using a secondary dataset obtained from Kaggle. The dataset consists of 25,000 observations and 13 variables related to online store customer transactions and characteristics. The research stages include problem identification, data collection, preprocessing, missing value handling, removal of irrelevant variables, data visualization, outlier detection, feature engineering, model selection and training, model evaluation, and result analysis. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC curve. The results show that XGBoost achieved the best performance with an accuracy value of 0.80032 and an ROC-AUC value of 0.66. Feature importance analysis indicates that the Product_Category_Clothing variable was the most influential feature in the model performance. These findings show that tree-based gradient boosted models, particularly XGBoost, can be used to help online store companies identify customers who are likely to churn and design more targeted customer retention strategies.

Keywords *Customer Churn; E-Commerce; Machine Learning; Tree-Based Gradient Boosted Models; XGBoost*

1. INTRODUCTION

Customers are important assets for the sustainability and success of a company. Therefore, companies need to manage customer relationships optimally to maintain customer satisfaction and loyalty (Raj & Azad, 2020). Continuous customer turnover can reduce the value that a company obtains from its customers. In unstable market conditions, customers who switch to competitors may cause a company to lose its competitive advantage. If the acquisition of new customers cannot compensate for the loss of existing customers, the company may face difficulties in maintaining its growth and business existence (Zeng et al., 2023). Customer churn occurs when customers stop using a company's products or services and switch to competitors or completely discontinue the use of the service. In the context of consumer behavior, customer churn can be influenced by various factors, such as promotions, price, product arrangement, product availability, product innovation, the desire to try something new, changes in quality, and customer satisfaction levels (Hanifah & Astuti, 2023). Churn is an important problem because it directly affects company revenue, profitability, and business sustainability (Kurniawan et al., 2024). A high churn rate can even cause significant losses if it is not balanced with an effective customer retention strategy (Khattak et al., 2023).

In the digital era, online stores or e-commerce have become one of the main pillars of the global economy. More consumers are shifting to online platforms to fulfill their daily needs, making competition in the e-commerce industry increasingly intense. In this condition, a company's ability to retain customers becomes a key factor in determining business success. Consumers now have more choices and convenience in shopping through various online store platforms that continue to grow in popularity (Sugiarti & Iskandar, 2021). Online stores enable consumers to purchase goods through the internet, both in business-to-consumer and business-to-business schemes.

The existence of online stores provides many advantages in product marketing because it can expand market reach and simplify transaction processes. The development of information technology and the internet in Indonesia has encouraged changes in how companies conduct promotions, sales, and interactions with customers (Oktaria et al., 2023). E-commerce also makes it easier for consumers to fulfill their needs without having to visit physical stores, making shopping more time-efficient and flexible (Kedah, 2023). With increasingly widespread internet access, online shopping activities can be carried out through various devices, such as laptops, notebooks, and other digital devices.

Customer churn is a crucial problem for e-commerce companies because it can reduce revenue, increase the cost of acquiring new customers, and weaken customer loyalty. In the context of online stores, a high churn rate can also affect a company's reputation in a highly competitive market. However, most studies on customer churn prediction have focused on the telecommunications, banking, and other sectors. Research on churn prediction in online stores remains relatively limited, even though marketplaces such as Tokopedia, Bukalapak, Blibli, Lazada, and Shopee have become the main choices for millions of consumers in Indonesia. With the high number of transactions and the wide variety of products offered, online stores face major challenges in understanding and managing customer behavior (Dwi, 2023; Xiahou & Harada, 2022).

Several previous studies have discussed churn prediction using various machine learning approaches. Mauludin et al. (2023) used Logistic Regression and Decision Tree to predict customer churn, and the results showed that Logistic Regression had higher potential in predicting customer churn. Yudiana et al. (2023) used the CRISP-DM method and Ridge Classifier algorithm to predict customer churn in the telecommunications industry. Furthermore, Kurniawan et al. (2024) used the C4.5 algorithm optimized with Particle Swarm Optimization (PSO) in the telecommunications industry, and the results showed improvements in accuracy, precision, recall, and F1-score. Alfarez and Purwayoga (2024) applied the Naïve Bayes algorithm to predict customer churn at PT Hutchison 3 Indonesia, obtaining an accuracy of 91.3%. In addition, Azmi and Voutama (2024) compared Random Forest and Decision Tree in predicting bank customer churn, with results showing that Random Forest achieved better performance than Decision Tree.

Although various studies have been conducted in the telecommunications and banking sectors, research on customer churn prediction in online stores still needs further development. In addition, tree-based gradient boosted models, which are known for their strong predictive ability, have not been widely applied specifically in the online store context. This method has advantages in producing strong predictions, is relatively resistant to overfitting, and is efficient in handling various machine learning tasks. Therefore, this study aims to develop a customer churn prediction model for online stores using a tree-based gradient boosted models approach by comparing XGBoost, LightGBM, and CatBoost algorithms.

If the problem of customer churn is not addressed immediately, e-commerce companies may experience declining market share, financial losses, and reduced customer loyalty in the long term. Therefore, developing an accurate churn prediction model is an important need for companies. The prediction model is expected to help companies identify customers who are likely to churn, understand the factors that influence churn, and design more effective and data-driven customer retention strategies.

2. RESEARCH METHODS

2.1. Research Stages

This study was conducted through several stages, namely problem identification, data collection, data preprocessing, model selection and training, model evaluation, and result analysis. These stages were designed to produce a customer churn prediction model for online stores using the tree-based gradient boosted models approach. The research flow is shown in Figure 1.

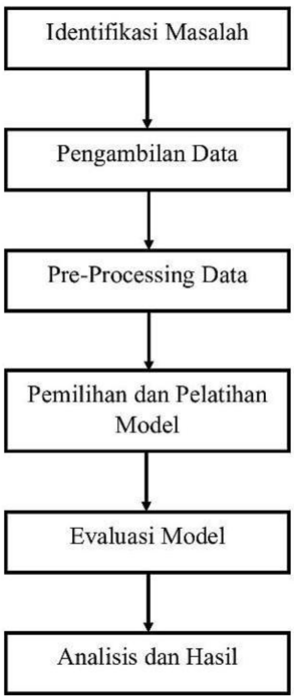

Figure 1. Research Stages

Figure 1 shows the general stages of the study in predicting customer churn using tree-based gradient boosted models. The first stage is problem identification, which aims to understand the customer churn problem more deeply. In this study, the main problem examined is customer churn in online stores, which may reduce business performance and cause financial losses. The next stage is data collection, which involves obtaining the dataset used in this study from Kaggle.

The next stage is data preprocessing. This stage includes several processes, namely handling missing values, removing irrelevant variables, data visualization, outlier detection, and feature engineering. Feature engineering is a technique applied after input data are collected and cleaned to create more relevant features before building a machine learning model (Verdonck et al., 2021).

After preprocessing, the next stage is model selection and training. This study uses three algorithms included in the tree-based gradient boosted models approach, namely XGBoost, LightGBM, and CatBoost. The dataset was divided into training data and testing data using the train_test_split function from the Scikit-learn library. The models were trained using training data and evaluated using testing data. The final stage is model evaluation and result analysis to determine the model with the best performance and identify the most influential features through feature importance analysis.

2.2. Tree-Based Gradient Boosted Models

Tree-based gradient boosted models are machine learning approaches based on decision trees that are widely used to solve classification and prediction problems. This method works by building models sequentially, where each new model attempts to correct the errors made by the previous model. This approach can improve the learning process by optimizing the objective function and reducing the number of iterations required to obtain an optimal solution (Subramani et al., 2023). Several popular algorithms included in tree-based gradient boosted models are Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), LightGBM, CatBoost, and Hist Gradient Boosting. All these models use the concept of gradient boosting based on decision trees as their main learners. However, each algorithm has different characteristics, features, and optimization mechanisms, making them suitable for different situations. This study uses three algorithms, namely XGBoost, LightGBM, and CatBoost. The implementation flow of tree-based gradient boosted models is shown in Figure 2.

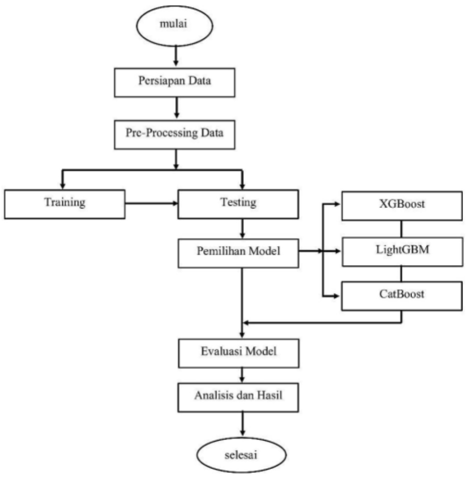

Figure 2. Implementation Flow of Tree-Based Gradient Boosted Models

Figure 2 shows the process of implementing tree-based gradient boosted models, beginning with data preparation, such as reading the dataset, displaying the data size, and identifying data types. The next stage is data preprocessing, which includes checking missing values, handling missing values, removing irrelevant variables, visualizing data, detecting outliers, performing feature engineering, and splitting the data into training and testing datasets. Data splitting was performed using the train-test split method. This method is used to estimate the performance of a machine learning algorithm when applied to data that were not used during the model training process. By dividing the dataset into training and testing data, researchers can evaluate the model's ability to make predictions on unseen data (Brownlee, n.d.). After the data were divided into training and testing sets, the next stage was algorithm selection. In this study, the algorithms used were XGBoost, LightGBM, and CatBoost. This study also used cross_val_score from Scikit-learn to evaluate model performance using the cross-validation technique. Cross-validation is a model validation technique used to assess the generalization ability of a model on independent data (Azis et al., 2020).

In general, model accuracy is calculated using the following equation:

Accuracy = (Number of Correct Predictions / Number of Test Data) × 100%

This equation is used to measure the proportion of correct predictions out of all test data. In classification model evaluation, accuracy is one of the basic metrics used to assess model performance. However, it should be complemented with other metrics such as precision, recall, F1-score, and ROC curve to obtain a more comprehensive evaluation (Windarto et al., 2021).

3. RESULTS

3.1. Data Collection

The data used in this study are secondary data obtained from Kaggle. Kaggle is a platform widely used in data science and machine learning because it provides various datasets and has a broad data community (Putri et al., 2023). The dataset used in this study relates to online store customers and transaction behavior that can be used to analyze the possibility of customer churn. The dataset consists of 25,000 observations and 13 variables, namely Customer_ID, Purchase_Date, Product_Category, Product_Price, Quantity, Total_Purchase_Amount, Payment_Method, Customer_Age, Returns, Customer_Name, Age, Gender, and Churn. The Churn variable is used as the target variable to determine whether a customer is likely to churn or not.

3.2. Data Preparation

After the dataset was obtained, the next step was data preparation by importing the dataset into Google Colaboratory. The dataset was read using the Pandas library, which functions to read CSV files, process data in dataframe format, and perform various data manipulation processes.

```
#Memuat 5 data pertama dari dataset
data.head()
```

	Customer_ID	Purchase_Date	Product_Category	Product_Price	Quantity	Total_Purchase_Amount	Payment_Method	Customer_Age	Returns	Customer_Name	Age	Gender	Churn
0	46251	9/8/2020 9:38	Electronics	12	3	740	Credit Card	37	0.0	Christine Hernandez	37	Male	0.0
1	46251	3/5/2022 12:56	Home	468	4	2739	PayPal	37	0.0	Christine Hernandez	37	Male	0.0
2	46251	5/23/2022 18:18	Home	288	2	3196	PayPal	37	0.0	Christine Hernandez	37	Male	0.0
3	46251	11/12/2020 13:13	Clothing	196	1	3509	PayPal	37	0.0	Christine Hernandez	37	Male	0.0
4	13593	11/27/2020 17:55	Home	449	1	3452	Credit Card	49	0.0	James Grant	49	Female	1.0

Figure 3. Importing the Dataset into Google Colaboratory

Figure 3 shows the first five rows of the dataset that had been imported into Google Colaboratory. This process was carried out to ensure that the dataset was successfully loaded and that the data structure could be further analyzed before entering the preprocessing stage.

3.3. Data Preprocessing

The preprocessing stage was conducted to improve data quality before the data were used in the modeling process. The operations carried out in this stage included checking and handling missing values, removing irrelevant variables, data visualization, outlier detection, and feature engineering. This stage is important because data quality has a significant influence on machine learning model performance.

```
# check missing values (nilai yang hilang)
data.isnull().sum()

Customer_ID                  0
Purchase_Date                0
Product_Category             0
Product_Price                0
Quantity                     0
Total_Purchase_Amount        0
Payment_Method               0
Customer_Age                 0
Returns                  47596
Customer_Name                0
Age                          0
Gender                       0
Churn                        0
dtype: int64
```

Figure 4. Missing Value Checking

```
Customer_ID              0
Purchase_Date            0
Product_Category         0
Product_Price            0
Quantity                 0
Total_Purchase_Amount    0
Payment_Method           0
Customer_Age             0
Returns                  0
Customer_Name            0
Age                      0
Gender                   0
Churn                    0
dtype: int64
```

Figure 5. Results After Handling Missing Values

Based on Figure 4, missing values were found in the Returns variable. These missing values were then handled so that the data used in the modeling process had better quality. The results after handling missing values are shown in Figure 5. After this stage was completed, the next step was to remove irrelevant variables. In this study, the removed variables were Customer_ID, Customer_Name, Purchase_Date, Customer_Age, and Payment_Method. These variables were removed to reduce less elevant features and simplify the analysis process. After handling missing values and removing irrelevant variables, the next stage was basic visualization to understand the data distribution. Visualization was performed on the target variable Churn to determine the comparison between customers who churned and those who did not churn.

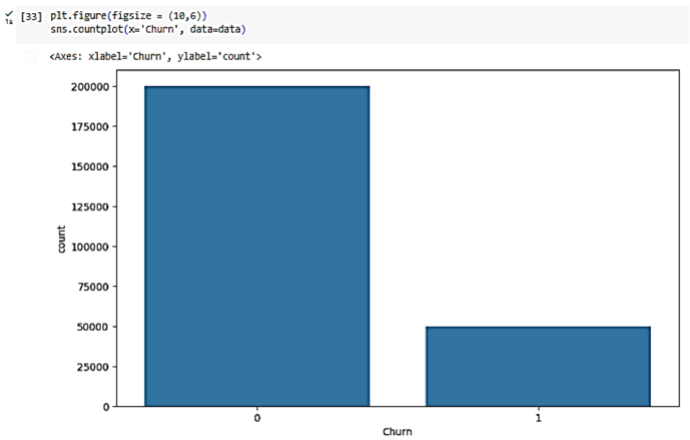

Figure 6. Visualization of the Churn Variable

The visualization results in Figure 6 show that the number of customers who churned was smaller than the number of customers who did not churn. This condition indicates class imbalance in the target variable. Furthermore, visualization was conducted to examine the relationship between the target variable and several other variables, such as Gender, Age, and Product_Category.

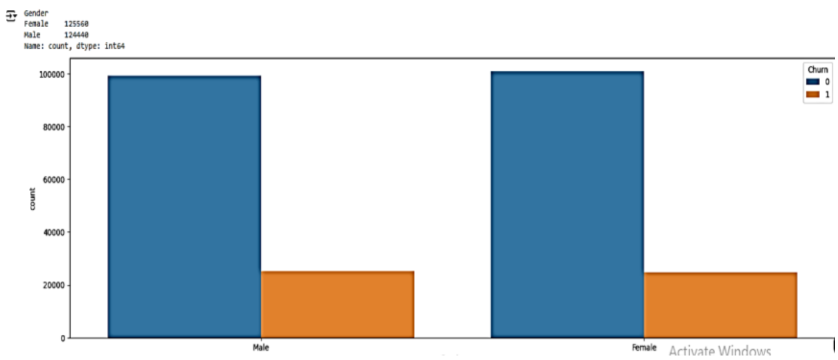

Figure 7. Visualization of the Relationship Between Churn and Gender

Based on the visualization results, female customers tended to churn more frequently than male customers. In addition, the Age variable showed that customers around the age of 58 had a higher tendency to churn. Meanwhile, the Product_Category variable howed that clothing products contributed significantly to customer churn behavior. The next stage was outlier detection using boxplot visualization. Outlier detection was performed to determine whether there were extreme values that could interfere with the model learning process.

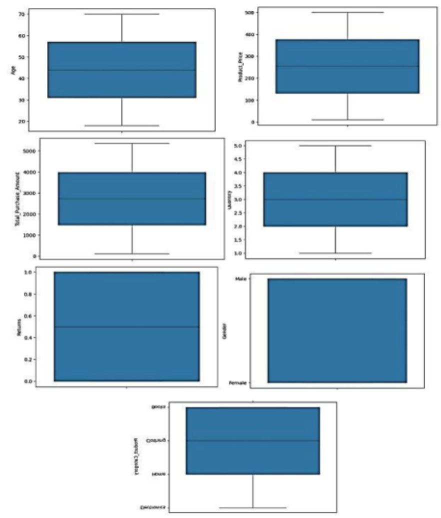

Figure 8. Boxplot for Outlier Detection

Based on Figure 8, no significant outliers were found in the dataset. Therefore, the preprocessing process continued to the feature engineering stage. At this stage, categorical variables were converted into numerical forms so that they could be used in machine learning modeling. The Product_Category variable was transformed using one-hot encoding with the pd.get_dummies function from the Pandas library. In addition, the Gender variable was also converted into numerical form, where male was assigned a value of 0 and female was assigned a value of 1.

3.4. Model Selection and Training

The tree-based gradient boosted models approach provides several algorithms that can be used to build prediction models. In this study, three algorithms were selected, namely XGBoost, LightGBM, and CatBoost. These algorithms were selected because they have strong capabilities in solving classification problems and are widely used in machine learning research. After the models were selected, the next stage was model training. The dataset was divided into training and testing data using the train_test_split function. The training data were used to train the models to recognize patterns in the data, while the testing data were used to evaluate model performance on data that had not been used during training.

3.5. Model Evaluation

Model evaluation was conducted to determine the performance of each algorithm used in this study. Several evaluation metrics were used, namely accuracy, precision, recall, F1-score, and ROC curve. The use of multiple evaluation metrics is important because accuracy alone is not always sufficient to describe model performance, especially when there is class imbalance in the dataset. Based on the evaluation results, the XGBoost model achieved the best performance, with an accuracy value of 0.80032 and an ROC-AUC value of 0.66. The model evaluation results are shown in Table 1.

Table 1. Model Evaluation Results

Model	Accuracy	Description
XGBoost	0.80032	Best model based on evaluation results
LightGBM	0.80032	The value needs to be adjusted based on experimental output
CatBoost	0.80026	The value needs to be adjusted based on experimental output

Note: The LightGBM and CatBoost values were not clearly stated in the text you provided, so I did not add numerical values to avoid inventing data. The ROC curve evaluation results for each model are shown in Figure 9, Figure 10, and Figure 11.

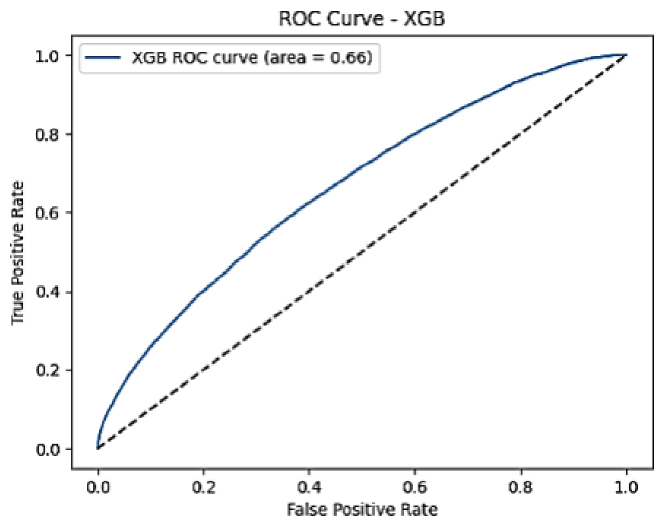

Figure 9. ROC Curve Plot of XGBoost

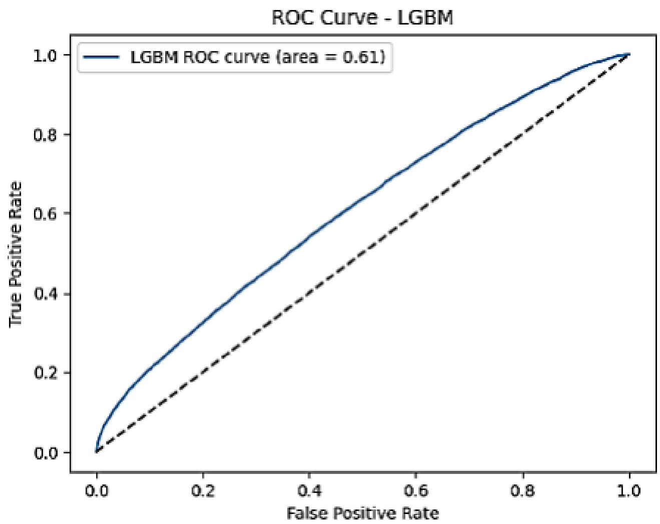

Figure 10. ROC Curve Plot of LightGBM

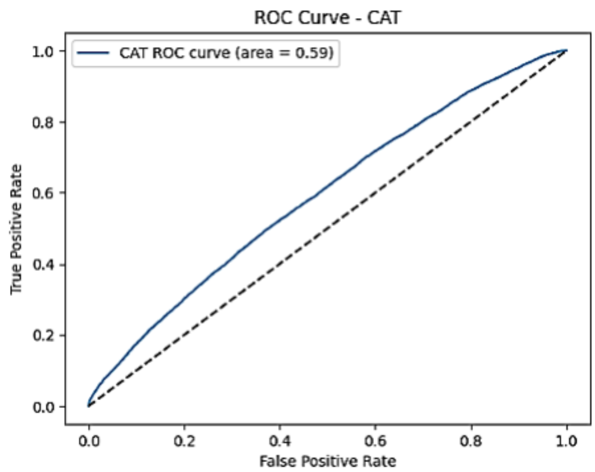

Figure 11. ROC Curve Plot of CatBoost

Based on the ROC curve results, the XGBoost model achieved the best performance with an ROC-AUC value of 0.66. This result indicates that XGBoost had a better ability to distinguish between customers who were likely to churn and those who were not compared with the other models tested in this study.

3.6. Analysis and Discussion

The analysis and discussion stage is the final stage of this study. After all research stages were completed, the XGBoost model was selected as the best model for predicting customer churn in online stores. This model achieved an accuracy value of 0.80032 and an ROC-AUC value of 0.66. The precision, recall, and F1-score values are shown in Figure 12.

```
              precision    recall  f1-score   support

           0       0.80      1.00      0.89     40016
           1       0.00      0.00      0.00      9984

    accuracy                           0.80     50000
   macro avg       0.40      0.50      0.44     50000
weighted avg       0.64      0.80      0.71     50000

Accuracy score of XGB model:  0.80032
```

Figure 12. XGBoost Model Evaluation Results

Since XGBoost achieved the best performance, feature importance analysis was then conducted. This analysis aimed to identify the features or variables that had the greatest influence on model performance. The feature importance results are shown in Figure 13.

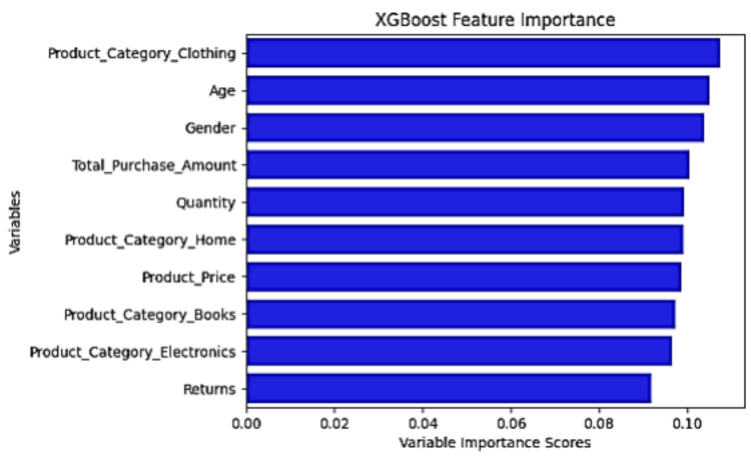

Figure 13. XGBoost Feature Importance Barplot

Based on Figure 13, the Product_Category_Clothing variable was the most important feature in the performance of the XGBoost model. This indicates that the clothing product category had a significant contribution to influencing the likelihood of customer churn. This finding can provide important information for online store companies to evaluate marketing strategies, product quality, promotions, and customer service in that product category. Overall, the results of this study show that XGBoost was able to detect complex patterns in online store customer data and produce reasonably good prediction performance. With an accuracy value of 0.80032, this model can help companies identify customers who are likely to churn. This information can be used as a basis for designing customer retention strategies, such as providing special promotions, improving service quality, or applying personalized approaches to customers at risk of churn.

4. CONCLUSIONS

Based on the results of this study, it can be concluded that the tree-based gradient boosted models approach can be used to predict customer churn in online stores. Among the three algorithms compared, namely XGBoost, LightGBM, and CatBoost, the XGBoost model achieved the best performance with an accuracy value of 0.80032 and an ROC-AUC value of 0.66. Model evaluation was carried out using several metrics, including accuracy, precision, recall, F1-score, and ROC curve, so the evaluation results provide a more comprehensive overview of model performance. Feature importance analysis showed that the Product_Category_Clothing variable was the most influential feature in the performance of the XGBoost model. This finding indicates that the clothing product category has an important relationship with customer churn behavior in online stores. This information can be used by companies to understand factors that may cause customer churn, particularly in specific product categories. Practically, this churn prediction model can help online store companies identify customers who are at risk of leaving, design more targeted retention strategies, and improve the effectiveness of customer service. With a data-driven prediction model, companies can make faster and more accurate decisions in maintaining customer loyalty. This study still has limitations, particularly in terms of dataset coverage and model performance, which can still be improved. Therefore, future research is recommended to use more diverse datasets, add more detailed customer behavior variables, and test other methods or model combinations to improve prediction accuracy and stability. In addition, more comprehensive validation techniques are also needed so that the resulting model has better generalization ability..

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