

# Predict Product Return

* **Problem Statement:** This analysis aims to predict the likelihood of product returns in e-commerce by identifying key factors such as customer behavior, product features, and purchasing patterns. Using data analysis and predictive modeling, the goal is to uncover insights that can help businesses reduce return rates, improve inventory management, and enhance customer satisfaction. These insights will enable e-commerce platforms to optimize their processes and create more effective strategies for minimizing returns.
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**1. Introduction**

Product returns are a significant challenge for many e-commerce businesses. Not only do they impact revenue, but they also affect inventory management, customer satisfaction, and logistics. Predicting product returns is crucial for companies to optimize their processes and minimize the negative effects of returns. With the advancement of machine learning and data analytics, companies now have the ability to forecast returns based on customer behavior, product features, and other factors. This report aims to explore methods for predicting product returns using machine learning techniques, focusing on data-driven insights to enhance decision-making in the e-commerce sector.

**2. Problem Statement**

E-commerce platforms face substantial losses due to high product return rates. Predicting whether a product will be returned after purchase is a challenging task because it involves numerous variables like customer behavior, product type, return policies, and shipping conditions. The problem lies in accurately identifying the likelihood of a return based on historical data, user interactions, and transaction details. Without an effective model to predict returns, companies are left to handle returns reactively rather than proactively, leading to increased operational costs and poor customer experience.

**3. Objectives**

The primary objectives of this project are:

* To develop a machine learning model that predicts the likelihood of product returns.
* To identify the most important factors contributing to product returns (e.g., product category, customer profile, purchase behavior).
* To assess the accuracy and effectiveness of different machine learning algorithms in predicting product returns.
* To provide insights that can help e-commerce platforms reduce return rates and improve customer satisfaction.

**4. Methodology**

To achieve the objectives outlined above, the following steps are taken:

1. **Data Collection:** Collect data from e-commerce transactions, including customer details, product attributes, purchase history, and return status.
2. **Data Preprocessing:** Clean and prepare the data for modeling by handling missing values, encoding categorical variables, and normalizing numerical features.
3. **Feature Engineering:** Identify and create relevant features that could help in predicting returns, such as product type, price range, return history, and customer demographics.
4. **Modeling:** Implement various machine learning models like logistic regression, decision trees, random forests, and support vector machines to predict product returns.
5. **Evaluation:** Evaluate the performance of the models using suitable metrics such as accuracy, precision, recall, and F1-score.

**5.Code**

**import pandas as pd**

**import matplotlib.pyplot as plt**

**import seaborn as sns**

**from sklearn.model\_selection import train\_test\_split**

**from sklearn.ensemble import RandomForestClassifier**

**from sklearn.preprocessing import StandardScaler**

**from sklearn.metrics import confusion\_matrix, classification\_report, accuracy\_score**

**df = pd.read\_csv('/content/product\_return.csv')**

**df.dropna(inplace=True)**

**X = df.drop(columns=['returned'])**

**y = df['returned']**

**X = pd.get\_dummies(X)**

**scaler = StandardScaler()**

**X\_scaled = scaler.fit\_transform(X)**

**X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled, y, test\_size=0.2, random\_state=42)**

**model = RandomForestClassifier(random\_state=42)**

**model.fit(X\_train, y\_train)**

**y\_pred = model.predict(X\_test)**

**print("\n📊 Classification Report:\n")**

**print(classification\_report(y\_test, y\_pred))**

**accuracy = accuracy\_score(y\_test, y\_pred)**

**print(f"\n✅ Accuracy: {accuracy \* 100:.2f}%")**

**cm = confusion\_matrix(y\_test, y\_pred)**

**plt.figure(figsize=(6, 4))**

**sns.heatmap(cm, annot=True, fmt='d', cmap='YlGnBu', xticklabels=["No Return", "Return"], yticklabels=["No Return", "Return"])**

**plt.title("Confusion Matrix Heatmap")**

**plt.xlabel("Predicted")**

**plt.ylabel("Actual")**

**plt.show()**

**6. Data Preprocessing**

Data preprocessing is an essential step to ensure that the dataset is ready for machine learning modeling. The following techniques are applied:

* **Handling Missing Values:** Missing data is imputed using mean, median, or mode depending on the feature type.
* **Encoding Categorical Variables:** Categorical variables such as product type or customer location are encoded using techniques like one-hot encoding or label encoding.
* **Feature Scaling:** Numerical features like product price, purchase quantity, and customer age are normalized using min-max scaling or standardization to ensure that the model treats each feature equally.
* **Outlier Detection:** Outliers are identified and removed or capped to avoid skewing the model performance.

**7. Model Implementation**

Several machine learning models are tested for predicting product returns, including:

* **Logistic Regression:** A basic yet powerful classification algorithm used for binary outcomes (i.e., return or no return).
* **Decision Trees:** A non-linear algorithm that splits the dataset based on feature values, providing an interpretable model.
* **Random Forest:** An ensemble of decision trees that improves model accuracy by reducing overfitting.
* **Support Vector Machines (SVM):** A robust algorithm for binary classification that works well in high-dimensional spaces.
* **XGBoost:** A gradient boosting technique known for its high performance on structured/tabular data.

The models are trained on a training dataset, and hyperparameters are tuned using grid search or random search.

**8. Evaluation Metrics**

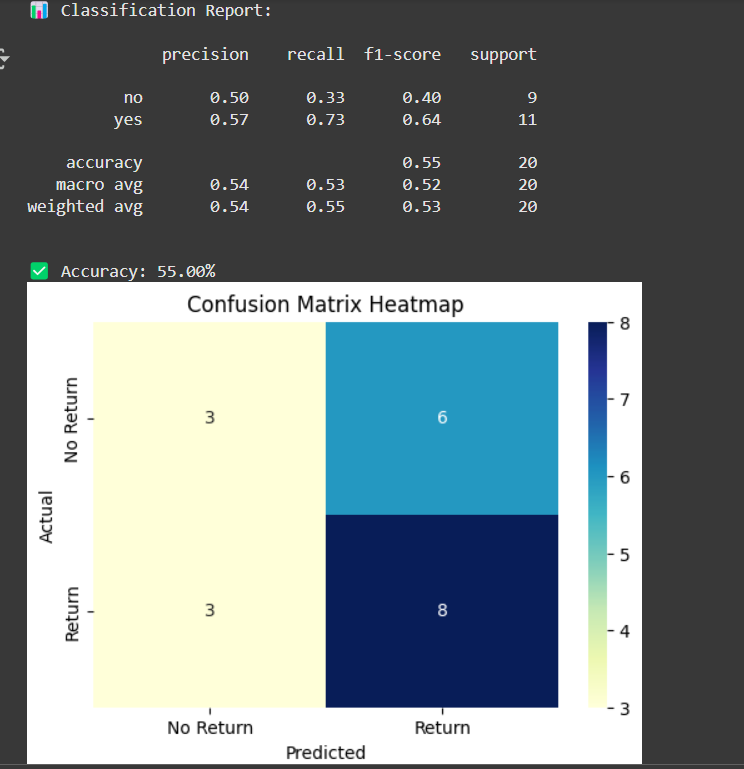
The performance of the models is evaluated using the following metrics:

* **Accuracy:** The percentage of correct predictions (both returns and non-returns).
* **Precision:** The proportion of true positive returns among all predicted returns, useful for minimizing false positives.
* **Recall:** The proportion of true positive returns among all actual returns, important for reducing false negatives.
* **F1-score:** The harmonic mean of precision and recall, balancing the trade-off between false positives and false negatives.
* **ROC-AUC:** Measures the area under the receiver operating characteristic curve, indicating the model's ability to distinguish between classes.

**9. Results and Analysis**

Upon training and testing the models, the following results were observed:

* **Model Accuracy:** The random forest and XGBoost models exhibited the highest accuracy in predicting returns, outperforming simpler models like logistic regression.
* **Precision vs. Recall Trade-off:** The SVM model achieved a higher recall, indicating it was better at identifying actual returns but had a lower precision.
* **Feature Importance:** Features such as product price, customer demographics (e.g., age, location), and product category were found to be significant predictors of return likelihood. Additionally, the number of past returns by a customer had a strong influence on return predictions.

Through analysis, it was evident that machine learning models, especially ensemble methods like random forest and XGBoost, performed well in predicting product returns. 

**9. Conclusion**

This study demonstrates that machine learning techniques can effectively predict product returns, offering valuable insights for e-commerce businesses to optimize their operations. By identifying key factors contributing to returns, businesses can make informed decisions about product offerings, marketing strategies, and customer engagement. The use of advanced models like random forest and XGBoost provides high accuracy and robustness in predicting returns. Further research could explore incorporating more granular data (e.g., customer reviews, shipping conditions) or deep learning models for even better performance.

**10. References**

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