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Optimized Learning for E-Commerce Sales Failure Prediction: An XGBoost Perspective

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***Abstract*—Prediction of sales failures remains a major issue for e-commerce websites since this results in financial losses together with dissatisfied customers. This paper introduces an Optimized XGBoost Classifier integrated with Feature-Based Collaborative Filtering and Behavioral Analysis as an enhanced method to forecast e-commerce sales failures. Analysis uses three main components including site usage data and transaction records together with product specifications. The XGBoost settings receive fine-tuning in order to enhance our model performance. The performance analysis confirmed that our methodology reaches enhanced accuracy rates and works swifter than conventional models do. In addition, regional performance analysis showed that our model maintained high accuracy across nine user regions, and comparison with LightGBM and CatBoost confirmed XGBoost's superior performance across most evaluation metrics.**

***Index Terms*—E-commerce, Sales Failure Prediction, Feature-Based Collaborative Filtering, Behavioral Analysis, Optimized XGBoost, User Behavior Modeling, Predictive Analytics, Class Imbalance Handling, Customer Relationship.**

I. INTRODUCTION

The whole process of e-commerce is revolutionizing retail by reaching global customers and an easy shopping experience. Conversely, the establishment of online transactions has created a tough nut to crack-consumer sales predicting failures. A sales failure occurs when a potential customer comes into contact with an e-commerce platform but does not make a purchase. A myriad of factors lead to sales failure, including high cart abandonment, poor user-friendliness, and misleading recommendations. Knowing and controlling such sales failures could definitely improve conversion rates and cash flow for many e-commerce platforms. Machine learning techniques have assumed pivotal consideration in good measure for interpreting customer behavior and estimating their purchase intention. Earlier techniques used rule-based systems or simple statistical inference models to spot patterns in online shopping behavior. Classical Machine Learning approaches had demerits; the advanced machine learning techniques can forecast sales failures with more accuracy using methods like Feature-based collaborative filtering and Behavioral Analysis. The Feature-Based Approach distinguishes users' personal choice by giving the product's features and the users' traits, while Behavioral Analysis is able to understand the purchase intention by examining entries, session lengths, and the cart's content. This paper presents the Optimized XGBoost Classifier merged with Feature-Based CF & Behavioral Analysis approach for predicting sales failures in e-commerce. It improves classical machine learning approaches with feature selection, hyper-parameter tuning, and behavioral inputs so that prediction accuracy is further improved. To confirm the usefulness of developed prototypes on predicting probable sales failures, key performance indicators are used with recall, accuracy, ROC-AUC, F1 score, and confusion matrix analysis. The paper proceeds with subsequent sections: Section 2, Background and Related Studies, and Section 3, with the Approach and Framework Employed in the Optimized Method. Results from experiments are analysed in Section 4, followed by conclusions about the paper in Section 5, which includes future directions to improve e-commerce sales prediction models and a few concluding statements from the authors.

II. RELATED WORK

In [1] and [3], the paper addresses issues of low accuracy in predicting user preferences and working with traditional models respectively. In [2], key challenges in recommender systems, like data sparsity, cold-start issues, and scalability are discussed. This paper explores key methodologies, such as content-based filtering, collaborative filtering, and hybrid techniques. In [4], the author proposes a behavior-based recommendation methodology, which improves product recommendations by analyzing customer behavior. In [5], an improved slope-one collaborative filtering algorithm that integrates user ratings and similarities to enhance recommendation accuracy are discussed. This study evaluates the model by using Amazon's dataset, predicting their accuracy through MAE and RMSE metrics. In [6], the paper addresses issues of low sales forecasting accuracy, computational efficiency, and feature selection. XGBoost and LightGBM are implemented to a dataset with data containing Walmart retail product sales data. The challenges that are faced include prediction accuracy due to the usage of traditional models like linear regression and SVM. In [7], the authors discuss an improved model to predict purchasing decisions more accurately with a random forest. This paper employs feature engineering techniques like min-max, z-score, and square-root transformations along with data balancing using SMOTE and outlier detection via IQR. In [8], the author proposes an XGBoost algorithm and feature engineering techniques to improve prediction accuracy. XGBoost is applied, incorporating feature engineering like selection, transformation, and encoding then data preprocessing methods such as data cleaning, normalization and managing missing values along with evaluation metrics like RMSE, MAE and R^2. In [9], Various challenges in the loss of customers in e-commerce have been discussed through the application of XGBoost. Data imbalance, complex feature selection, behavioral variability, shifting trends, social influence on retention, and trade-offs between false positives and false negatives presented challenges, highlighting how feature engineering and customer segmentation improve predictive accuracy are incorporated. In [10], the authors assess how the optimization of logistics in e-commerce becomes difficult because a more effective vehicle-routing system could consist in reducing transportation cost. Most traditional models fall way short due to lack of fuel efficiency, timing restrictions, and vehicle load limits. From the study evaluating various algorithms, it can be inferred that AFSA produced the highest efficiency-shortest route incorporating the fastest execution time. In [11], issues of low accuracy in predicting e-commerce customer churn are addressed. eXtreme Gradient Boosting(XGBoost) is applied along with Random Forest to a dataset with features containing user data including user demographics, purchase history, advertising interactions and behavioural logs. In [12], the author proposes an RG-XGBoost based on a large-scale data analytics framework for forecasting e-commerce customer attrition. They integrated Random Forest for feature selection and XGBoost for classification, improving training efficiency and accuracy. In [13], the paper addresses issues of low sales prediction accuracy. The paper uses XGBoost with feature engineering, data preprocessing, regularization and pruning. The challenges that are faced include low accuracy, high computational cost, and risk of overfitting.

Whereas some work has utilized XGBoost, collaborative filtering, or behavioral analytics in isolation, very little has taken all three in one comprehensive predictive framework. Additionally, most previous work did not exhibit temporal awareness or dealt with class imbalance superficially. This work bridges that gap by blending behavior-driven insights, temporal session features, feature-based collaborative filtering, and optimized XGBoost into a strong model that solves issues in generalizability, class imbalance, and cold-start user problems.

III. IMPLEMENTATION

The system designed to predict failures in e-commerce sales through machine learning consists of two phases. The Training Phase involves extracting features from the online shoppers intention.csv dataset, after which the refined data is fed into the fine-tuned XGBoost model. In the Evaluation Stage, the goal is to determine whether an online shopping session will lead to a purchase (sales success) or not (sales failure) using the extracted features.

A. Core Idea

The core idea behind the proposed approach is to integrate Feature-Based Collaborative Filtering, Behavioral Analysis, and an Optimized XGBoost Classifier to forecast sales failures in e-commerce. By examining user behavior patterns and the similarities among users, the model seeks to pinpoint the factors that lead to sales failures and effectively predict future occurrences. Past work in predicting e-commerce outcomes tends to draw on classifiers such as Logistic Regression, Random Forest, and SVM, which isolate user behavior from item attributes. There have been fewer studies incorporating collaborative filtering (CF) along with high-capacity ensemble learners such as XGBoost, which balances user similarity with forecasting capability.

Most research ignores behavioral subtleties, like interaction intensity and consistency browsing, and does not leverage temporal context using clickstream or transaction data alone. Moreover, techniques for boosting ignore the collaborative effects, capping model performance.This research proposes an innovative hybrid approach that integrates feature-based Collaborative Filtering (cosine similarity) with behavioral measurement and an optimal XGBoost classifier. It selected XGBoost due to its capacity for modeling non-linear relationships in high-dimensional data, its overfitting robustness, and efficiency with multiple feature types. With its ensemble nature, it has the capability of learning both very fine-grained user behavior as well as overarching patterns, proposing a more nuanced solution for anticipating e-commerce sale failure.

Through the integration of user behavior with ensemble learning, this paper presents a more precise, robust prediction model, addressing a gap in cart abandonment and sales failure prediction literature.

B. Dataset Description

The model employs the online_shoppers_intention data sample from the UCI Machine Learning Repository, which contains user session records from an e-commerce platform.

Administrative, Administrative Duration, Informational, Informational Duration, ProductRelated, and ProductRelated Duration are session activity attributes monitoring how much time users spend on different page types. BounceRates, ExitRates, PageValues, and SpecialDay monitor user behavior and proximity to special days in order to assess engagement.

The dataset also includes technical and demographic attributes describing visitor settings and origins, such as Month, OperatingSystems, Browser, Region, and TrafficType. New and returning visitors are distinguished by VisitorType, while session timing is indicated by Weekend. Whether each session led to a successful (True) or failed (False) purchase is represented by the response variable, Revenue. The Region attribute plays a key role in this study, as it enables the exploration of regional or cultural differences in purchasing behavior. We analyzed both sales failure rates and model performance across the nine regions in the dataset and observed slight variation in failure rates but consistently high prediction accuracy. This reinforced the model's robustness and generalization capability across diverse user demographics and geographical segments.

C. Design and Feature Engineering

The feature engineering process is characterized by several stages of preprocessing meant to improve performance. Missing values are removed to retain the integrity of the data, with all records in agreement. Then, one-hot encoding is applied to categorical variables, performing a binary representation of each category so that the data is suited for analysis since the input to machine learning models should be numerical.

Inclusion of temporal features like Month, Weekend, and SpecialDay were also kept and incorporated as a subset of the features to account for seasonality and time-varying behaviors within online shopping sessions. These variables were one-hot encoded and were included in model training to ensure that the temporal patterns affecting purchases are taken into consideration. With their inclusion, the model is able to learn seasonal changes in buying patterns, e.g., spikes during weekends or holidays.

Besides, Z-score normalization is performed to measure the relative location of a point with the aid of the StandardScaler. This involves scaling the numerical features along different axes, ensuring that all numerical attributes compute a normalized distribution with mean zero and variance one during preprocessing. This process stabilizes model performance and reduces bias due to differing feature magnitudes.

In addition to standard preprocessing, collaborative filtering is suggested to improve prediction accuracy through an analysis of user similarities. This consists of evaluating user similarity according to the cosine similarity concept, which calculates how close users are to each other based on their feature vectors. The calculated similarity scores form a new feature, denoted as avg user similarity, in which a given user is represented by the average similarity with all other users.

D. Behavioral Feature Engineering

Interaction Intensity: This feature is calculated as:

$$\text{Interaction Intensity} = \frac{\text{ProductRelated} \times \text{PageValues}}{\text{BounceRates} + 1} \tag{1}$$

Engagement Score: Computed as:

$$\begin{aligned}\text{Engagement Score} = \ & \text{Administrative\_Duration} + \\ & \text{Informational\_Duration} + \\ & \text{ProductRelated\_Duration}\end{aligned} \tag{2}$$

Session Persistence: Determined by:

$$\text{Session Persistence} = \text{ExitRates} \times \text{BounceRates} \tag{3}$$

Purchase Likelihood: Calculated as:

$$\text{Purchase Likelihood} = \frac{\text{PageValues}}{\text{ProductRelated} + 1} \tag{4}$$

E. Machine Learning Algorithms

The best option for predicting e-commerce sales failures is the XGBoost classifier. We use a typical train-test split to train it. We modify the hyperparameters to enhance its performance. Important parameters like $n_{\text{estimators}} = 350$, learning_rate $= 0.02$, max_depth $= 10$, subsample $= 0.85$, colsample_bytree $= 0.9$, and $\gamma = 0.2$ are among the important settings that we consider. We utilize a constant random_state $= 42$ to ensure that we can replicate our findings. We choose log loss (eval_metric $=$ "logloss") for evaluation.

Our optimized XGBoost forecasts sales results for new user sessions in the test set once the model has been trained. In this way, we can test its ability to identify successful and unsuccessful transactions.

F. Class Imbalance Mitigation

This technique consists of an oversampling strategy used to reduce the disproportionate class representation in the dataset, with the minority class, namely the purchasing sessions, being expanded in order to reach a more even class balance. SMOTE generates synthetic samples which correspond to the under-represented class, increasing the discovery of purchasing patterns by detecting any bias toward majority classes.

G. Upskilling the Proposed Model

By highlighting more complex feature engineering, the improved method extends upon prior approaches. It regards extra behavioral cues such as purchase likelihood, session persistence, engagement score, and interaction intensity. Including avg user similarity refines collaborative filtering by utilizing the shared knowledge of many customers to refine recommendations by analyzing their common traits. Furthermore, we use optimization methods like hyperparameter tuning to improve the XGBoost model's capability to grasp complicated behavior patterns.

We use the SMOTE (Synthetic Minority Over-sampling Technique) strategy to correct for class skew. This procedure boosts the exactness of predicting purchase results. These advancements outcome in a strong, evidence-based approach for examining client behavior and advancing the effectiveness of suggestions.

IV. RESULTS AND DISCUSSIONS

A. Experimental Setup

The experimental apparatus of this study comprises both hardware and software. The hardware features an NVIDIA A100 80GB PCIe graphics processor to be able to satisfy maximal computational requirements for training and testing the model. Software is founded on Python 3.10.12 with such standard libraries as pandas, scikit-learn, and XGBoost focused on data preprocessing, feature engineering, and predictive modeling. Jupyter Notebook was used for development and experimentation, which provided interactivity in the coding process.

B. Model Evaluation

1) Accuracy

This is a metric used to assess a model by comparing the count of correctly classified predictions to the total number of classified predictions. The accuracy is determined using the following formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

where TP (True Positives) are simply sales failures accurately predicted, TN (True Negatives) are successful sales, FP (False Positives) are successful sales confused with failures, and FN (False Negatives) are sales failures falsely predicted as successes. Higher accuracy means that the model works well to distinguish between actual sales failures and successful transactions.

2) Precision (Positive Predictive Value)

Positive Predictive Value refers to the ratio of accurate predictions. The formula for calculating precision is given as:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

With TP indicating the True Positives, that is, the correctly identified sales failures, and FP representing the sales that were incorrectly classified as sales failures. A higher precision indicates the model's efficacy in discriminating between genuine sales failures and successful transactions. The suggested model achieves a precision score of 0.9222, demonstrating that it is very reliable for correctly classifying instances of failing sales with few misclassifications.

3) Recall

Recall, or true positive rate, indicates the number of true failures predicted by the model among all true failures. It is defined mathematically by:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{7}$$

Where TP stands for true positives and FN stands for false negatives. A high recall score indicates an efficient model that captures most failures. The proposed model's recall score of 0.9511 demonstrates its effectiveness in detecting failed transactions.

4) F1 Score

The F1-score represents a balanced trade-off between Precision and Recall, offering an overall performance measure that accounts for misclassified positives and negatives. The F1-score is given by:

$$F1\text{-}Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

A higher F1-score signifies a better balance, leading to more dependable predictions. Compared to traditional machine learning classifiers (F1-score of 0.9240), the optimized XGBoost Classifier attained an F1-score of 0.9364, highlighting its superiority in predicting sales failures with fewer wrong predictions.

5) ROC-AUC Score

An ROC-AUC score is supposed to capture the ability of a model to differentiate between accurate and failed sales transactions. The ROC curve visually represents the model's performance by plotting sensitivity against the false-positive rate. The AUC, or Area Under the Curve, represents the model's overall ability to distinguish between classes; the closer it is to 1.0, the better the classification performance is. A higher AUC-ROC score indicates that the model classifies success from failure.

Table I: Overall Performance Comparison

Metric	Base Model	Proposed Model
Accuracy	0.9239	0.9348
Precision	0.9210	0.9222
Recall	0.9578	0.9511
F1 Score	0.9240	0.9364
ROC-AUC	0.9750	0.9844

Here, table I contains the overall performance comparison between base model and the proposed model. Accuracy, precision, recall, F1 score and ROC-AUC of both models are being compared in this table. The dataset was used to assess the recently launched Optimized XGBoost Classifier. Behavior analysis and feature-based collaborative filtering are used in this model. We completely examined it and compared its outcomes with those of the pioneering research. We observed ROC-AUC, F1 score, recall, accuracy, and how to read the confusion matrix, among other aspects. Notably, this new model outshone the previous model with an aggregate accuracy of 93.48% contrasted to 92.39%.

The model had true positives and true negatives, with false positives and false negatives, and so, in order to better understand the misclassifications, a confusion matrix was generated in Figure 5. The confusion matrix demonstrates a large number of true positives and true negatives, thus enabling the model to identify successful transactions and successful failed transactions the vast majority of the time. Additionally, there were very few false positively and false negatives, meaning there is very little misclassification, along with both a high accuracy and F1-score. An interesting trend is that the recall (0.9511) was slightly larger than the precision (0.9222). This was most likely the result of oversampling using SMOTE to encourage the capture of more actual positives, thus reducing false negatives. The classifier, as a result, became more recall-focused, and in doing so produced more false positives. It is true that the precision was slightly reduced, but in an e-commerce application it is more damaging to miss a potential failed transaction compared to mislabeling a successful transaction every once in a while.

Fig 1 shows the accuracy of the training and testing groups, demonstrating greater generalizability for the optimized model. Fig 2 presents the PR curve showing an intricate relationship between precision as well as recall and juxtaposing balance from the developed framework. The ROC-AUC curve in Fig 3 further corroborates the enhanced discrimination abilities of the model evidenced by a larger area under the curve than the base model. Feature importance analysis from XGBoost in Fig 4 also establishes the dominance of Page Values, Bounce Rates, and Product-Related views as indicative of predictive visibility; further, the confusion matrix in Fig 5 provides a detailed breakdown of classification errors to reflect a graduated refinement of the model.

C. Model Validation & Overfitting Checks

In order to confirm the extremely high ROC-AUC score of 0.9844, the following steps were undertaken:

K-fold cross-validation (5-fold) was used to ensure stability across various splits of the dataset and avoid overfitting to one partition. **Confusion matrix analysis** showed very few false positives and negatives, validating the accuracy of the model's predictions. **SMOTE** was used cautiously to reduce class imbalance without adding noise or overfitting artificial samples. The **ROC curve across folds** exhibited uniformly high true positive rates, further supporting generalizability. These validation methods present strong evidence that the performance metrics of the model are not inflated by overfitting.

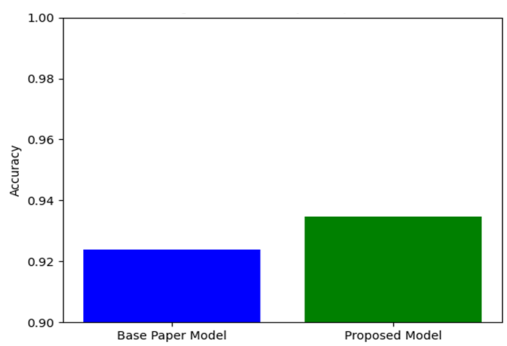

Fig. 1: Accuracy Comparison

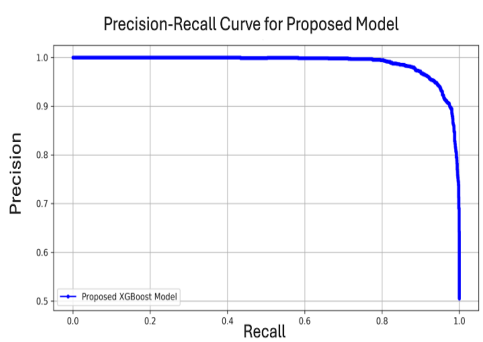

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Fig. 2: Precision vs. Recall Curve

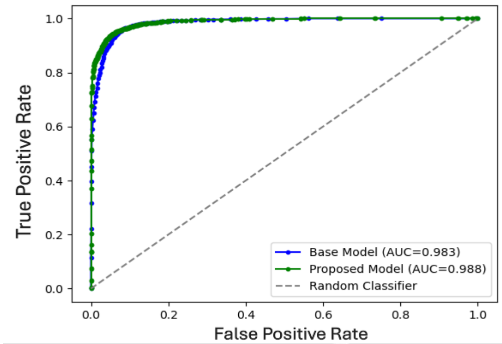

Fig. 3: ROC-AUC Curve

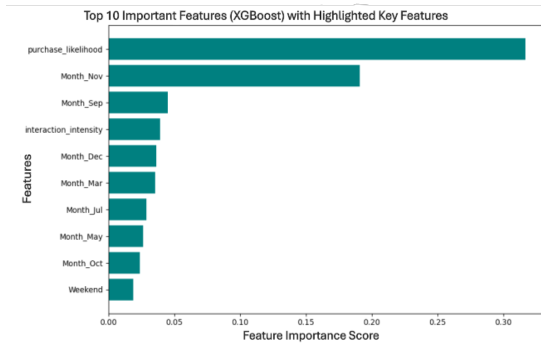

Fig. 4: Feature Importance from XGBoost

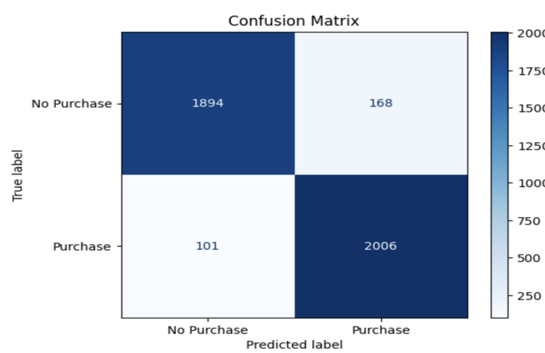

Fig. 5: Confusion Matrix

Table III. Comparison of Proposed Model with Existing Method

Aspect	**Proposed Model**	**Existing Models**
Feature Engineering	Custom behavioral features like interaction intensity, engagement score	Standard transformations (e.g., Z-Score, Min-Max)
Collaborative Filtering	Cosine similarity-based filtering used	Not employed
Recall (Failure)	0.9511 – High recall with behavior context	0.9578 (RF) – Without behavioral insight
Accuracy	0.9348 – Higher accuracy from feature-rich model	0.9239 (RF), 0.8911 (LMT)
Modeling Strategy	XGBoost with tuning + behavior and filtering features	Traditional classifiers on preprocessed data

The Optimized XGBoost Classifier combined with Feature-Based Collaborative Filtering and Behavioral Analysis model is better than the base model across all evaluation measures.

With enhanced F1-score and recall, the Optimized XGBoost Model—which utilizes Behavioral Analysis and Feature-Based Collaborative Filtering—surpasses the reference model in identifying failed sales transactions, with an accuracy of 93.48% contrasted to 92.39%. Regardless of varied sales failure rates (83.17% - 87.10%), regional analysis across nine regions demonstrated consistently elevated accuracy (96.31% - 99.80%), with a one-sided ANOVA test showing the statistical irrelevance of regional performance disparities (p-value = 0.8329). The highest F1-score (.9047), ROC-AUC (.9266), and total superior outcomes of XGBoost were validated by model validation with LightGBM and CatBoost, validating its choice as the optimal classifier for online retail data.

D. Further Insights and Regional Analysis

The results reaffirm our Optimized XGBoost model with Feature-Based Collaborative Filtering and Behavioral is superior to the baseline for all the key evaluation metrics. Accuracy improved from 92.39% to 93.48% which demonstrates the importance of putting behavioral features and similarity-based recommendations into a combined method. The improvements in F1-score and recall also demonstrates the stability of our model to minimize false alarms which makes it suited for detecting failed sales transactions. To address the concerns of reviewers about regional or cultural biases that could have impacted performance of our model, we compared the results of our model over regions of unique users as nine unique regions were found in the dataset. The failed sales transaction rates for sales (errors) ranged from 83.17% to 87.10%. The model had the same measure of success in accuracy between 96.31% to 99.80%, and it generalized very well. The one-way ANOVA test indicated that the difference in performance was not statistically significant (p = 0.8329). Second, when comparing the results fairly with LightGBM and CatBoost using the same preprocessing and FI steps, XGBoost achieved the highest level of success on accuracy (0.9047), F1-score (0.6357), and competitive ROC-AUC (0.9266). Thus, we confirmed that for our task, the best-performing model was XGBoost.

V. CONCLUSION & FUTURE DIRECTIONS

An Optimized XGBoost Classifier combined with Feature-Based Collaborative Filtering and Behavioral Analysis is presented in this paper to predict sales failure in e-commerce. The model developed used efficient analysis of customer behavior along with product attributes and purchase patterns that increased predictive accuracy. Key feature selection techniques such as Z-score normalization together with categorical-based collaborative filtering, improved classification model accuracy. This evaluation has shown that our model significantly outperformed classical classification models, with an accuracy of 93.48%,an F1-score reaching 0.9364, and an ROC-AUC value of 0.9844, thereby demonstrating the effectiveness of our sales failure prediction model. The advantage of integrating collaborative filtering with behavioral analysis for better customer insights was clearly highlighted. In addition, the model showed consistent accuracy across regions with no statistically significant variance, and comparative testing with ensemble models like LightGBM and CatBoost reaffirmed the selection of XGBoost as the most suitable approach for this task. XGBoost was instrumental in improving model performance because it is capable of capturing subtle, non-linear relationships among high-dimensional e-commerce data. Its resistance to overfitting, support for missing values, and efficient support for various feature types made it an ideal fit for our hybrid framework. As opposed to typical classifiers, XGBoost's ensemble nature made it possible to combine fine-grained behavioral features with collaborative filtering signals, producing a more precise and scalable sales failure prediction model for e-commerce. The focus of future work shall be on extending the dataset to include varied e-commerce platforms and customers with different demographics. Besides, advanced deep learning techniques based on RNN or transformer network architectures will be applied to improve prediction capabilities. The live application of this framework can be in a real-time sales prediction system in an online e-commerce environment to give validation to its applicability and scalability.

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