Predictive and Adaptive Payment Network (PAPN):

Innovating Cash Flow Management and Payment Strategies with AI

Team -43

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Introduction:

Problem Description:

The challenge of efficiently managing payment methods and timing to minimize costs, maintain cash flow, and ensure security.
Consequences of misaligned payment schedules leading to cash flow disruptions, delayed payments, and strained relationships.

Solution Overview:

Predictive Analysis as a comprehensive solution leveraging real-time data analytics and machine learning to determine the best payment options and it's suitability from three dimensions: fraud, fees and the processing time.

Survey & Proposed Work

Existing Solutions

Traditional Payment Gateways such as paypal, Stripe, Flagging fraud detection for Fraud Detection, Invoice Automation

Proposed Unique Features of PAPN

Predictive Cash Flow Management, Adaptive Payment Method Selection, Global Financial Market Integration, Comprehensive Security and Fraud Prevention.

Milestones: Charting the Path to PAPN's Development

01 Data Collection

02 Model Development

03 System Integration

04 Testing

05 Evaluation

06 Deployment and Optimization

07 Finalization and Documentation

08 Launching for live users

Implementation Overview: Designing the Predictive Payment Application

User Interface (UI)

Developed using Tkinter, the UI offers an intuitive platform for users to interact with the predictive payment application effortlessly.

Users can input transaction details with ease and access real-time predictions and insights regarding payment methods and timing.

Data Preprocessing Module

The data preprocessing module plays a crucial role in preparing and refining user input before it is fed into the prediction models.

By handling data preprocessing tasks such as normalization and feature engineering, this module ensures that the predictive models receive clean and structured data for analysis.

Prediction Models:

Trained machine learning models form the backbone of the predictive payment application, enabling accurate predictions across various aspects of financial transactions.
These models will utilize sophisticated machine algorithms to analyze historical data and user input, offering personalized recommendations and insights tailored to each transaction.

Implemented Models

Fraud Detection Model

Architecture: Logistic Regression.
Evaluation Metrics: Precision, Recall.

Payment Fee Optimization Model

Architecture: Regression Model.
Evaluation Metrics: Mean Absolute Error, R-squared, Median Absolute Percentage Error.

Payment Preference Prediction Model

Architecture: RandomForestClassifier.
Evaluation Metrics: Accuracy.

Payment Sentiment Analysis Model:

Architecture: Natural Language Processing (NLP) Model.
Evaluation Metrics: F1 Score.

Payment Timing Prediction Model

Architecture: Time-Series Forecasting Model (LSTM).
Evaluation Metrics: R-squared (R2) Score.

Customized Payment Offers Recommendation Model:

Architecture: Collaborative and Content-Based Filtering.
Evaluation Metrics: Cosine Similarity.

Results and Evaluation Metrics: Assessing PAPN's Performance

Fraud Detection Model

The model indicated high precision by correctly identifying fraudulent transactions with a low rate of false positives, and high recall by capturing most fraudulent transactions with a low rate of false negatives.

Payment Fee Optimization Model

The model had a Mean Absolute Error (MAE) of 24.01%, indicating precise predictions of payment fees with minimal error. Additionally, the model had an R-squared value of 0.82, signifying a strong fit between the observed and predicted values.

Payment Preference Prediction Model

The model's high accuracy indicated that the model correctly predicted the preferred payment method for transactions, ensuring personalized payment recommendations for users.

Results and Evaluation Metrics: Assessing PAPN's Performance

Payment Sentiment Analysis Model:

The high balance between true positives and false positives is indicated by the F1 score, which measures precision and recall's harmonic mean, indicated the model's sentiment prediction accuracy.

Payment Timing Prediction Model

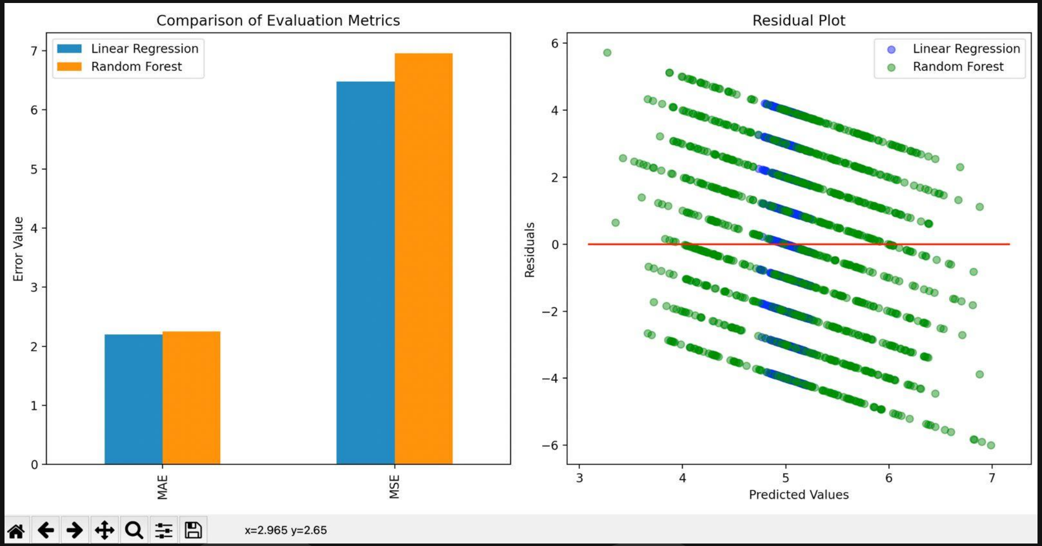
The model indicated a low Mean Absolute Error (MAE) of 2.20 and a Mean Squared Error (MSE) of 6.48, effectively capturing the variance in payment timing and providing valuable insights into the timing patterns of financial transactions.

Customized Payment Offers Recommendation Model:

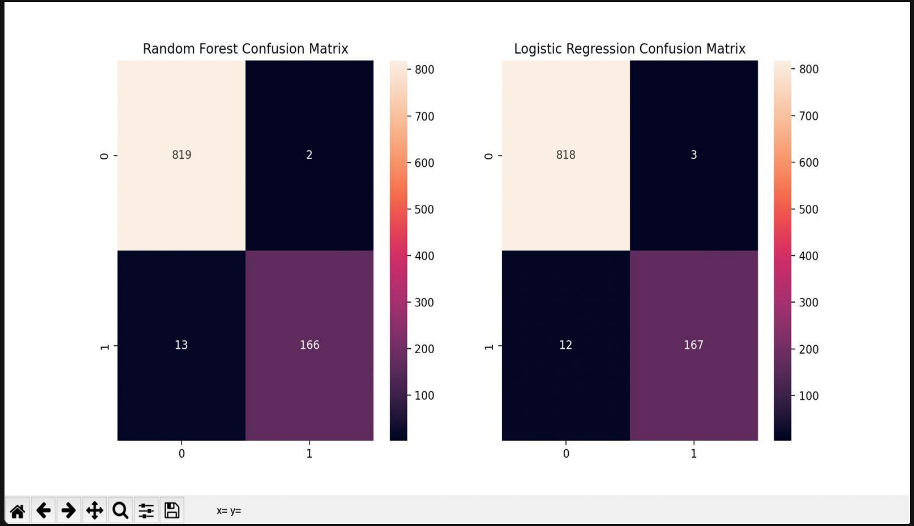
High cosine similarity scores indicated that the model closely aligned user preferences with customized payment offers, ensuring that the recommendations provided were relevant and personalized for the users.

Comparison of Models

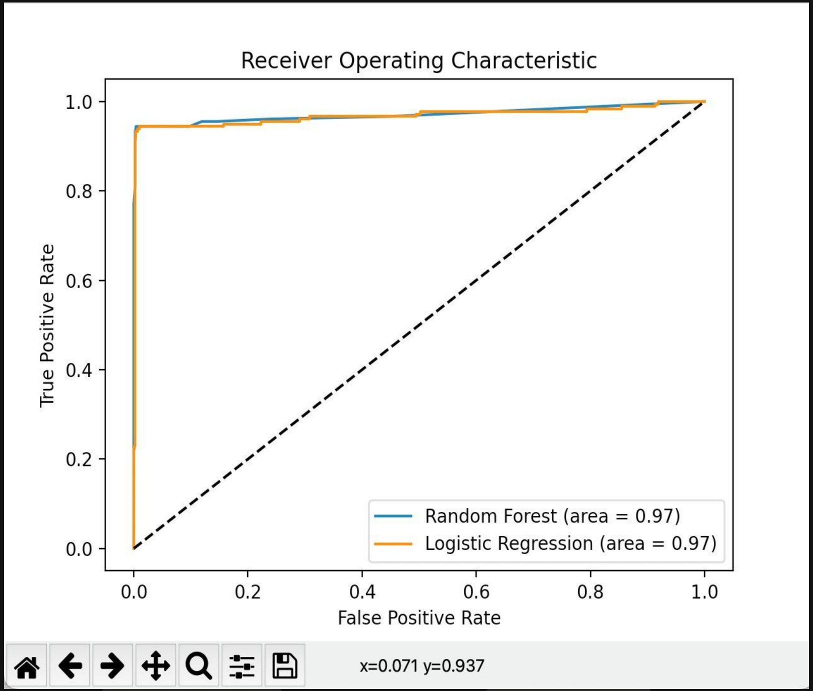
The graph compares the performance of Linear Regression and Random Forest Regression models in predicting payment processing times using Mean Absolute Error (MAE) and Mean Squared Error (MSE) as evaluation metrics. The bar plot illustrates the error values for each model, while the residual plot shows the distribution of prediction errors around the predicted values.



The graph displays the confusion matrices for both the Random Forest and Logistic Regression classifiers in a side-by-side comparison. Each matrix illustrates the classification results, including true positives, true negatives, false positives, and false negatives, enabling a visual assessment of model performance in detecting fraud instances.



The Receiver Operating Characteristic (ROC) curve plot presents the trade-off between true positive rate (sensitivity) and false positive rate (1 - specificity) for both classifiers. The area under the ROC curve (AUC) quantifies the classifiers' ability to discriminate between positive and negative instances, with higher AUC values indicating superior performance in fraud detection.



User Interface Overview

Intuitive Design

The UI features a clean and intuitive design, making it easy for users to navigate and input transaction details effortlessly.
With clear and concise prompts and options, users can quickly enter transaction information and access predictions without any technical complexities.

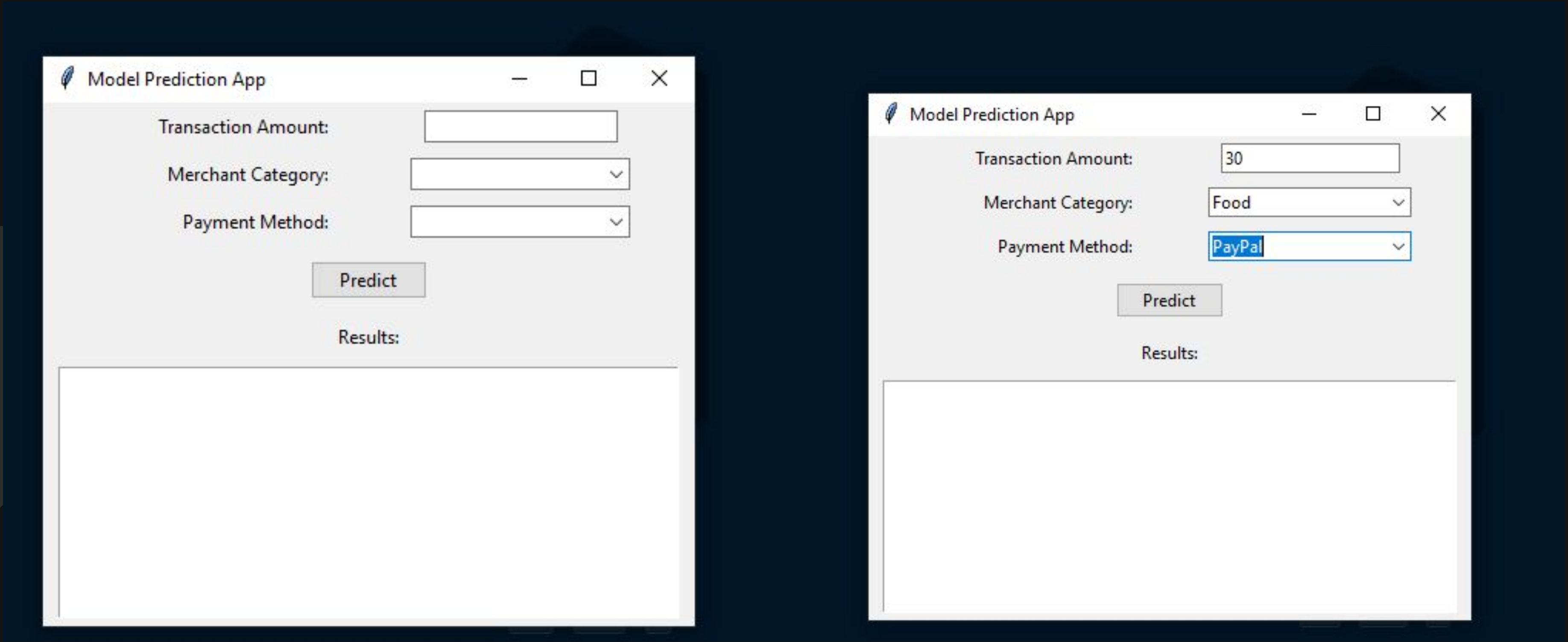
Transaction Input:

Users can input transaction details such as transaction amount, category, and payment method through the UI.
The UI provides a seamless experience for users to input data accurately, ensuring reliable predictions and recommendations.

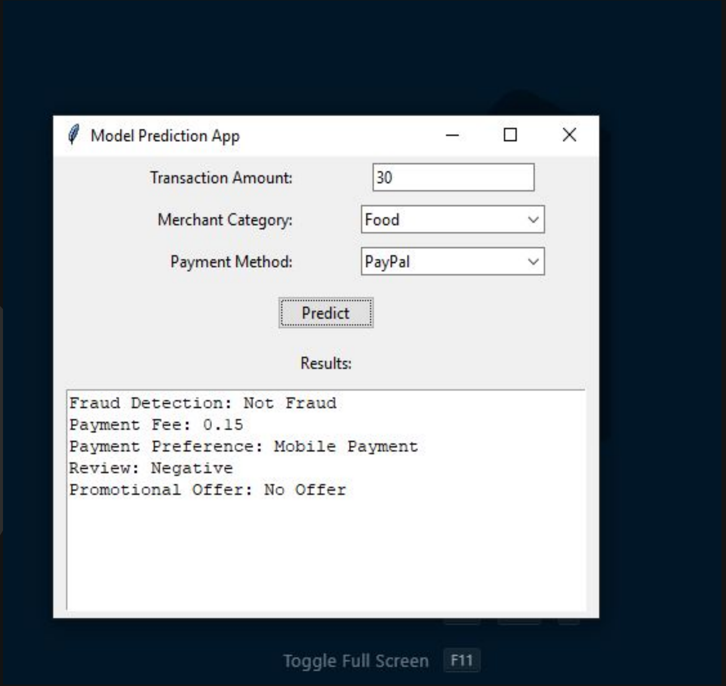
Real-time Predictions:

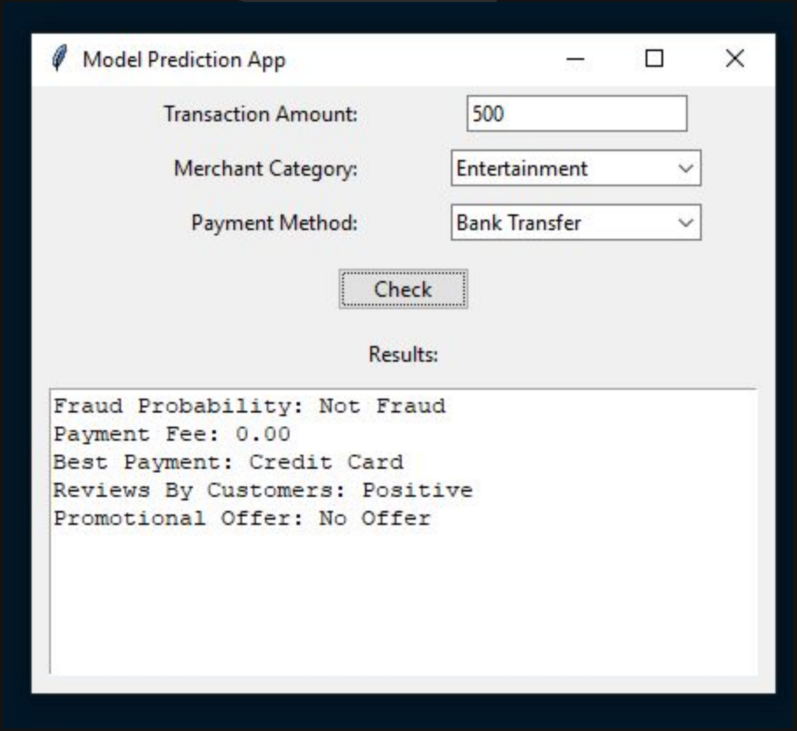
Upon entering transaction details, users can instantly view real-time predictions and insights generated by the predictive models.
The UI presents predictions regarding payment methods, timing, and other relevant factors in a clear and understandable format, empowering users to make informed decisions.

Appendix: User Interface Idle and Input States

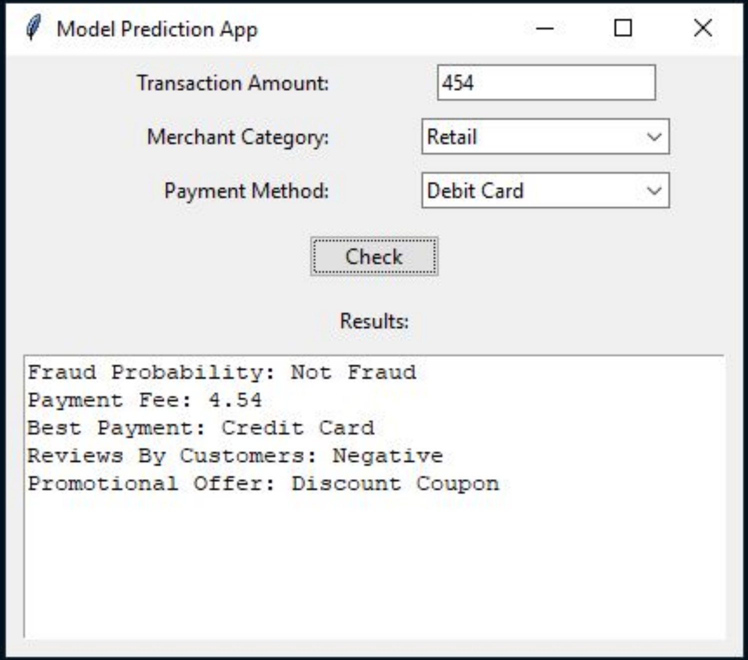


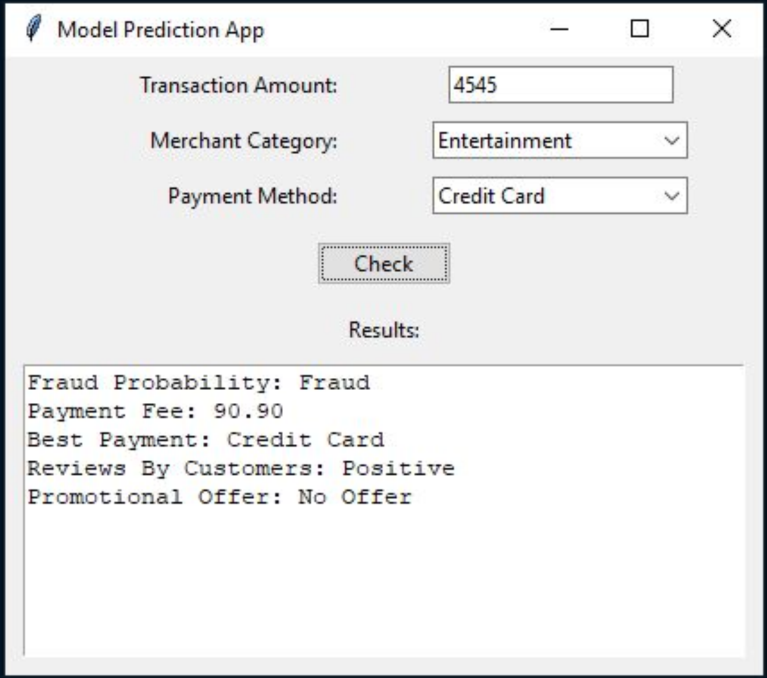
Appendix: User Interface Prediction State





Appendix: User Interface Prediction State





Appendix :Model Training outputs

```
Accuracy: 0.1616

Classification Report:
               precision    recall  f1-score   support

Bank Transfer       0.14      0.15      0.15       398
         Cash       0.17      0.17      0.17       444
  Credit Card       0.17      0.15      0.16       443
   Debit Card       0.16      0.17      0.17       402
     E-Wallet       0.15      0.17      0.16       389
       Paypal       0.18      0.15      0.17       424

     accuracy                           0.16      2500
    macro avg       0.16      0.16      0.16      2500
 weighted avg       0.16      0.16      0.16      2500
```

Payment Preference

```
rkspaces/PAPN/Scripts/Customized Payment Offers.py"
      customer_id  ...                                  features
897             1  ...        Clothing NoPromo Russia Paypal LowFee
4150          837  ...        Clothing NoPromo Russia Paypal LowFee
1357            1  ...    Beauty & Health NoPromo Spain Cash LowFee
2349          459  ...    Beauty & Health NoPromo Spain Cash LowFee
1049            1  ...    Toys & Games NoPromo France Paypal LowFee
2956          715  ...    Toys & Games NoPromo France Paypal LowFee
1585            1  ...       Clothing Promo Japan E-Wallet LowFee
4940          901  ...       Clothing Promo Japan E-Wallet LowFee
2760            1  ... Sports & Outdoors Promo Spain E-Wallet LowFee
4330          673  ... Sports & Outdoors Promo Spain E-Wallet LowFee
```

Payment Offers

Appendix :Model Training outputs

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/codespace/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /home/codespace
[nltk_data]   Package punkt is already up-to-date!
Sentiment analysis for Debit Card:
Positive: 790, Neutral: 852, Negative: 846
Sentiment analysis for PayPal:
Positive: 756, Neutral: 869, Negative: 836
Sentiment analysis for Bank Transfer:
Positive: 813, Neutral: 812, Negative: 868
Sentiment analysis for Credit Card:
Positive: 861, Neutral: 839, Negative: 858
```

Payment Sentiment

Fraud Detection

	precision	recall	f1-score	support
0	0.98	1.00	0.99	821
1	0.99	0.93	0.96	179
accuracy			0.98	1000
macro avg	0.99	0.96	0.97	1000
weighted avg	0.99	0.98	0.98	1000

Appendix :Model Training outputs

	customer_id	purchase_id	...	payment_fee_percentage	features
897	1	898	...	2.89	Clothing NoPromo Russia Paypal LowFee
4150	837	4151	...	0.70	Clothing NoPromo Russia Paypal LowFee
1357	1	1358	...	1.22	Beauty & Health NoPromo Spain Cash LowFee
2349	459	2350	...	2.87	Beauty & Health NoPromo Spain Cash LowFee
1049	1	1050	...	1.86	Toys & Games NoPromo France Paypal LowFee
2956	715	2957	...	2.67	Toys & Games NoPromo France Paypal LowFee
1585	1	1586	...	1.63	Clothing Promo Japan E-Wallet LowFee
4940	901	4941	...	2.19	Clothing Promo Japan E-Wallet LowFee
2760	1	2761	...	3.00	Sports & Outdoors Promo Spain E-Wallet LowFee
4330	673	4331	...	2.00	Sports & Outdoors Promo Spain E-Wallet LowFee

Payment fee Optimization

Future Steps in Deployment: Ensuring Seamless Integration

Deployment Platform Selection

Considerations: Scalability, Accessibility, Resource Requirements.

Preparing the Deployment Environment

Installing Necessary Software, Configuring Environment.

Packaging Application Components

Bundling Components into a Deployable Format.

Configuring the Deployment Platform:

Setting up Networking, Security Settings, Environment Variables.

Deploying the Application:

Utilizing Cloud Services for Accessibility.

Testing the Deployment:

Verifying Functionality, Accuracy, Responsiveness.

Conclusion:

Positive evaluation metrics across all models indicated robust performance and reliability in predicting various aspects of financial transactions, including fraud detection, payment fees, user preferences, sentiment analysis, timing patterns, and customized offers.

By harnessing the power of machine learning and real-time data analytics, PAPN has not only addressed existing challenges but has also paved the way for enhanced financial efficiency, reduced transaction costs, and strengthened security measures.

With the implementation of the proposed future steps the PAPN System will be a valuable Business Intelligence(BI) tool.