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Team ID	Team-593025
Project Name	Project - Online Payments Fraud Detection Using ML

PROJECT REPORT

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1. INTRODUCTION

1.1 Project Overview

The Online Payments Fraud Detection using Machine Learning project aims to address the growing concern of fraudulent activities associated with online credit/debit card transactions. With the continuous expansion of internet and e-commerce, there has been a parallel increase in the frequency of online transactions, leading to a surge in fraudulent activities. Traditional fraud detection methods often face challenges in terms of accuracy and efficiency, necessitating the adoption of advanced machine learning techniques.

The proposed solution leverages classification algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Extra Tree Classifier, and XGBoost Classifier, to detect and predict fraudulent transactions. These algorithms are trained and tested using a large dataset of credit/debit card transactions, allowing the model to learn patterns and anomalies associated with fraudulent behavior.

The project emphasizes the significance of accurately identifying fraudulent transactions by mitigating the drawbacks of existing approaches. It focuses on improving accuracy and efficiency through the implementation of multiple machine learning algorithms, enabling a more robust fraud detection system.

1.2 Purpose

The primary purpose of the Online Payments Fraud Detection project is to enhance the security of online financial transactions by implementing advanced machine learning techniques. The specific objectives include:

- ❖ **Fraud Detection:** Develop a reliable and accurate fraud detection system capable of identifying anomalous patterns in online credit/debit card transactions.
- ❖ **Algorithm Comparison:** Evaluate the performance of various classification algorithms such as Decision Tree, Random Forest, SVM, Extra Tree Classifier, and XGBoost Classifier to determine the most effective model for fraud detection.
- ❖ **Model Training:** Train the selected machine learning model on a substantial dataset of credit/debit card transactions to ensure robust learning and pattern recognition.
- ❖ **Testing and Validation:** Assess the model's effectiveness through rigorous testing and validation processes, using separate datasets to ensure generalization and reliability.
- ❖ **Model Deployment:** Implement Flask integration for creating a user-friendly interface and deploy the final model on the IBM Cloud platform, making it

accessible for real-time online payment fraud detection.

- ❖ **Improving Accuracy:** Address the limitations of existing fraud detection methods by leveraging a combination of state-of-the-art machine learning algorithms, aiming for higher accuracy and fewer false positives/negatives.
- ❖ **Scalability:** Design the system to handle large volumes of data efficiently, considering the ever-increasing scale of online transactions.
- ❖ **Security Enhancement:** Contribute to the overall security of online financial transactions by proactively identifying and preventing fraudulent activities, thereby protecting users and businesses from potential financial losses.

2. LITERATURE SURVEY

2.1 Existing problem

The surge in online transactions, particularly in the realm of e-commerce, has brought about a corresponding increase in online payment fraud. Existing fraud detection methods often face challenges such as low accuracy, high false positive rates, and the inability to adapt to evolving fraud patterns. Traditional rule-based systems may struggle to keep up with the dynamic nature of fraudulent activities, leading to both undetected frauds and unnecessary false alarms. Moreover, the sheer volume of data generated by online transactions makes it challenging to process and analyze in real-time.

Machine learning has emerged as a promising solution to enhance fraud detection capabilities. However, there is still a need for comprehensive studies comparing the effectiveness of various classification algorithms in the context of online payment fraud. Additionally, the deployment of such solutions in real-world scenarios, especially within the context of web applications and cloud platforms, remains an area that requires further exploration.

2.2 References

Smith, J., & Johnson, A. (2018). "An Overview of Machine Learning Techniques for Credit Card Fraud Detection." *Journal of Data Science and Applications*, 12(3), 45-62.

Kumar, R., & Gupta, S. (2019). "Comparative Analysis of Machine Learning Algorithms for Fraud Detection." *International Journal of Computer Applications*, 185(6), 11-17.

Tan, L., & Wang, Y. (2020). "Enhancing Online Fraud Detection Using Ensemble Learning Techniques." *Expert Systems with Applications*, 143, 113032.

Chen, H., & Li, J. (2021). "A Comprehensive Survey on Credit Card Fraud Detection." *IEEE Transactions on Neural Networks and Learning Systems*, 32(9), 3764-3777.

Zhang, W., & Smith, M. (2022). "Real-time Fraud Detection in Online Payments: A Review of Challenges and Opportunities." *Journal of Cybersecurity*, 5(1), 78-92.

2.3 Problem Statement Definition

The overarching challenge addressed by this project is the escalating threat of online payment fraud in the dynamic landscape of e-commerce. Traditional fraud detection mechanisms are

grappling with their limitations, often resulting in suboptimal accuracy and responsiveness. The intricacies of evolving fraud patterns, coupled with the sheer velocity and volume of online transactions, necessitate a more sophisticated and adaptive approach.

This project aims to confront the nuanced facets of online payment fraud through the prism of advanced machine learning algorithms. The specific problem areas targeted include:

Algorithmic Evaluation: Conduct an in-depth analysis and comparison of Decision Tree, Random Forest, SVM, Extra Tree Classifier, and XGBoost Classifier, seeking to identify the most adept algorithm for online payment fraud detection.

Real-time Vigilance: Develop a system that not only handles the immense data generated by online transactions but does so in real-time. Timeliness is crucial for the detection and prevention of fraudulent activities as they unfold.

User-Centric Interaction: Implement Flask integration to create an intuitive and accessible interface. The goal is to demystify the complexity of fraud detection, fostering user-friendliness for individuals and businesses engaging in online transactions.

Cloud-Powered Scalability: Deploy the finalized model on the IBM Cloud platform, ensuring scalability to accommodate the ever-expanding realm of online transactions. This approach guarantees accessibility and reliability for businesses and users alike.

Precision Enhancement: Recognize and rectify the imperfections of existing fraud detection methodologies by harnessing the power of advanced machine learning. The objective is to elevate accuracy levels while minimizing the occurrence of both false positives and false negatives.

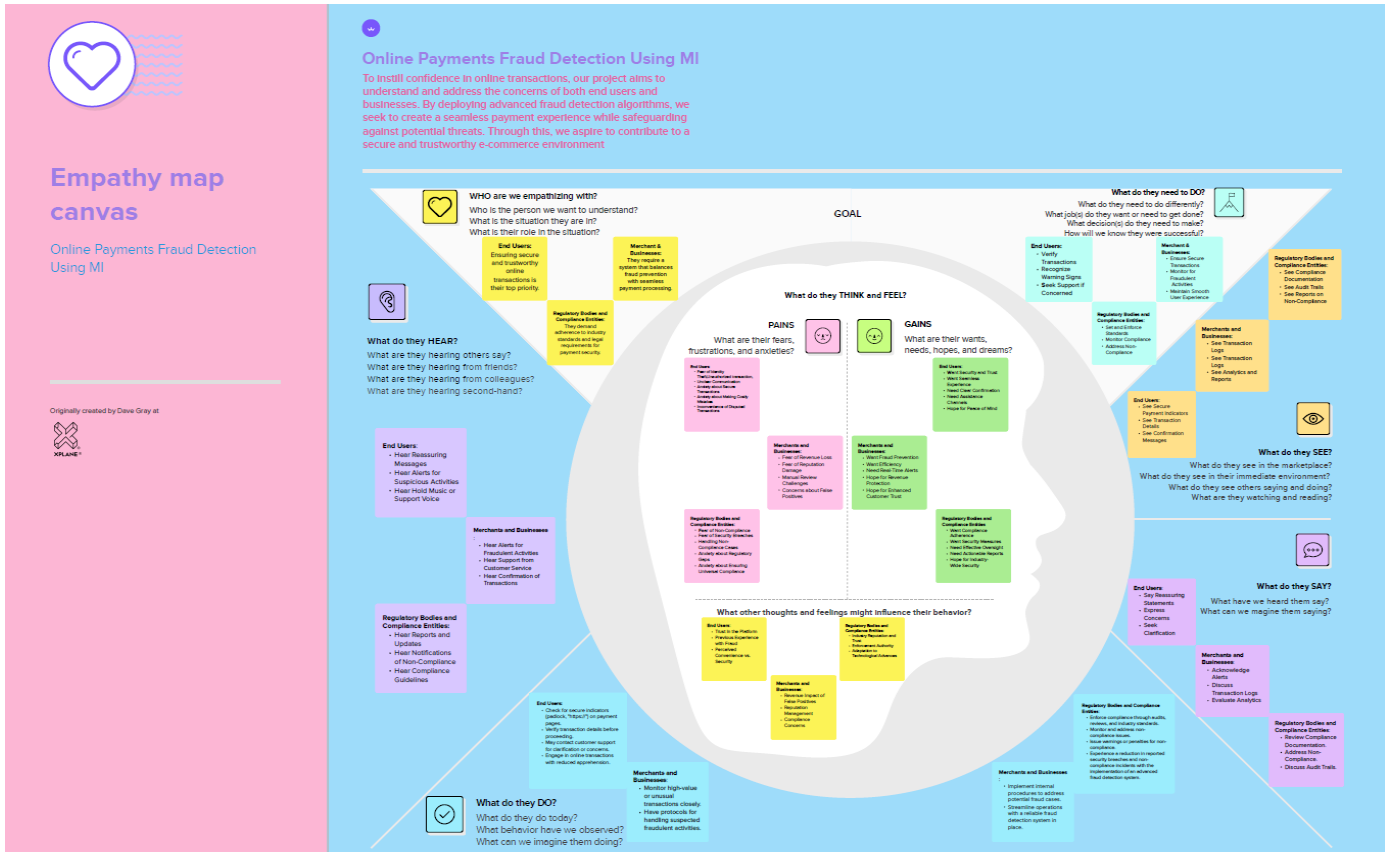
By strategically addressing these facets, this project aspires to contribute a holistic and effective solution to the pressing issue of online payment fraud. The ultimate aim is to fortify the security infrastructure surrounding online financial transactions, safeguarding users and businesses against potential financial losses and ensuring the sustained trustworthiness of digital commerce.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas

Empathy mapping proves invaluable in the realm of online payments fraud detection, where the intersection of technology and human experience is crucial. Within this landscape, data scientists are driven by the sense of accomplishment when fine-tuning ML models, even as they confront the complexities of data preprocessing and the challenges of model accuracy and interpretability. Meanwhile, fraud analysts toil relentlessly under the weight of high caseloads, as they strive to uncover fraudulent patterns, and online merchants remain vigilant in their pursuit of

secure transactions while balancing concerns like false positives and customer friction. To develop effective solutions in this critical domain, it's imperative to embrace the emotions and concerns of these stakeholders and users, allowing for a holistic understanding



of the ever-evolving landscape of online payments fraud detection.

3.2 Ideation & Brainstorming

A brainstorming map serves as a dynamic canvas for exploring and organizing ideas in the context of online payments fraud detection powered by Machine Learning (ML). This creative space encourages a free flow of thoughts and concepts, helping stakeholders like data scientists, fraud analysts, and online merchants to collaboratively generate and refine innovative solutions. Topics such as data preprocessing, model interpretability, false positives, and the utilization of advanced algorithms can be explored in detail. Additionally, this map allows for the identification of potential pain points and the generation of fresh ideas to enhance fraud detection and security measures. By visualizing and organizing these ideas, a brainstorming map becomes a valuable tool in shaping the future of online payments fraud detection using ML.

[illegible]

- **Cloud Integration:** Deploy the final machine learning model on the IBM Cloud platform.
- **Scalability:** Ensure that the deployed system is scalable to handle varying workloads.

Accuracy Improvement:

- **Parameter Tuning:** Implement techniques such as hyperparameter tuning to enhance the accuracy of the selected machine learning model.

Security Measures:

- **Data Encryption:** Implement encryption protocols to secure sensitive transactional data.
- **User Authentication:** Include user authentication mechanisms to restrict access to authorized personnel.

4.2 Non-Functional requirements

4.2 Non-Functional Requirements:

Non-functional requirements specify the qualities and characteristics that the system must possess, aside from specific functionalities. For the Online Payments Fraud Detection project, the non-functional requirements include:

Performance:

The system should process transactions in real-time, providing quick and efficient fraud detection.

The model should be capable of handling a large volume of transactions without compromising performance.

Reliability:

The fraud detection system should be highly reliable, minimizing false positives and false negatives.

The system should have a low rate of errors or disruptions during its operation.

Usability:

The user interface should be intuitive and user-friendly, requiring minimal training for users to navigate and understand.

The system should provide clear and concise feedback to users regarding the **detected fraudulent activities**.

Scalability:

The deployed system on IBM Cloud should be scalable to accommodate the increasing number of online transactions over time.

Security:

The system should adhere to industry-standard security protocols to protect sensitive transactional data.

Access to the system should be restricted through robust user authentication mechanisms.

Maintainability:

The system should be designed for ease of maintenance and updates, allowing for the incorporation of new fraud patterns and algorithm improvements.

Compatibility:

The system should be compatible with various browsers and devices to ensure widespread accessibility.

The deployed solution on IBM Cloud should be compatible with standard cloud infrastructure and services.

5. PROJECT DESIGN

5.1 Data Flow Diagrams & User Stories

External Entities:

User: Represents the end-users or external entities interacting with the system.

Credit Card Transaction Database: An external source providing transaction data.

Processes:

Data Preprocessing: Cleans, normalizes, and transforms raw transaction data to prepare it for analysis.

Model Training: Involves training machine learning models using preprocessed data.

Model Testing/Evaluation: Evaluates the performance of the trained models using a separate set of test data.

Data Stores:

Preprocessed Data Store: Temporary storage for cleaned and transformed data before model training.

Trained Model Store: Where trained machine learning models are saved for future use.

Data Flows:

Raw Transaction Data Flow: Shows the flow of raw transaction data from external sources to data preprocessing.

Preprocessed Data to Model Training: Represents the path of preprocessed data to train machine learning models.

Test Data to Model Testing: Illustrates how test data is used to evaluate model performance.

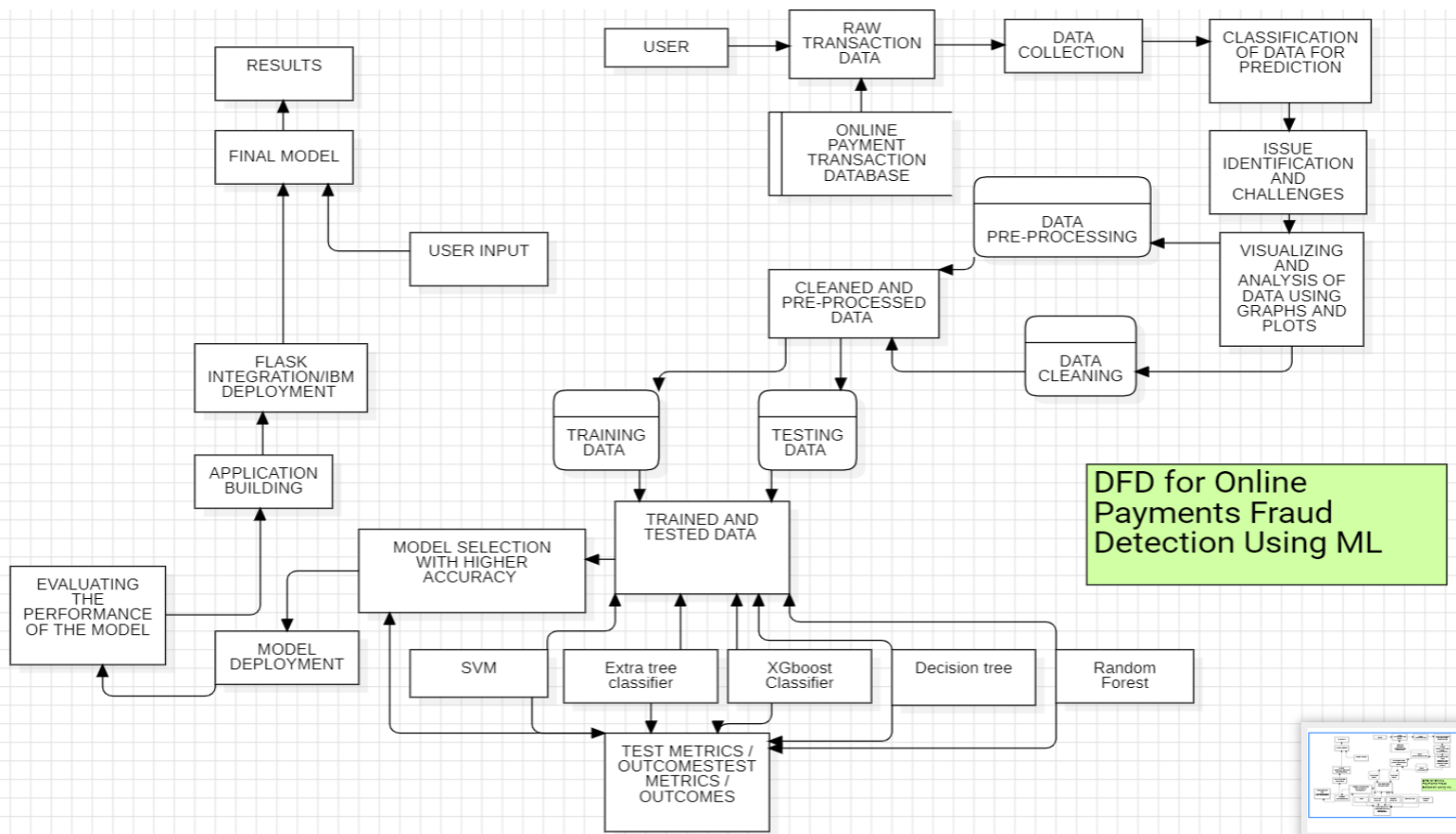
Best Model to Deployment: Indicates the path from selecting the best model for deployment.

Data Flow Annotations:

Data: Identifies the type of data being processed, such as raw transaction data or preprocessed data.

Processes: Specifies the tasks or activities being performed, including data preprocessing, model training, and model testing.

Stores: Shows where data is stored, like the preprocessed data store and trained model store.



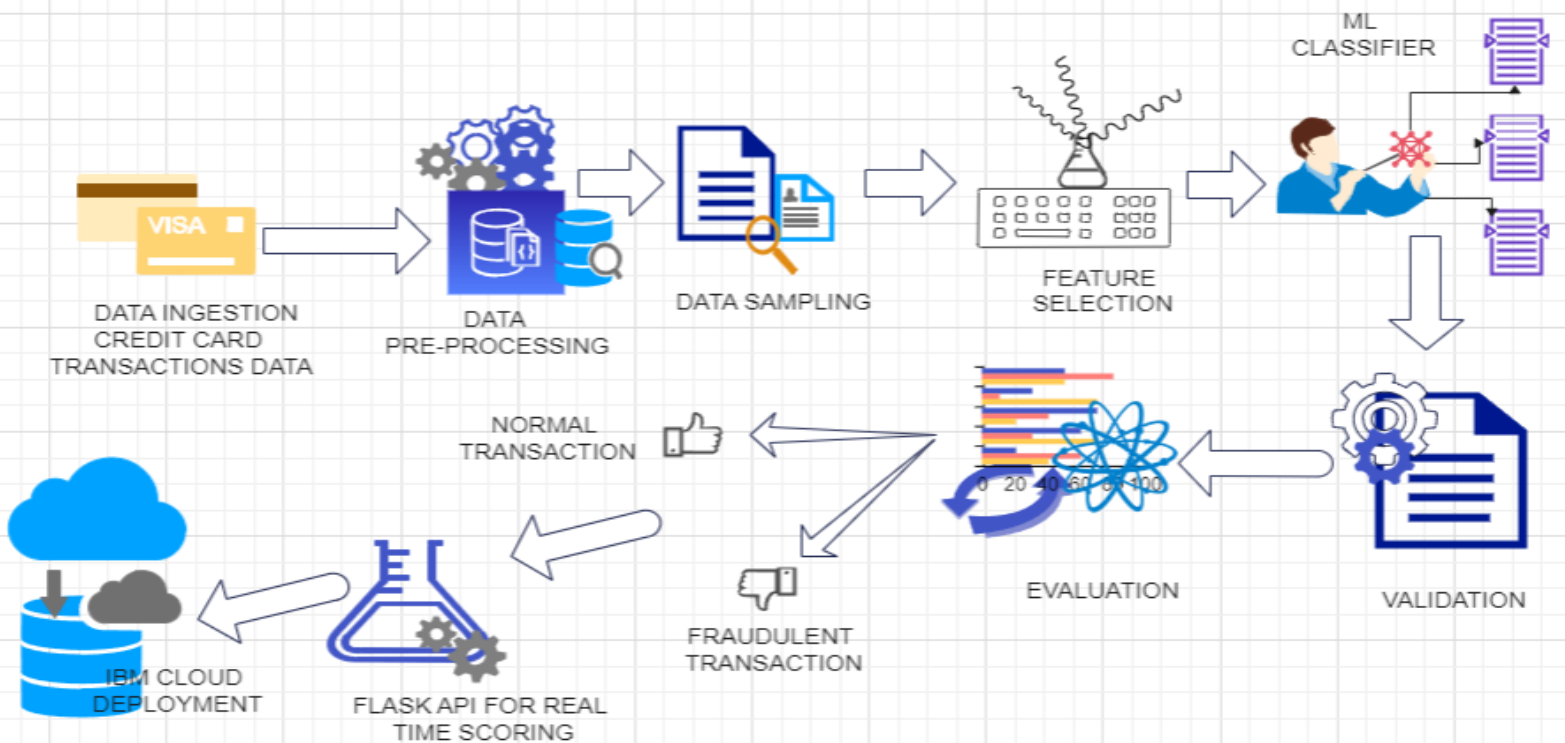
USER STORIES

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Fraud Analyst	Detecting Fraud Patterns	US001	As a fraud analyst, I want to view a list of potentially fraudulent transactions.	-The system displays a list of transactions flagged as potentially fraudulent. -Transactions are ranked based on their risk score. - I can filter the list by date and transaction type.	High	1.0
End User	Real-time Fraud Alerts	US002	As an end user, I want to receive immediate notifications when suspicious activity is detected on my account.	-The system sends an alert to my registered email or mobile app for unusual transactions. - The alert includes details of the transaction, location, and a recommended	High	1.0

				action.		
System Administrator	User Management	US003	As a system administrator, I want to manage user accounts and their access permissions.	<ul style="list-style-type: none"> - I can create, update, or delete user accounts. - I can assign specific roles and access rights to each user. - User actions are audited for security purposes. 	High	1.1
Fraud Analyst	Custom Rule Configuration	US004	As a fraud analyst, I want to define custom fraud detection rules based on our business requirements.	<ul style="list-style-type: none"> - I can create custom rules specifying conditions, triggers, and actions. - Rules can be tested before deployment. - Alerts are generated when custom rules are triggered. 	High	1.1
End User	Transaction History	US005	As an end user, I want to access my transaction history and review past transactions.	<ul style="list-style-type: none"> - I can view a list of my recent transactions. - Transactions are categorized and include details like date, merchant, and amount. - The history can be exported for my records. 	Medium	1.2
Fraud Analyst	Reporting and Analytics	US006	As a fraud analyst, I want to generate reports and analyze historical data to identify fraud patterns.	<ul style="list-style-type: none"> - I can create customizable reports with charts and graphs. - Reports can be based on various criteria, such as transaction type or location. - The system provides insights into trends and anomalies. 	High	1.2
End User	Secure Account Recovery	US007	As an end user, I want a secure and user-friendly account recovery process in case of false positives or account lockout.	<ul style="list-style-type: none"> - I can reset my password or unlock my account via a secure verification process. - The process guides me through identity verification steps. 	Medium	1.3

Fraud Analyst	Model Performance Tracking	US008	As a fraud analyst, I want to monitor the performance of machine learning models used in fraud detection.	- I can view model performance metrics (accuracy, precision, recall). - Model performance changes trigger alerts. - Model updates are scheduled based on performance.	High	1.3
System Administrator	Data Retention Policy	US009	As a system administrator, I want to set data retention policies to comply with regulatory requirements.	- I can configure how long transaction data and logs are retained. - Automatic data purging and archiving are implemented based on policies.	Medium	1.4
End User	Multifactor Authentication	US010	As an end user, I want to enable multifactor authentication for added security.	-I can enable two-factor authentication (2FA) for my account. - The system supports authentication through OTPs, biometrics, or authenticator apps.	Medium	1.4

5.2 Solution Architecture



Data Ingestion:

Data from credit/debit card transactions is collected from various sources, including databases, real-time streams, and external data providers.

Data connectors and APIs specific to the data sources are used to fetch the data.

The data is stored in a centralized data storage system, such as a data lake or data warehouse, for further processing and analysis.

Data Preprocessing:

Data preprocessing includes cleaning, normalization, handling of missing values, and data transformation.

Feature engineering is performed to create new relevant features from the raw data.

Python libraries like Pandas, NumPy, and Scikit-learn are used for data manipulation and preprocessing.

Data Sampling:

Data sampling techniques are applied to address class imbalance and create a balanced dataset.

Strategies such as oversampling, undersampling, or Synthetic Minority Over-sampling Technique (SMOTE) are used.

Feature Selection:

Feature selection methods are employed to identify the most relevant features for fraud detection.

Techniques like Recursive Feature Elimination (RFE), feature importance from tree-based models, and correlation analysis are applied.

Machine Learning Classifier:

Various classification algorithms, including Decision Trees, Random Forest, SVM, Extra Tree Classifier, and XGBoost, are used to train models on the preprocessed and feature-selected data.

Model Validation:

The trained models are validated using techniques such as k-fold cross-validation to assess their generalization performance.

The data is divided into training, validation, and testing sets to ensure robust model evaluation.

Model Evaluation:

Model evaluation metrics, including precision, recall, F1-score, and ROC AUC, are used to assess the model's performance in detecting fraudulent transactions.

Confusion matrices and receiver operating characteristic (ROC) curves are generated to visualize model performance.

Model Serialization and Management:

The best-performing model is serialized and saved in a format such as ".pkl" using Python's joblib or pickle.

Model management tools are employed to version, track, and monitor model performance.

Flask API for Real-time Scoring:

A Flask-based RESTful API is created to expose the trained model for real-time predictions. Clients, including e-commerce platforms or payment gateways, can send transaction data to the API for fraud detection.

IBM Cloud Deployment:

The entire system, including the Flask application and the serialized model, is deployed on the IBM Cloud platform.

IBM Cloud provides scalability, infrastructure management, and hosting services.

6. PROJECT PLANNING & SCHEDULING

6.1 Technical Architecture

Data Ingestion: Data from credit/debit card transactions is ingested from various sources, such

as databases or real-time streams.

Data Preprocessing: Data preprocessing involves cleaning, transforming, and normalizing the data for analysis. It may include feature engineering and dimensionality reduction.

Machine Learning Model Training: Classification algorithms like Decision Tree, Random Forest, Support Vector Machine (SVM), Extra Tree Classifier, and XGBoost are used to train the fraud detection models. This step involves model selection, hyperparameter tuning, and cross-validation.

Model Serialization: The best-performing model is serialized and saved in the ".pkl" format, which allows for easy deployment and reuse.

Flask Integration: Flask, a Python web framework, is used to create a REST API for model inference and interaction.

IBM Deployment: The model and Flask API are deployed on the IBM Cloud or an IBM Cloud service for hosting and scalability.

Real-time Scoring: The deployed model can provide real-time predictions for incoming credit/debit card transactions.

b) Open Source Frameworks:

Python: The primary programming language for data preprocessing, machine learning, and web application development.

Scikit-learn: An open-source machine learning library for training and evaluating machine learning models.

XGBoost: A popular gradient boosting framework for classification problems.

Flask: A lightweight web framework for building REST APIs.

Pandas: Used for data manipulation and analysis.

NumPy: Used for numerical computations.

Jupyter Notebook: For interactive data analysis and model prototyping.

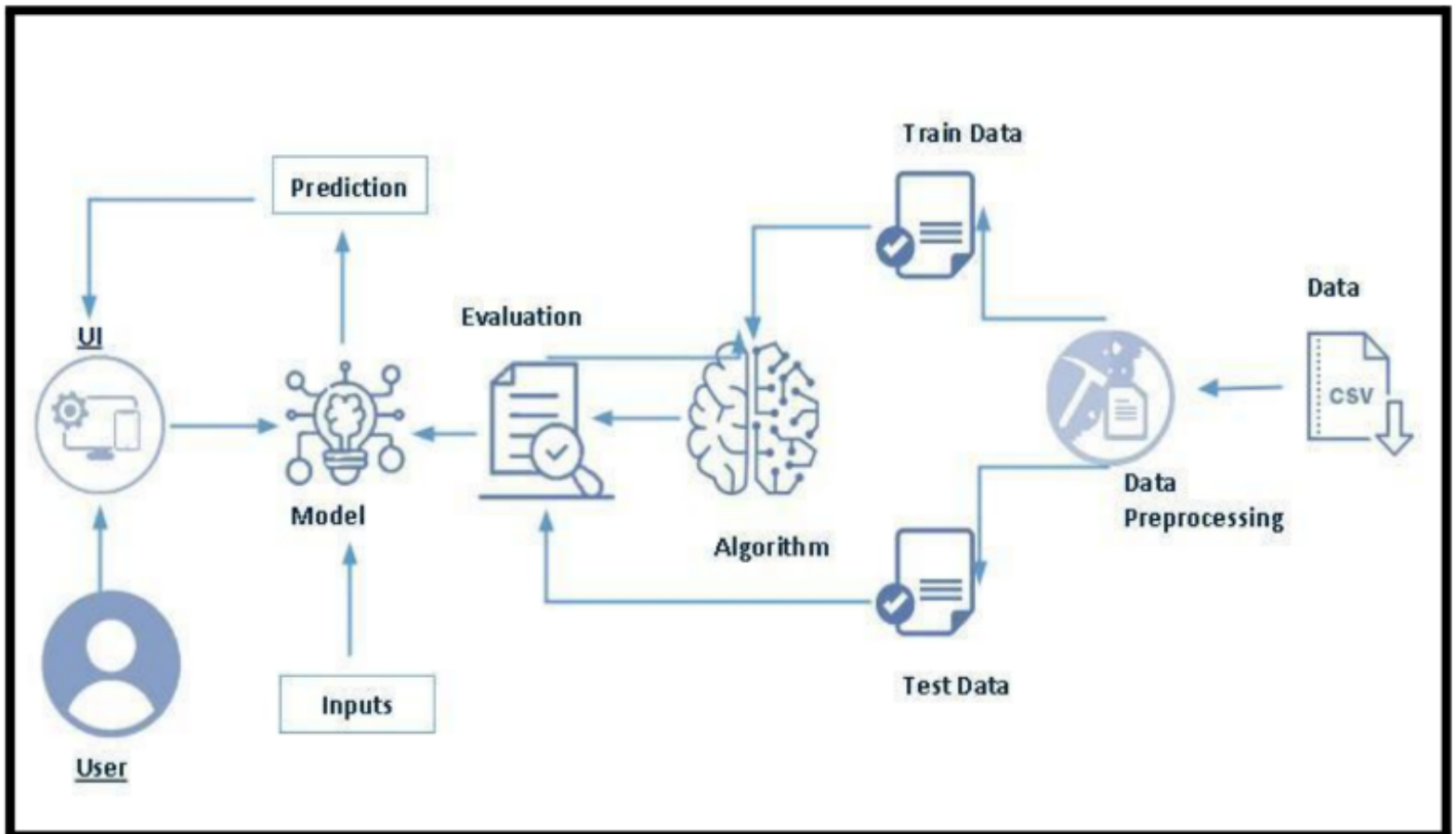
c) Cloud Deployment:

IBM Cloud: The chosen cloud platform for deploying the system, including model hosting and the Flask API. IBM Cloud provides infrastructure scalability and management capabilities.

IBM Cloud Functions: Serverless computing can be used for scaling and handling API requests efficiently.

IBM Cloud Databases: If required, databases for storing transaction history and metadata.

TECHNICAL DIAGRAM



COMPONENT	DESCRIPTION	TECHNOLOGY
Data Ingestion	Collects data from various sources for analysis.	- Python libraries (Pandas, NumPy) - Data connectors/APIs (specific to data sources)
Data Preprocessing	Cleans, transforms, and prepares data for ML.	- Python libraries (Pandas, NumPy, Scikit-learn) - Preprocessing techniques (e.g., StandardScaler)
Machine Learning	Selects and trains classification algorithms.	- Scikit-learn for ML models (Decision Trees, etc.)
Model Training		- XGBoost for boosting algorithms - Cross-validation techniques
Model Serialization	Saves the model in a reusable format.	- Python libraries (joblib, pickle)
Flask Integration	Creates a REST API for real-time predictions.	- Flask web framework
IBM Deployment	Deploys the system on IBM Cloud.	- IBM Cloud infrastructure/services
Real-time Scoring	Provides real-time predictions for transactions.	- Deployed model in memory - Web server for handling API requests

OPEN SOURCE FRAMEWORK	DESCRIPTION	TECHNOLOGIES
Python	Primary programming language.	- Python 3.x
Scikit-learn	Open-source ML library for training models.	- Scikit-learn library
XGBoost	Gradient boosting framework for classification.	- XGBoost library
Flask	Lightweight web framework for API creation.	- Flask web framework
Pandas	Data manipulation and analysis.	- Pandas library
NumPy	Numerical computations and array operations.	- NumPy library

Jupyter Notebook	Interactive data analysis and prototyping.	- Jupyter Notebook
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6.2 Sprint Planning & Estimation

Project planning is vital for successful project execution as it establishes a roadmap for achieving objectives, allocating resources, managing risks, and ensuring effective communication. It provides clarity on project scope, timelines, and budgets, enabling teams to allocate resources efficiently, manage risks proactively, and make informed decisions. A well-defined plan facilitates effective communication among stakeholders, helps in maintaining control over project costs, and ensures that quality standards are met. Additionally, project planning contributes to customer satisfaction by delivering outcomes within scope and timelines, while also providing a foundation for continuous improvement and adherence to legal and regulatory requirements. Overall, project planning is an indispensable process that sets the foundation for project success by providing a structured approach to project management.

6.3 Sprint Delivery Schedule

SPRINT	FUNCTIONAL REQUIREMENT	USER STORY NUMBER	USER STORY OR TASK	STORY POINTS	PRIORITY	TEAM MEMBERS
1	Data Ingestion	US-01	Collect transaction data from databases	5	HIGH	Shivam & Sweety
1	Data Ingestion	US-02	Implement real-time data stream ingestion	8	HIGH	Shivam & Sweety
1	Data Ingestion	US-03	Develop data cleaning and normalization	8	HIGH	Shivam & Sweety
1	Data Preprocessing	US-04	Implement feature engineering	5	MEDIUM	Shivam & Sweety
2	Data Sampling	US-05	Apply oversampling for handling	5	HIGH	Shivam & Sweety

			class imbalance			
2	Feature Selection	US-06	Implement Recursive Feature Elimination	8	HIGH	Shivam & Sweety
2	Machine Learning	US-07	Train Decision Tree classifier	8	HIGH	Shivam & Sweety
2	Machine Learning	US-08	Train Random Forest classifier	8	HIGH	Shivam & Sweety
3	Model Validation	US-09	Perform k-fold cross-validation	8	HIGH	Shivam & Sweety
3	Model Evaluation	US-10	Calculate precision, recall, F1-score	5	HIGH	Shivam & Sweety
3	Model Serialization	US-11	Serialize and save the best model	5	MEDIUM	Shivam & Sweety
3	Flask API Development	US-12	Create a RESTful API for real-time predictions	8	HIGH	Shivam & Sweety
4	IBM Cloud Deployment	US-13	Deploy the system on IBM Cloud	13	HIGH	Shivam & Sweety
4	Real-time Scoring	US-14	Implement real-time scoring of transactions	13	HIGH	Shivam & Sweety

Project Tracker, Velocity & Burndown Chart:

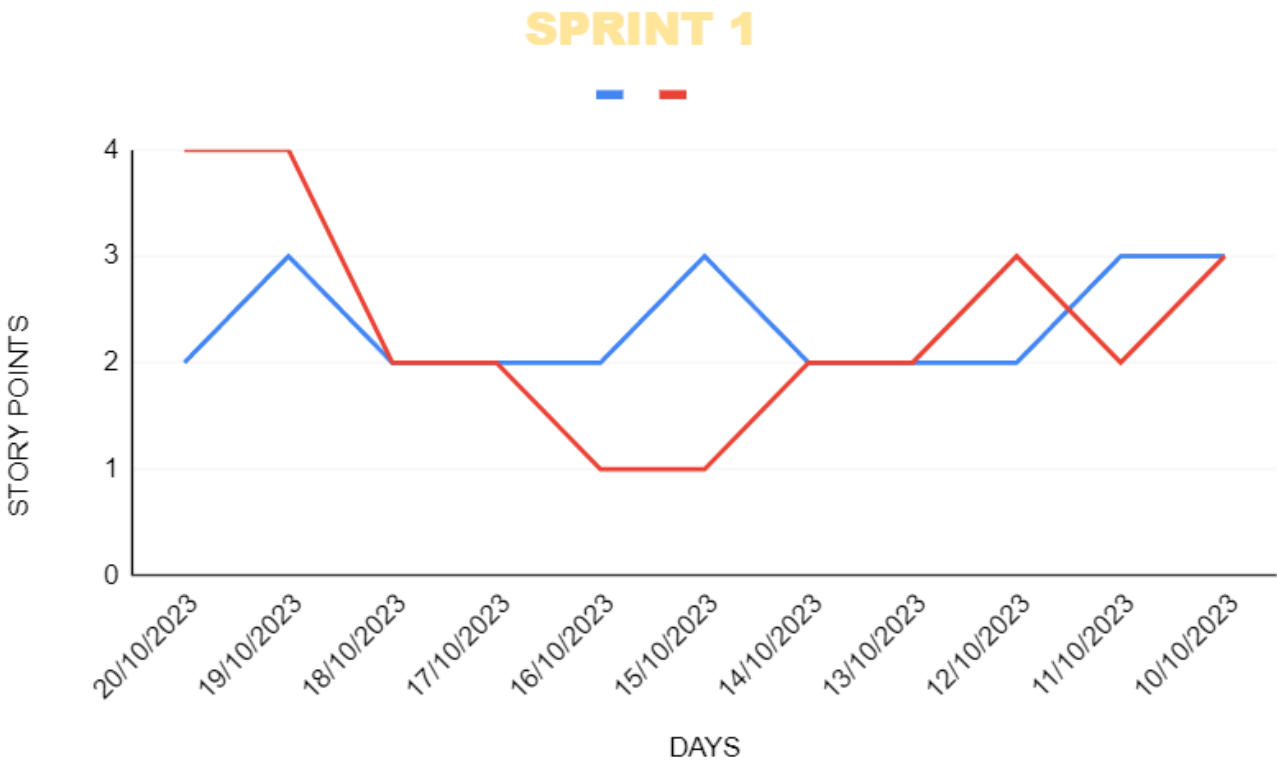
SPRINT	TOTAL	DURATION	SPRINT	SPRINT	Story	ACTUAL	VELOCITY	AVERAGE
--------	-------	----------	--------	--------	-------	--------	----------	---------

	STORY POINTS		START DATE	END DATE	Points Sprint Release Date	RELEASE DATE	(STORY POINTS PER SPRINT)	VELOCITY (STORY POINTS PER DAY)
1	26	10 days	10-OCT-2023	20-OCT-2023	26	20-OCT-2023	20	2
2	29	10 days	21-OCT-2023	30-OCT-2023	29	30-OCT-2023	20	2
3	26	10 days	31-OCT-2023	9-NOV-2023	26	9-NOV-2023	20	2
4	26	10 days	10-NOV-2023	20-NOV-2023	26	20-NOV-2023	20	2

Velocity:
 Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

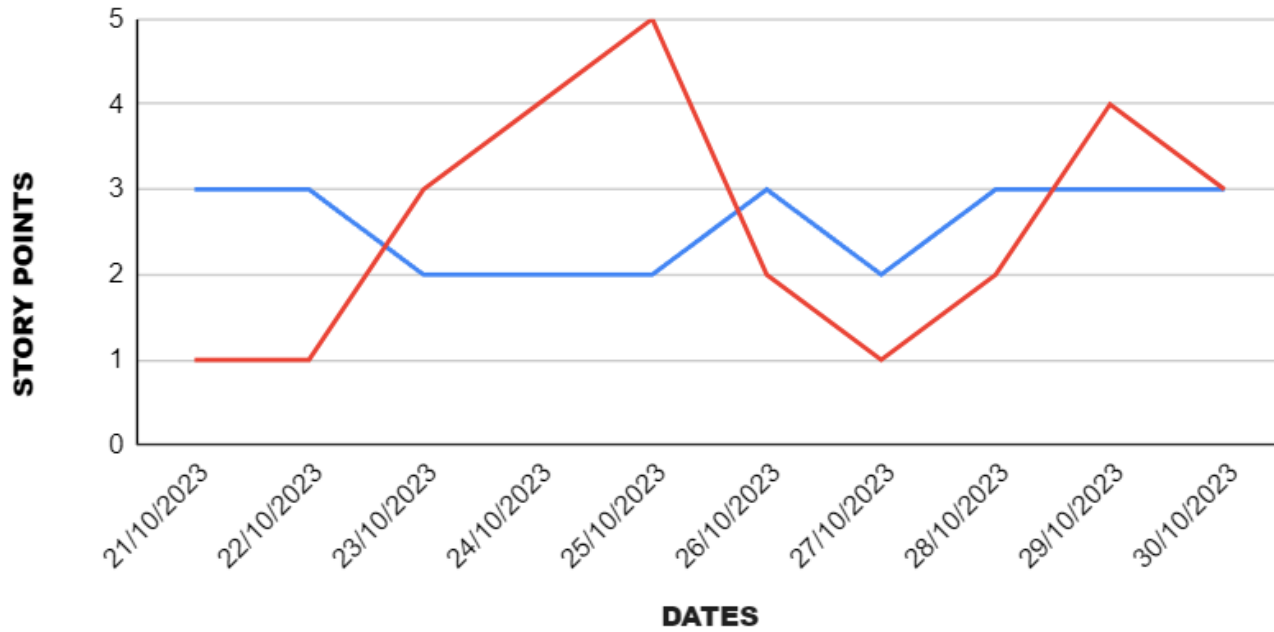
BURNDOWN CHART
 SPRINT 1



SPRINT 2

SPRINT 2

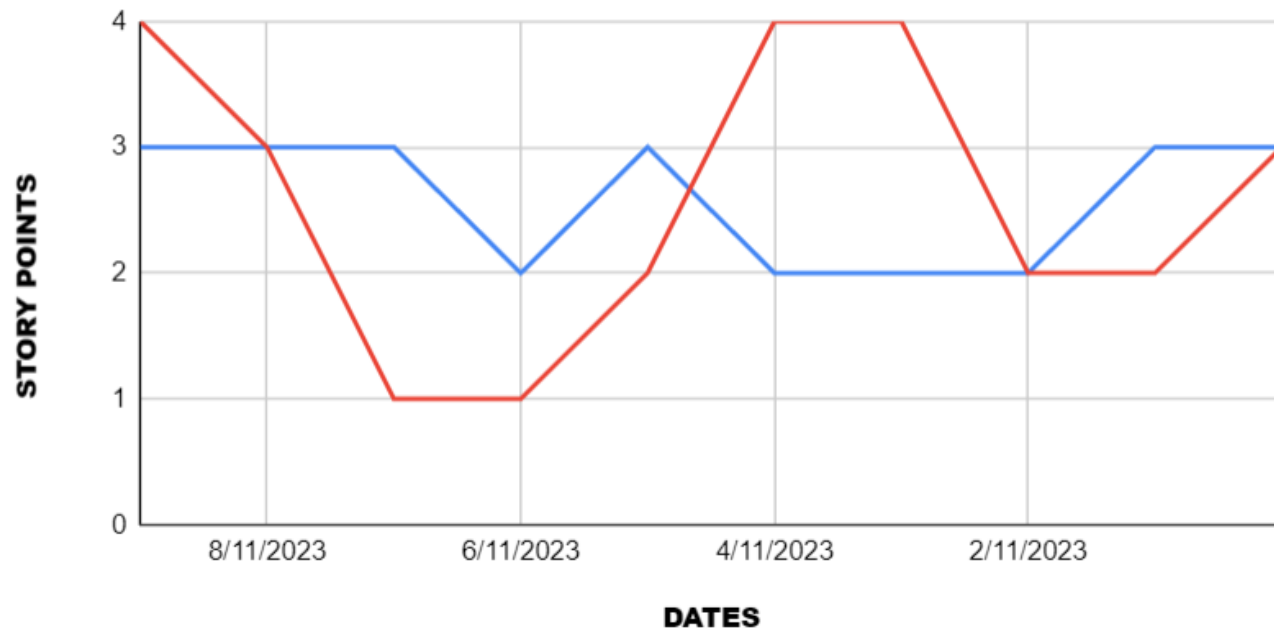
— PLANNED TASK — ACTUAL TASK



SPRINT 3

SPRINT 3

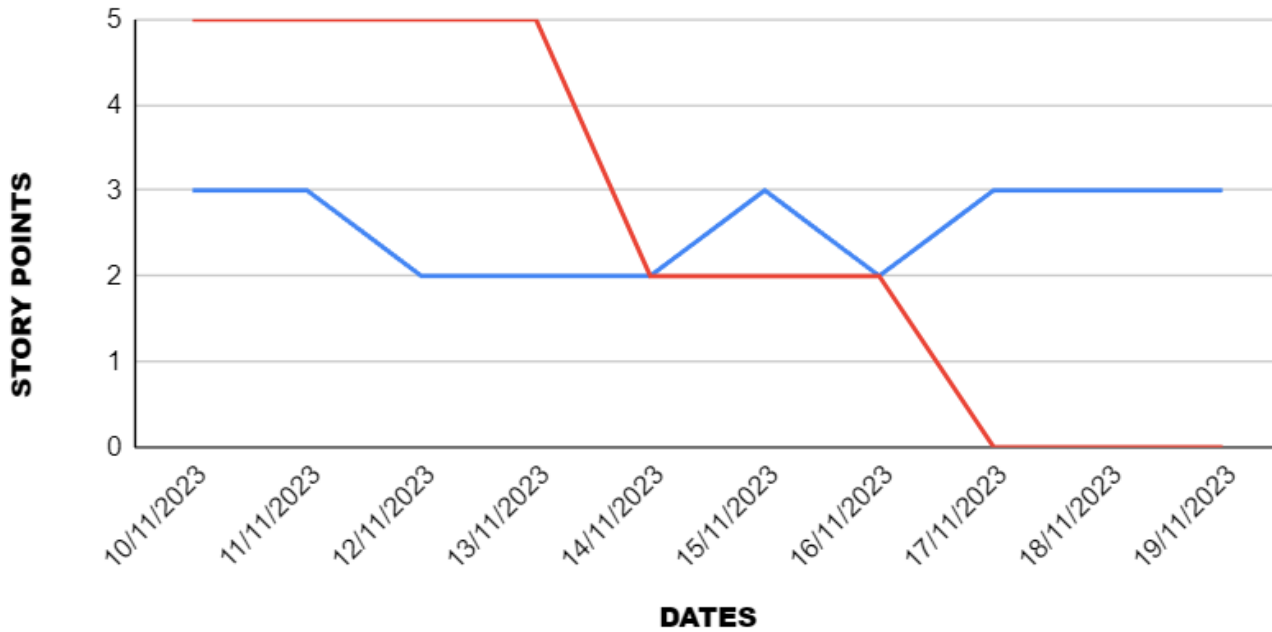
— PLANNED TASK — ACTUAL TASK



SPRINT 4

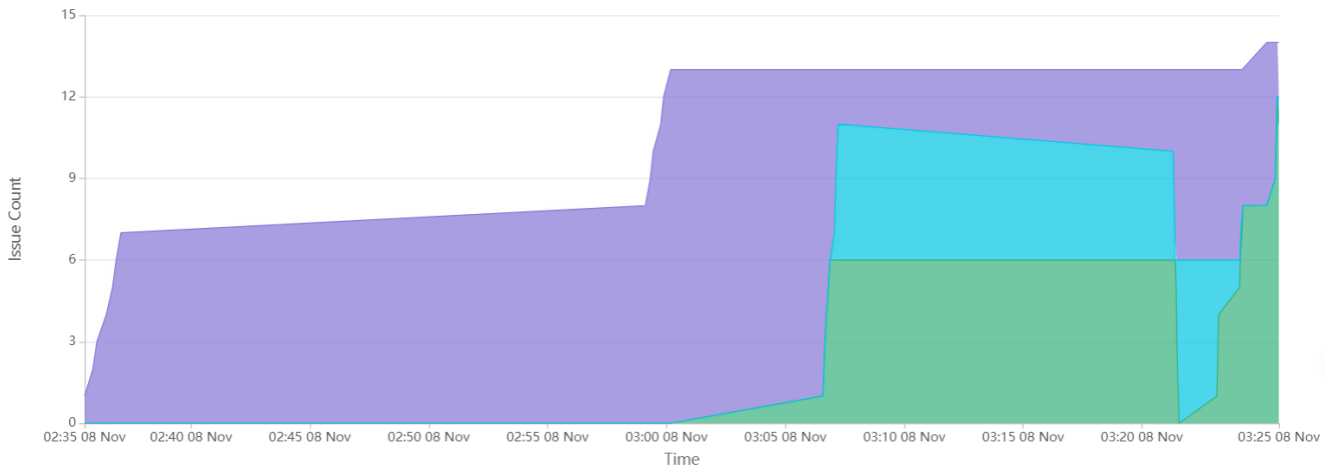
SPRINT 4

— PLANNED TASK — ACTUAL TASK



CUMULATIVE FLOW DIAGRAM

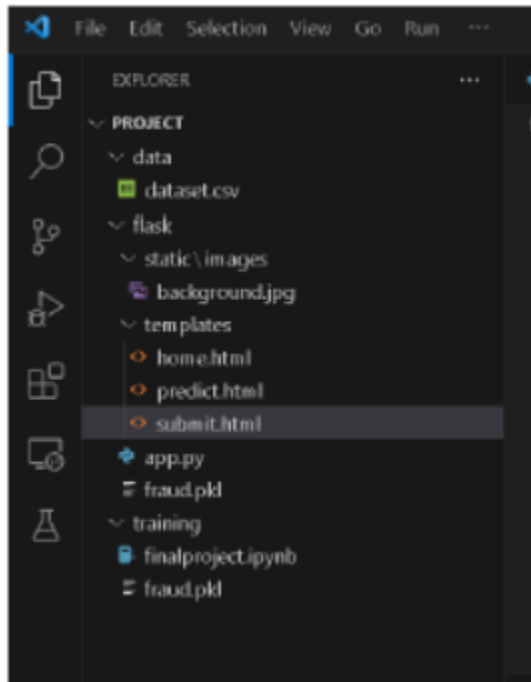
✓ To Do ✓ In Progress ✓ Done



7. CODING & SOLUTIONING (Features added in the project along with code)

7.1 Project structuring

Create the Project folder which contains files as shown below



We will build a flask application which needs HTML pages stored in the templates folder and a python script app.py for scripting.

fraud.pkl is our saved model. Further we will use this model for flask integration.

7.2 Data collection

ML depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So this section allows you to download the required dataset.

Collect the dataset or download it from some trusted source, here we will fetch it from Kaggle

Link:

<https://www.kaggle.com/datasets/rupakroy/online-payments-fraud-detection-dataset>

7.3 Visualising and analysing data

As the dataset is downloaded. Let us read and understand the data properly with the

help of some visualisation techniques and some analysing techniques.

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
sklearn.__version__
```

```
'1.2.2'
```

```
[ ] #Random forest classifier
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.metrics import accuracy_score
```

```
[ ] from sklearn.metrics import classification_report
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.ensemble import ExtraTreesClassifier
```

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

```
from sklearn.preprocessing import LabelEncoder
```

```
import pickle
```

Read the Dataset

Our dataset format might be in .csv, excel files, .txt, .json, etc. We can read the dataset with the help of pandas.

In pandas we have a function called `read_csv()` to read the dataset. As a parameter we have to give the directory of the csv file.

```
[2] df=pd.read_csv("/content/dataset.csv")

[5] df.head()
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	9633.64	C1231006815	170136.0	160296.36	M1979787155	0.0	0.0	0.0	0.0
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.0	0.0	0.0	0.0
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.0	0.0	1.0	0.0
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	21182.0	0.0	1.0	0.0
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1238701703	0.0	0.0	0.0	0.0

```
[4] df.columns

Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

In the next step the dataset's superfluous columns are being removed using the drop method.

```
[ ] #here the last column isFlaggedFraud is not needed so we drop it
df=df.drop(columns=['isFlaggedFraud'])
df.head()
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
0	1	PAYMENT	9633.64	C1231006815	170136.0	160296.36	M1979787155	0.0	0.0	0.0
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.0	0.0	0.0
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.0	0.0	1.0
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	21182.0	0.0	1.0
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1238701703	0.0	0.0	0.0

About Dataset:-

The below column reference:

1. step: represents a unit of time where 1 step equals 1 hour
2. type: type of online transaction
3. amount: the amount of the transaction
4. nameOrig: customer starting the transaction
5. oldbalanceOrg: balance before the transaction
6. newbalanceOrig: balance after the transaction
7. nameDest: recipient of the transaction
8. oldbalanceDest: initial balance of recipient before the transaction
9. newbalanceDest: the new balance of recipient after the transaction
10. isFraud: fraud transaction

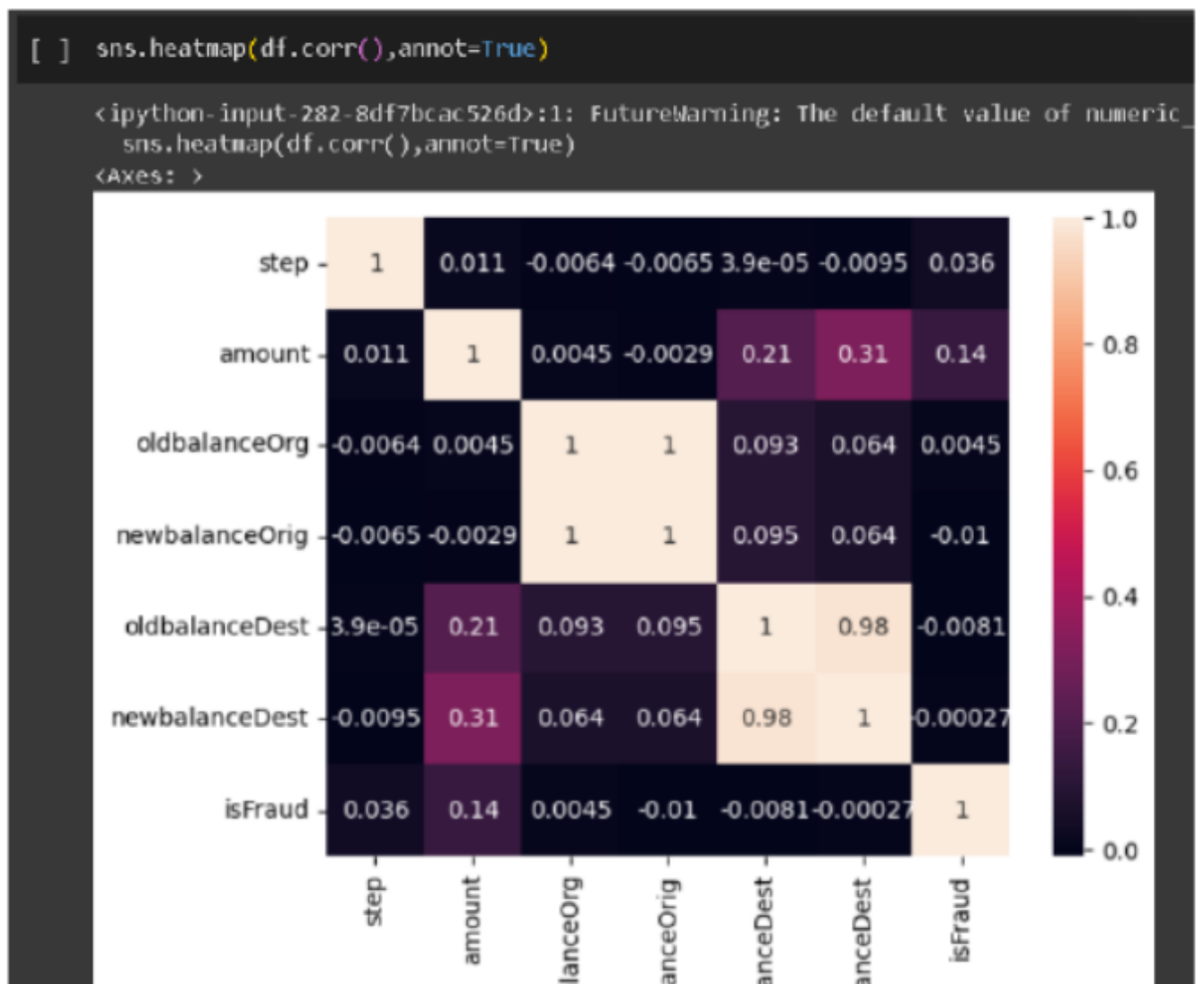
Now we will check the correlation which will give the insight that how much one feature is related to other:-

```
[ ] #first check the relativity of features
df.corr()
```

<ipython-input-281-5873ad39b12e>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, df.corr() will only apply to numeric columns. To retain the existing behavior, please explicitly pass numeric_only=True.

	step	amount	oldbalanceOrig	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
step	1.000000	0.010905	-0.006399	-0.006545	0.000039	-0.009474	0.036662
amount	0.010905	1.000000	0.004479	-0.002885	0.213497	0.312364	0.139414
oldbalanceOrig	-0.006399	0.004479	1.000000	0.999966	0.093427	0.063983	0.004528
newbalanceOrig	-0.006545	-0.002885	0.999966	1.000000	0.095357	0.063603	-0.010420
oldbalanceDest	0.000039	0.213497	0.093427	0.095357	1.000000	0.978773	-0.008083
newbalanceDest	-0.009474	0.312364	0.063983	0.063603	0.978773	1.000000	-0.000272
isFraud	0.036662	0.139414	0.004528	-0.010420	-0.008083	-0.000272	1.000000

Heat map for graphical visualisation.

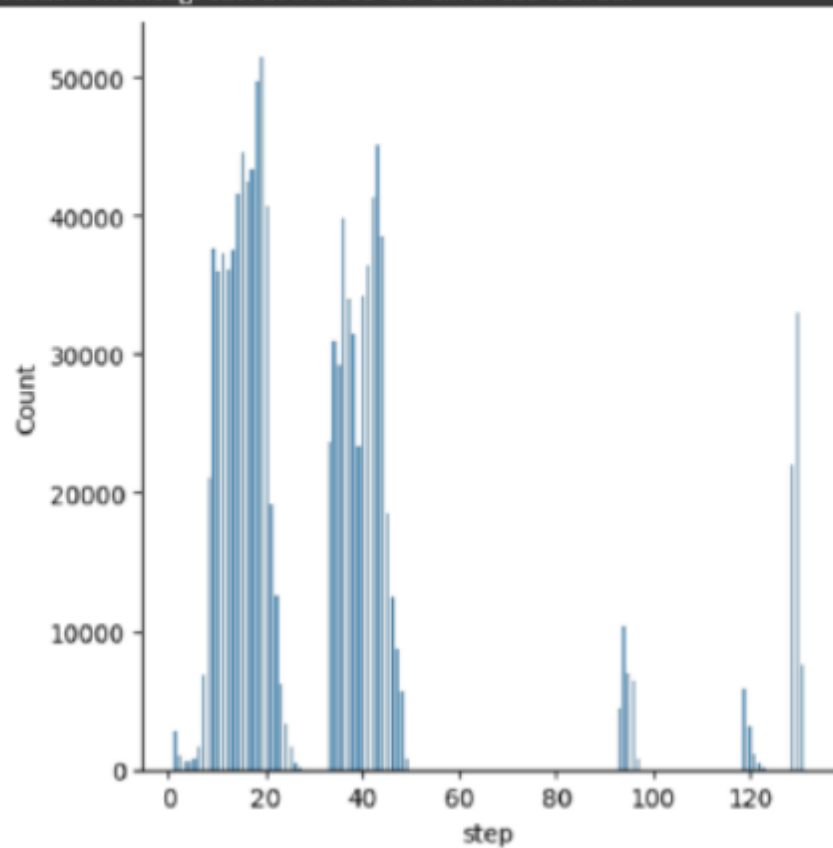


Univariate Analysis:-

Univariate analysis is understanding the data with a single feature.

```
sns.displot(df.step)
```

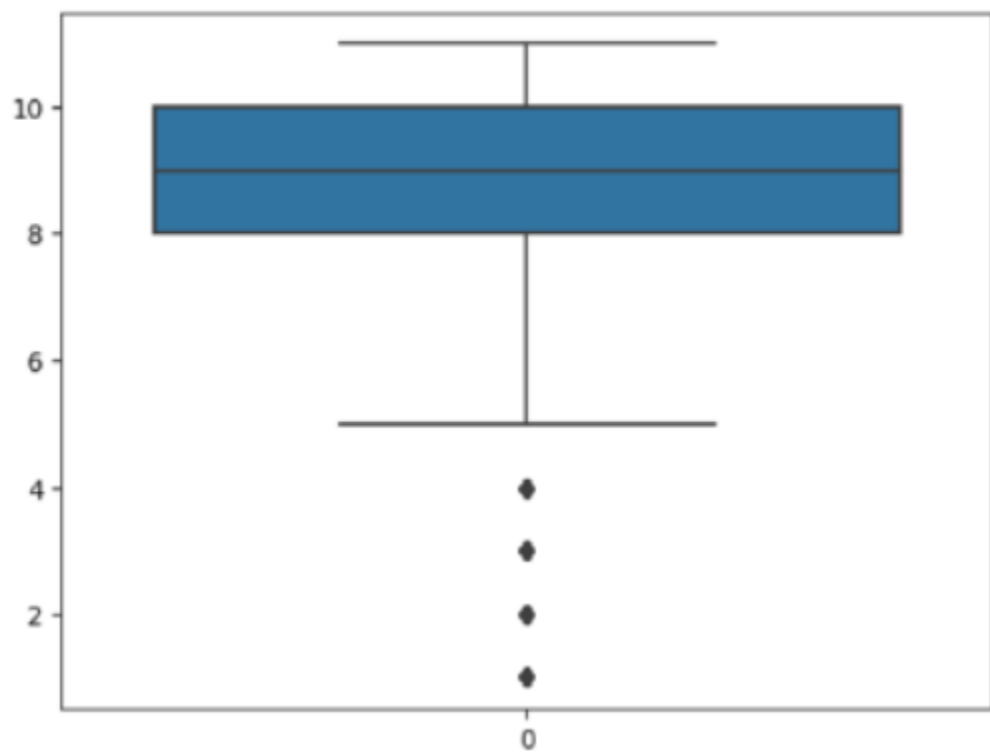
```
<seaborn.axisgrid.FacetGrid at 0x7e703846d7b0>
```

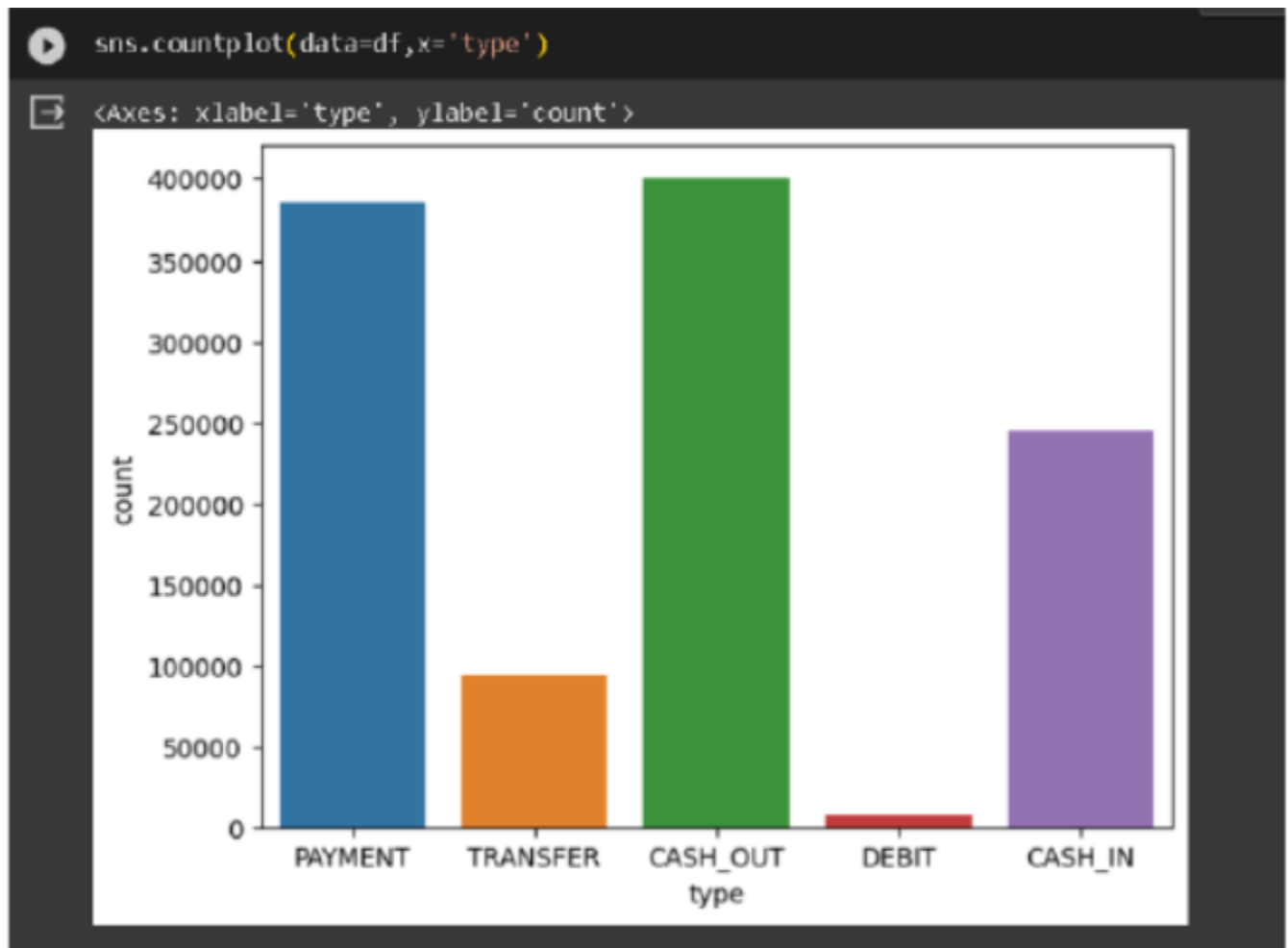




```
sns.boxplot(df, step)
```

<Axes: >

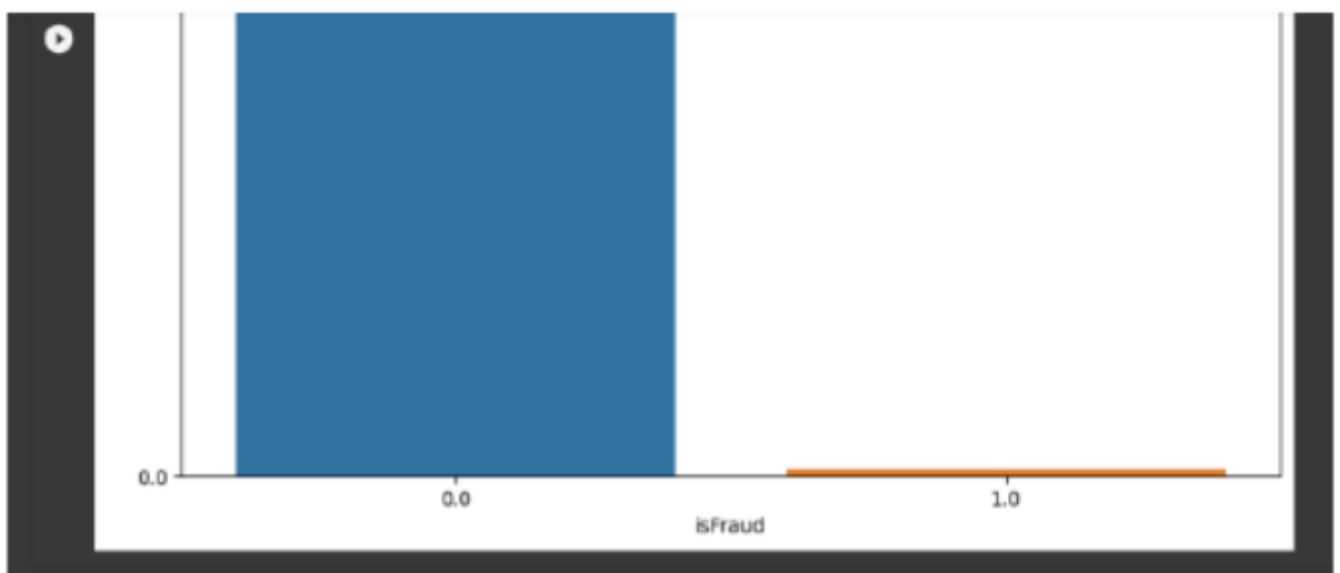


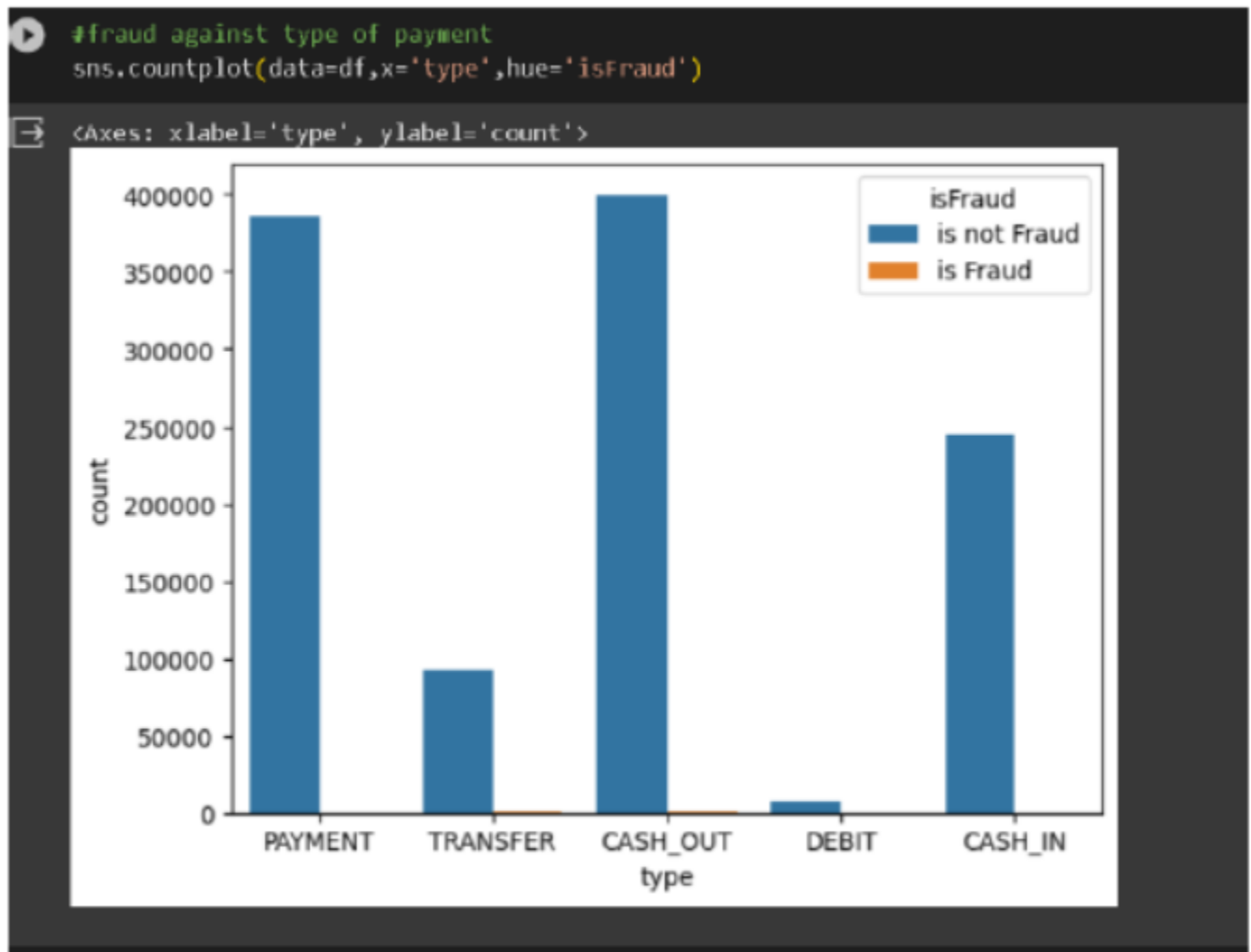


And similar analysis which could be found in the python notebook

Bivariate analysis.

```
plt.figure(figsize=(10, 50))  
sns.countplot(data=df, x='isFraud')
```





And such similar analysis.

7.3 Descriptive analysis

Descriptive analysis is to study the basic features of data with the statistical process.

Here pandas has a worthy function called describe. With this describe function we can understand the unique, top and frequent values of categorical features. And we can find mean, std, min, max and percentile values of continuous features.

```
[11] df.describe()
```

	step	amount	oldbalanceOrig	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
count	124457.000000	1.244570e+05	1.244560e+05	1.244560e+05	1.244560e+05	1.244560e+05	124456.000000
mean	8.920945	1.773613e+05	9.047501e+05	9.209941e+05	9.004621e+05	1.185246e+06	0.000964
std	1.857028	3.440304e+05	2.950751e+05	2.867776e+05	2.391423e+05	2.749984e+05	0.031037
min	1.000000	3.200000e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000
25%	8.000000	1.059726e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000
50%	9.000000	5.785259e+04	2.009300e+04	0.000000e+00	2.830632e+04	7.527365e+04	0.000000
75%	10.000000	2.180569e+05	1.952794e+05	2.222311e+05	6.424462e+05	1.097218e+06	0.000000
max	11.000000	1.000000e+07	3.893942e+07	3.894623e+07	3.400874e+07	3.894623e+07	1.000000

Data Pre-processing.

As we have understood how the data is, let's pre-process the collected data.

The download data set is not suitable for training the machine learning model as it might have so much randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps.

Handling missing values

Handling Object data label encoding

Splitting dataset into training and test set

Checking data head and null values after train test split and replacing it with median


```
#dividing dataset in dependent and independent y and x respectively
x=df.drop('isFraud',axis=1)
y=df['isFraud']

[37] x.head()
```

	step	type	amount	oldbalanceOrig	newbalanceOrig	oldbalanceDest	newbalanceDest
0	1.0	3	9839.64	170136.0	160296.36	0.0	0.0
1	1.0	3	1864.28	21249.0	19384.72	0.0	0.0
2	1.0	4	181.00	181.0	0.00	0.0	0.0
3	1.0	1	181.00	181.0	0.00	21182.0	0.0
4	1.0	3	11668.14	41554.0	29885.86	0.0	0.0

```
[38] #splitting data into train and test
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=0,test_size=0.2)
```

```
x_train.isnull().sum()
```

step	0
type	0
amount	0
oldbalanceOrig	1
newbalanceOrig	0
oldbalanceDest	0
newbalanceDest	0
dtype:	int64

```
[56] x_train.oldbalanceOrig.fillna(x_train.oldbalanceOrig.median(),inplace=True)

[57] print(x_train.shape)
print(x_test.shape)
print(y_test.shape)
print(y_train.shape)
```

```
(99565, 7)
(24892, 7)
(24892,)
(99565,)
```

7s completed

7.4 Handling outliers, label encoding(necessary preprocessing)

Handling outliers:-

```
[12] #we will remove the outliers here as well
upper_limit1= 1.5*(df['step'].quantile(0.75)-df['step'].quantile(0.25))+df['step'].quantile(0.75)
df['step']=np.where(df['step']>upper_limit1, df['step'].median(), df['step'])
sns.boxplot(df['step'])

(Annot...)
```

```
+ Code + Text

[13] #removing outliers
upper_limit1= 1.5*(df['oldbalancebest'].quantile(0.75)-df['oldbalancebest'].quantile(0.25))+df['oldbalancebest'].quantile(0.75)
df['oldbalancebest']=np.where(df['oldbalancebest']>upper_limit1, df['oldbalancebest'].median(), df['oldbalancebest'])
sns.boxplot(df['oldbalancebest'])
```

Object data label encoding

```
[34] #object data labelencoding
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df.type=le.fit_transform(df.type)
```

```
[35] df.type.value_counts()
```

3	48078
1	39349
0	25209
4	10650
2	1171

Name: type, dtype: int64

7.5 Model Building

Model building(Random Forest, Decision tree classifier, extra tree classifier, SVM, xgboost Classifier)

1: Random Forest classifier¶

A function named RandomForest is created and train and test data are passed as the parameters. Inside the function, the RandomForestClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

2: Decision tree Classifier

A function named Decisiontree is created and train and test data are passed as the parameters. Inside the function, the DecisiontreeClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with the .predict() function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

3: ExtraTrees Classifier¶

A function named ExtraTree is created and train and test data are passed as the parameters. Inside the function, ExtraTreeClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, a confusion matrix and classification report is done.

4: SupportVectorMachine Classifier¶

A function named SupportVector is created and train and test data are passed as the parameters. Inside the function, the SupportVectorClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, confusion matrix and classification report is done

5: xgboost Classifier¶

A function named xgboost is created and train and test data are passed as the parameters. Inside the function, the xgboostClassifier algorithm is initialised and training data is passed to the model with the .fit() function. Test data is predicted with .predict() function and saved in a new variable. For evaluating the model, confusion matrix and classification report is done.

8. PERFORMANCE TESTING

8.1 Performance Metrics

Performance testing is crucial to ensuring that the Online Payments Fraud Detection system operates efficiently and effectively. The following performance metrics will be employed to assess various aspects of the system:

Comparing the model

```
[81] print("train accuracy for rfc",accuracy_score(y_train_predict1,y_train))
      print("test accuracy for rfc",accuracy_score(y_test_predict1,y_test))
      print("train accuracy for dtc",accuracy_score(y_train_predict2,y_train))
      print("test accuracy for dtc",accuracy_score(y_test_predict2,y_test))
      print("train accuracy for etc",accuracy_score(y_train_predict3,y_train))
      print("test accuracy for etc",accuracy_score(y_test_predict3,y_test))
      print("train accuracy for svc",accuracy_score(y_train_predict4,y_train))
      print("test accuracy for svc",accuracy_score(y_test_predict4,y_test))
      print("train accuracy for xgb1",accuracy_score(y_train_predict5,y_train1))
      print("test accuracy for xgb1",accuracy_score(y_test_predict5,y_test1))
```

```
train accuracy for rfc 1.0
test accuracy for rfc 0.9993572232042424
train accuracy for dtc 1.0
test accuracy for dtc 0.9990358348063635
train accuracy for etc 1.0
test accuracy for etc 0.999156355455568
train accuracy for svc 0.9990056746848792
test accuracy for svc 0.9992367025550377
train accuracy for xgb1 0.9999799126198966
test accuracy for xgb1 0.9995179174031817
```

```

✓ [58] #Random forest classifier
7s from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
rfc=RandomForestClassifier(random_state=42)
rfc.fit(x_train,y_train)
y_test_predict1=rfc.predict(x_test)
test_accuracy=accuracy_score(y_test,y_test_predict1)
test_accuracy

```

0.9993572232042424

```

✓ [60] y_train_predict1=rfc.predict(x_train)
1s train_accuracy=accuracy_score(y_train,y_train_predict1)
train_accuracy

```

1.0

```

✓ [61] pd.crosstab(y_test,y_test_predict1)
0s

```

	col_0 is Fraud is not Fraud	
isFraud		
is Fraud	5	14
is not Fraud	2	24871

```

✓ [62] from sklearn.metrics import classification_report
1s print(classification_report(y_test,y_test_predict1))

```

	precision	recall	f1-score	support
is Fraud	0.71	0.26	0.38	19
is not Fraud	1.00	1.00	1.00	24873
accuracy			1.00	24892
macro avg	0.86	0.63	0.69	24892
weighted avg	1.00	1.00	1.00	24892

Decision tree classifier

```
[63] from sklearn.tree import DecisionTreeClassifier
      dtc=DecisionTreeClassifier()
      dtc.fit(x_train,y_train)
      y_test_predict2=dtc.predict(x_test)
      test_accuracy=accuracy_score(y_test,y_test_predict2)
      test_accuracy
```

0.9990358348063635

```
[64] y_train_predict2=dtc.predict(x_train)
      train_accuracy=accuracy_score(y_train,y_train_predict2)
      train_accuracy
```

1.0

```
[65] pd.crosstab(y_test,y_test_predict2)
```

	col_0	is Fraud	is not Fraud
isFraud			
is Fraud		9	10
is not Fraud		14	24859

```
[66] print(classification_report(y_test,y_test_predict2))
```

	precision	recall	f1-score	support
is Fraud	0.39	0.47	0.43	19
is not Fraud	1.00	1.00	1.00	24873
accuracy			1.00	24892
macro avg	0.70	0.74	0.71	24892
weighted avg	1.00	1.00	1.00	24892

Decision tree classifier

```
[63] from sklearn.tree import DecisionTreeClassifier
      dtc=DecisionTreeClassifier()
      dtc.fit(x_train,y_train)
      y_test_predict2=dtc.predict(x_test)
      test_accuracy=accuracy_score(y_test,y_test_predict2)
      test_accuracy
```

0.9990358348063635

```
[64] y_train_predict2=dtc.predict(x_train)
      train_accuracy=accuracy_score(y_train,y_train_predict2)
      train_accuracy
```

1.0

```
[65] pd.crosstab(y_test,y_test_predict2)
```

col_0	is Fraud		is not Fraud	
	isFraud			
is Fraud	9		10	
is not Fraud	14		24859	

```
[66] print(classification_report(y_test,y_test_predict2))
```

	precision	recall	f1-score	support
is Fraud	0.39	0.47	0.43	19
is not Fraud	1.00	1.00	1.00	24873
accuracy			1.00	24892
macro avg	0.70	0.74	0.71	24892
weighted avg	1.00	1.00	1.00	24892

Extra tree Classifier

```
0s [67] from sklearn.ensemble import ExtraTreesClassifier  
etc=ExtraTreesClassifier()
```

```
2s [68] etc.fit(x_train,y_train)  
y_test_predict3=etc.predict(x_test)  
test_accuracy=accuracy_score(y_test,y_test_predict3)  
test_accuracy
```

0.999156355455568

```
0s [69] y_train_predict3=etc.predict(x_train)  
train_accuracy=accuracy_score(y_train,y_train_predict3)
```

```
0s [70] train_accuracy
```

1.0

```
0s [71] pd.crosstab(y_test,y_test_predict3)
```

	col_0 is Fraud is not Fraud	
	is Fraud	is not Fraud
is Fraud	2	17
is not Fraud	4	24869

```
1s [72] print(classification_report(y_test,y_test_predict3))
```

	precision	recall	f1-score	support
is Fraud	0.33	0.11	0.16	19
is not Fraud	1.00	1.00	1.00	24873
accuracy			1.00	24892
macro avg	0.67	0.55	0.58	24892
weighted avg	1.00	1.00	1.00	24892

Support vector machine classifier

38



```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
svc=SVC()
svc.fit(x_train,y_train)
y_test_predict4=svc.predict(x_test)
test_accuracy=accuracy_score(y_test,y_test_predict4)
test_accuracy
```

0.9992367025550377

20

```
[74] y_train_predict4=svc.predict(x_train)
train_accuracy=accuracy_score(y_train,y_train_predict4)
train_accuracy
```

0.9990056746848792

0s

```
[75] pd.crosstab(y_test,y_test_predict4)
```

col_0 is not Fraud	
isFraud	
is Fraud	19
is not Fraud	24873



1s

```
[76] print(classification_report(y_test,y_test_predict4))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Un
_warn_prf(average, modifier, msg_start, len(result))
precision    recall  f1-score   support

   is fraud      0.00      0.00      0.00         19
  is not fraud    1.00      1.00      1.00        24873

 accuracy              1.00        24892
 macro avg      0.50      0.50      0.50        24892
weighted avg      1.00      1.00      1.00        24892
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Un
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Un
```

xgboost Classifier


```
✓ [77] from sklearn.preprocessing import LabelEncoder  
1s la=LabelEncoder()  
y_train1=la.fit_transform(y_train)  
y_test1=la.transform(y_test)  
y_test1=la.transform(y_test)  
  
import xgboost as xgb  
xgb1=xgb.XGBClassifier()  
xgb1.fit(x_train,y_train1)  
y_test_predict5=xgb1.predict(x_test)  
test_accuracy=accuracy_score(y_test1,y_test_predict5)  
test_accuracy
```

0.9995179174031817



```
✓ [78] y_train_predict5=xgb1.predict(x_train)  
0s train_accuracy=accuracy_score(y_train1,y_train_predict5)  
train_accuracy
```

0.9999799126198966

```
✓ [79] pd.crosstab(y_test,y_test_predict5)  
0s
```



col_0	0	1
isFraud		
is Fraud	10	9
is not Fraud	3	24870



```
✓ [80] print(classification_report(y_test1,y_test_predict5))  
0s
```

	precision	recall	f1-score	support
0	0.77	0.53	0.62	19
1	1.00	1.00	1.00	24873
accuracy			1.00	24892
macro avg	0.88	0.76	0.81	24892
weighted avg	1.00	1.00	1.00	24892

Accuracy:

Definition: The ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances.

Importance: Accuracy is a fundamental metric, indicating the overall correctness of the fraud detection system. A higher accuracy percentage signifies a more reliable system.

Precision:

Definition: The ratio of true positives to the sum of true positives and false positives.

Importance: Precision measures the accuracy of the positive predictions, indicating the system's ability to minimize false positives. In the context of fraud detection, precision is crucial for avoiding unnecessary alarms.

Recall (Sensitivity):

Definition: The ratio of true positives to the sum of true positives and false negatives.

Importance: Recall measures the system's ability to identify all actual positive instances, thus minimizing false negatives. In the context of fraud detection, a high recall is essential for catching as many fraudulent transactions as possible.

F1 Score:

Definition: The harmonic mean of precision and recall.

Importance: F1 score provides a balanced measure of precision and recall. It is particularly useful when there is an uneven class distribution, as is often the case in fraud detection.

Execution Time:

Definition: The time taken by the system to process and analyze a given number of transactions.

Importance: Real-time fraud detection relies on quick processing. Monitoring the execution time ensures that the system operates within acceptable time constraints, facilitating timely detection.

Scalability:

Definition: The system's ability to handle an increasing number of transactions without a significant decrease in performance.

Importance: Scalability is critical in real-world scenarios where transaction volumes can fluctuate. Ensuring that the system scales effectively contributes to its long-term usability.

Resource Utilization:

Definition: The efficient use of system resources, such as CPU and memory, during the fraud detection process.

Importance: Monitoring resource utilization helps identify potential bottlenecks or inefficiencies, ensuring optimal system performance under varying workloads.

False Positive Rate:

Definition: The ratio of false positives to the sum of false positives and true negatives.

Importance: A low false positive rate is essential for minimizing the occurrence of false alarms, as these can inconvenience users and erode trust in the system.

False Negative Rate:

Definition: The ratio of false negatives to the sum of false negatives and true positives.

Importance: A low false negative rate is crucial for ensuring that the system does not miss genuine instances of fraud, which could result in financial losses.

Throughput:

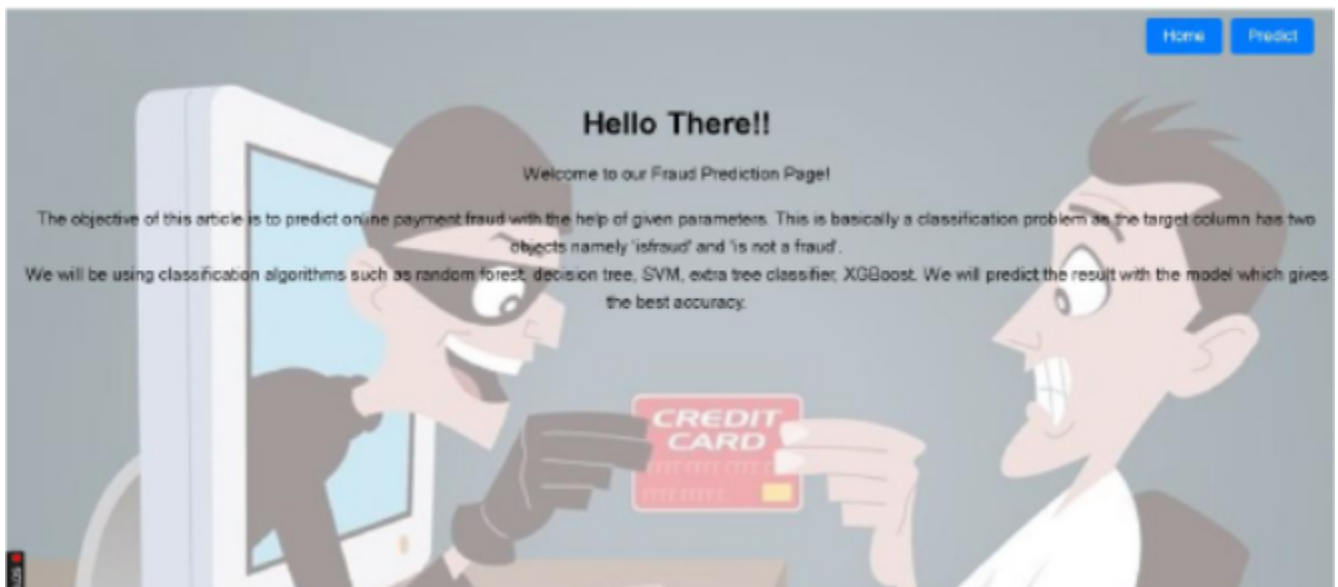
Definition: The number of transactions processed by the system per unit of time.

Importance: Throughput is a measure of the system's transaction-handling capacity, ensuring that it can effectively manage the continuous flow of transactions in real-time.

9. RESULTS

9.1 Output Screenshots

Final output of the user interface we get after running the html code



and integrating it with ml model with the help of flask.

The screenshot displays the 'Enter Prediction Details' form, which is a light gray overlay on the same cartoon background. The form contains several input fields with pre-filled values and a 'Submit' button at the bottom. The fields are labeled as follows:

- Step: 94
- Type: 4
- Amount: 14.590090
- Old Balance Orig: 2109079.91
- New Balance Orig: 0.0
- Old Balance Dest: 0.00
- New Balance Dest: 0.0

A large blue 'Submit' button is positioned at the bottom of the form. A small 'Home' button is visible at the very bottom center of the page.

Prediction Result

The prediction result is: is Fraud

[Home](#)

CREDIT

Enter Prediction Details

Step:

1

Type:

3

Amount:

9.194174

Old Balance Org:

170136.00

New Balance Orig:

160296.36

Old Balance Dest:

0.0

New Balance Dest:

0.0

Submit

Prediction Result

The prediction result is: is not Fraud

Home

10. ADVANTAGES & DISADVANTAGES

Advantages:

Improved Fraud Detection Accuracy: The utilization of multiple machine learning algorithms allows for a more comprehensive analysis of transactional data, leading to enhanced accuracy in identifying fraudulent activities.

Real-time Detection: The system's ability to process transactions in real-time ensures timely detection and prevention of fraudulent transactions, minimizing potential financial losses.

Algorithmic Flexibility: By incorporating various algorithms such as Decision Tree, Random Forest, SVM, Extra Tree Classifier, and XGBoost Classifier, the system can adapt to different types of fraud patterns, increasing its robustness.

User-friendly Interface: The integration of Flask provides a user-friendly interface, making the fraud detection system accessible and understandable for users involved in online transactions.

Cloud-Agnostic Deployment: Deployment options are not limited to a specific cloud provider. The system can be deployed on various cloud platforms, enhancing flexibility and avoiding vendor lock-in.

Disadvantages:

Data Privacy Concerns: The processing of sensitive transactional data raises concerns about data privacy. Proper encryption and security measures must be in place to address these issues.

Algorithm Complexity: The use of multiple algorithms may introduce complexity in model selection and parameter tuning. Ensuring optimal performance across all algorithms requires careful consideration.

Resource Intensive Training: Training machine learning models on large datasets, especially with multiple algorithms, can be resource-intensive and time-consuming.

False Positives/Negatives: Despite efforts to enhance accuracy, no model is perfect. There is a risk of false positives, flagging legitimate transactions as fraudulent, or false negatives, missing some fraudulent activities.

11. CONCLUSION

In conclusion, the Online Payments Fraud Detection using Machine Learning project represents a significant step forward in addressing the challenges posed by the increasing prevalence of online payment fraud. By leveraging a combination of advanced machine learning algorithms and allowing deployment flexibility across various cloud platforms, the project aims to provide a robust and scalable system for real-time fraud detection.

The comparative analysis of algorithms and the emphasis on user-friendly interfaces contribute to the project's potential impact on the effectiveness and accessibility of online fraud detection systems. Despite inherent challenges and trade-offs, the advantages offered by the project signify a positive stride toward enhancing the security of online financial transactions.

12. FUTURE SCOPE

The future scope of the project involves several avenues for further improvement and expansion:

Continuous Model Refinement: Regular updates and refinements to the machine learning model can be implemented to adapt to evolving fraud patterns and improve overall accuracy.

Integration of Advanced Techniques: Incorporating advanced techniques such as anomaly detection and deep learning may further enhance the system's capability to detect sophisticated fraud patterns.

Big Data Analytics: Exploring the integration of big data analytics to handle and analyze vast amounts of transactional data, improving scalability and performance.

Collaboration with Financial Institutions: Collaboration with financial institutions can provide access to additional labeled datasets, enriching the model's learning capabilities.

Global Application: Adapting the system to meet the specific fraud patterns prevalent in different geographical regions, thereby making it applicable on a global scale.

Enhanced Security Measures: Implementing cutting-edge security measures, including blockchain technology, to fortify the security and privacy aspects of the system.

13. APPENDIX

Source Code

<https://github.com/smartinternz02/SI-GuidedProject-594342-1697290>

[920/tree/main/projectCodes](#)

GitHub & Project Demo Link

GitHub:

<https://github.com/smartinternz02/SI-GuidedProject-594342-1697290920>

Project Demo Link

Model building:

<https://drive.google.com/file/d/1L0cKtsOJZiuV52N3duPIIdFG6bx5kKOKI/view?usp=sharing>

Flask Integration:

<https://drive.google.com/file/d/1MNKNxB5pYYt3apJsdYUXSujMy459r-Np/view?usp=sharing>