ONLINE PAYMENT FRAUD DETECTION

Project Report Format

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1. INTRODUCTION

1.1 Project Overview:

The increasing reliance on internet transactions, particularly in the realm of e-commerce, has led to a surge in online credit/debit card transactions. Unfortunately, this growth has also given rise to a parallel increase in fraudulent activities. To address this issue, our project focuses on implementing a robust fraud detection system using machine learning.

1.2 Purpose:

The purpose of this project is to develop a sophisticated fraud detection system that leverages machine learning algorithms to analyze and identify potential fraudulent activities in online credit/debit card transactions. By utilizing classification algorithms such as Decision tree, Random forest, SVM, Extra tree classifier, and XGBoost Classifier, we aim to improve the accuracy of fraud detection.

2. LITERATURE SURVEY

2.1 Existing problem

Here are a few noteworthy problems:

1. Imbalanced Datasets:
- Fraudulent transactions are frequently few in comparison to valid ones. The model's capacity to recognise fraudulent patterns effectively may be impacted by this mismatch.

- Solution: Unbalanced datasets can be addressed by employing strategies like under- or oversampling, as well as sophisticated algorithms like Synthetic Minority Over-sampling Technique (SMOTE).

2. Dynamic Nature of Fraud:
-Issue: Since fraudulent strategies change over time, it is difficult for static models to catch up with emerging trends.
- Solution: It is imperative that the model be updated and monitored continuously. It is crucial to have adaptive models that can modify their detection tactics in response to fresh data.

3. Feature Engineering Complexity:
-Issue: It might be difficult and require domain expertise to extract significant characteristics from transaction data.
Automated feature engineering is the solution. The model's capacity to identify fraud trends may be enhanced by the application of domain-specific features.

4. User Experience and False Positives:
-Issue: Excessively stringent fraud detection methods may result in false positives, causing inconvenience to authorised users and eroding their confidence in the system.
The key is to strike a balance between recall and precision. In order to reduce false positives and preserve high accuracy in identifying real fraud, models must be adjusted.

5. Intellectual Assaults:
-Issue: By creating transactions that are especially meant to avoid detection, adversarial actors may deliberately try to influence the model.
- Solution: Adversarial assaults can be lessened by putting strong security measures in place, updating models often, and using adversarial training methods.

6. Interpretability and Explainability:
-Issue: A lot of machine learning models are opaque, which makes it difficult to comprehend how they Make choices.
- Solution: Creating interpretable models or offering explanations for model decisions after the fact can help users and stakeholders feel more trusted and understand each other better.

7. Data Privacy Issues:
-Issue: Managing private transaction data gives rise to privacy issues.
- Solution: To safeguard user information and enable efficient fraud detection, implement privacy preserving strategies like secure multiparty computing or differential privacy.

8. Scalability:
-Issue: The scalability of fraud detection algorithms becomes a challenge as the amount of online transactions increases.
- Solution: Distributed computing methods and scalable machine learning architectures can help effectively manage high transaction volumes.

9. Fraud via Cross-Channel:
-Issue: Since fraudsters can use weaknesses in a variety of channels, detecting fraud needs to be approached from all angles.
- Solution: Combining fraud detection tools with different platforms and channels to build a thorough understanding of user conduct and transaction patterns.

10. Adherence to Regulations:
-Issue: It can be difficult to successfully use fraud detection techniques while adhering to data privacy requirements.
- Solution: Applying privacy-by-design principles and making sure the fraud detection system conforms with applicable data protection laws and regulations.

A multidisciplinary strategy including domain-specific knowledge of online payment systems, cybersecurity, machine learning, and data privacy is needed to address these issues. Researchers and industry professionals are always looking for novel ways to improve machine learning's efficacy and dependability in the identification of online payment fraud.

2.2References

1. https://ieeexplore.ieee.org/document/10142404

2. https://iopscience.iop.org/article/10.1088/1742-6596/2023/1/012054(Online Transaction Fraud Detection System Based on Machine Learning Bocheng Liu1, Xiang Chen1 and Kaizhi Yu1 Published under licence by IOP Publishing Ltd)

3.https://www.researchgate.net/publication/354937786_Online_Transaction_Fraud_Detection_Sy stem_Based_on_Machine_Learning , September 2021

4. https://www.kaggle.com/datasets/rupakroy/online-payments-fraud-detection-dataset , Kaggle

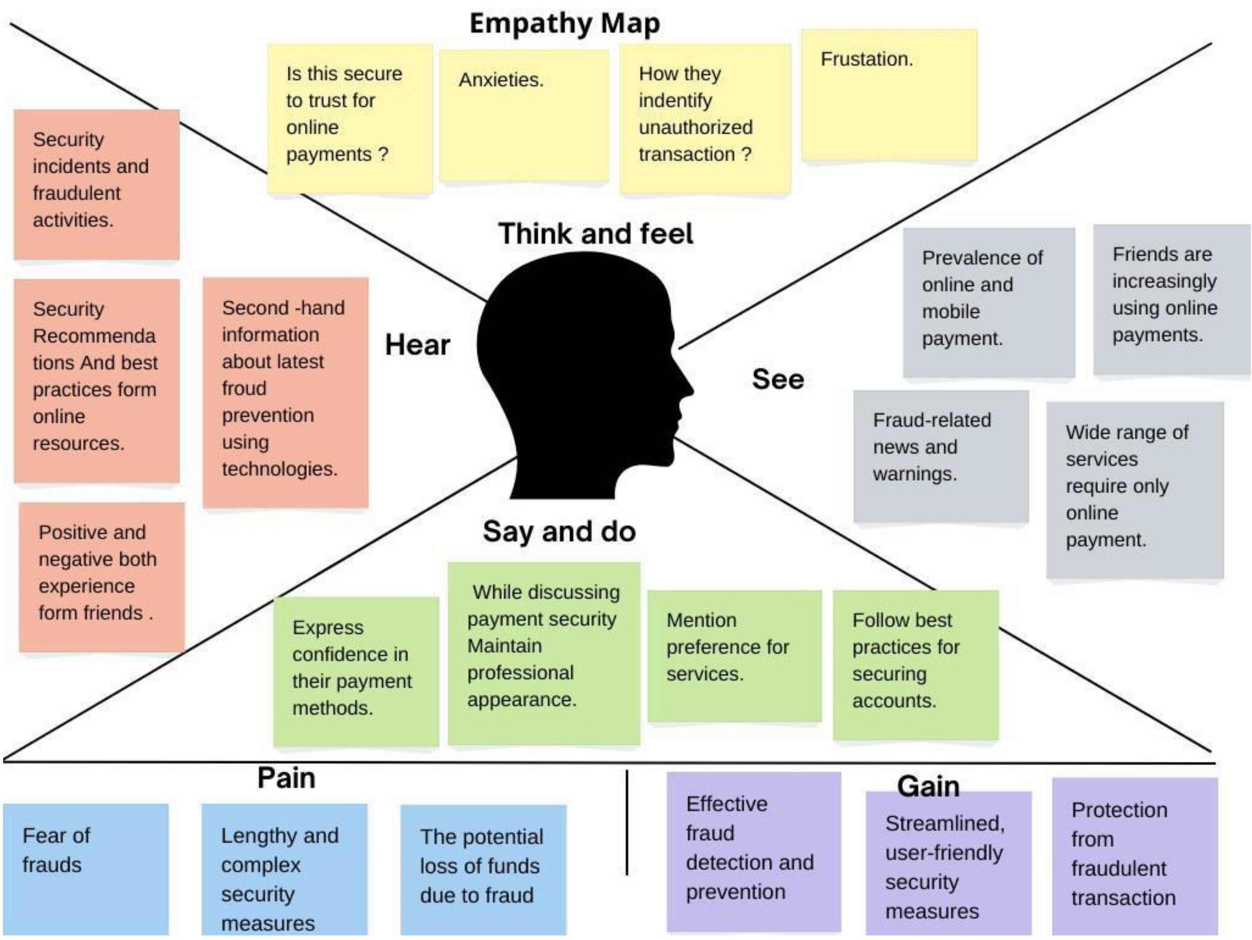
2.3 Problem Statement Definition

The rapid growth of online transactions has brought about an escalating threat of fraudulent activities in the realm of online payments. Fraudsters employ sophisticated techniques to exploit vulnerabilities in payment systems, leading to financial losses for both businesses and consumers. Traditional rule based fraud detection systems are often insufficient to adapt to the evolving nature of fraudulent tactics. Therefore, there is a pressing need to develop a robust and adaptive Online Payment Fraud Detection system using Machine Learning (ML) to enhance the security and reliability of online Transactions.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas

The empathy map revealed that users face anxiety and distrust in online transactions due to the prevalent fraud. The proposed solution aims to alleviate these concerns by implementing a robust fraud detection system.



3.2 Ideation & Brainstorming:

To build a robust online fraud detection system, consider implementing a combination of machine learning algorithms, anomaly detection techniques, and user behavior analysis. Leverage features like geolocation verification, graph analysis, and natural language processing to detect fraudulent activities in real-time.

Link- https://rb.gy/pzycb

Step-1: Team Gathering, Collaboration and Select the Problem Statement

Brainstorm & idea prioritization

To build a robust online fraud detection system, consider implementing a combination of machine learning algorithms, anomaly detection techniques, and user behavior analysis. Leverage features like geolocation verification, graph analysis, and natural language processing to detect fraudulent activities in real-time.

Before Colaboration

Team gathering

Reaching to all members and invite for the collabration sessions

Set the goal

aim is to solve the online payment fraud in real world .

Learn how to use the facilitation tools

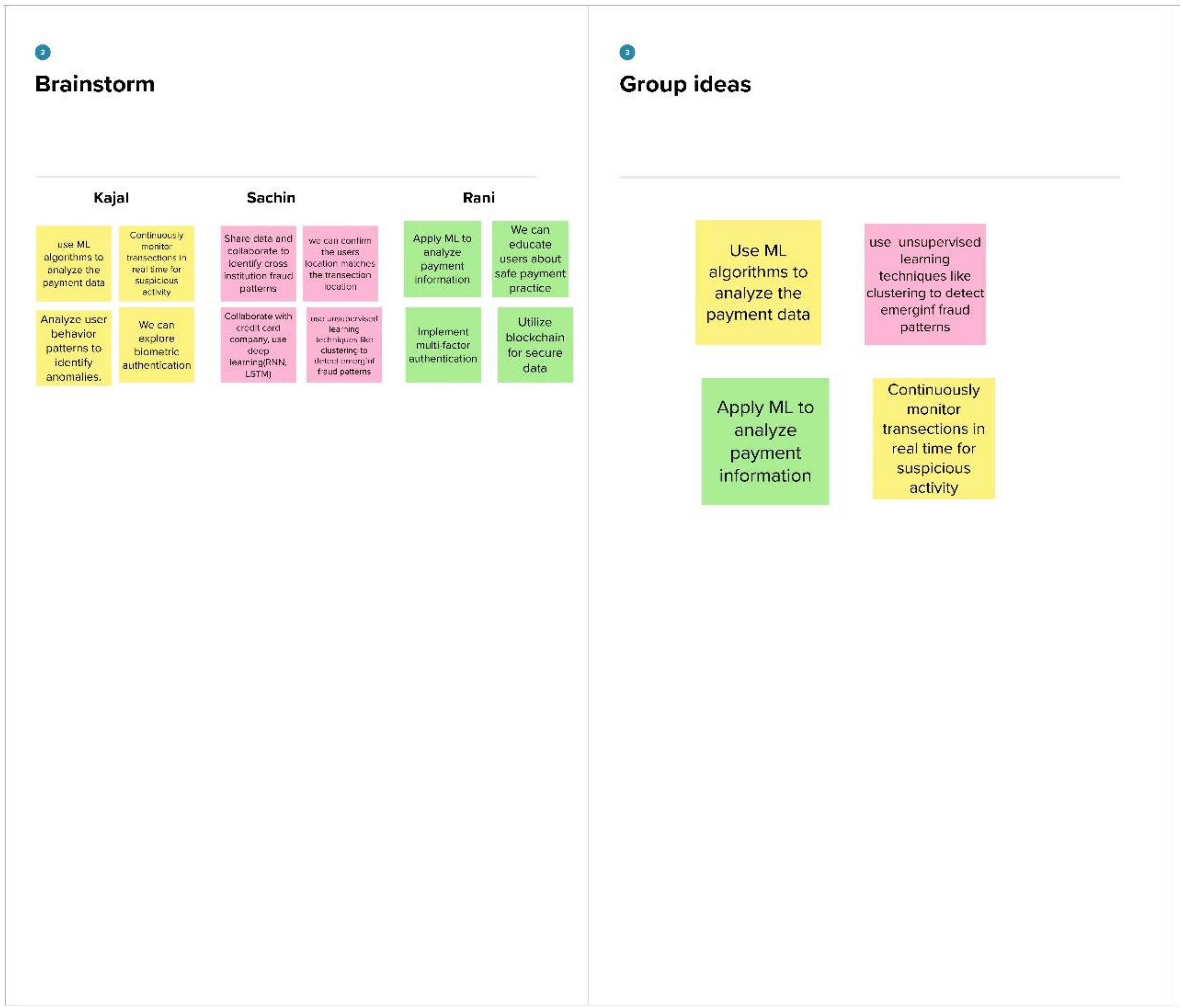
Encourage open communication and ensure team members feel comfortable sharing their ideas, even if they are unconventiona

Problem Statement

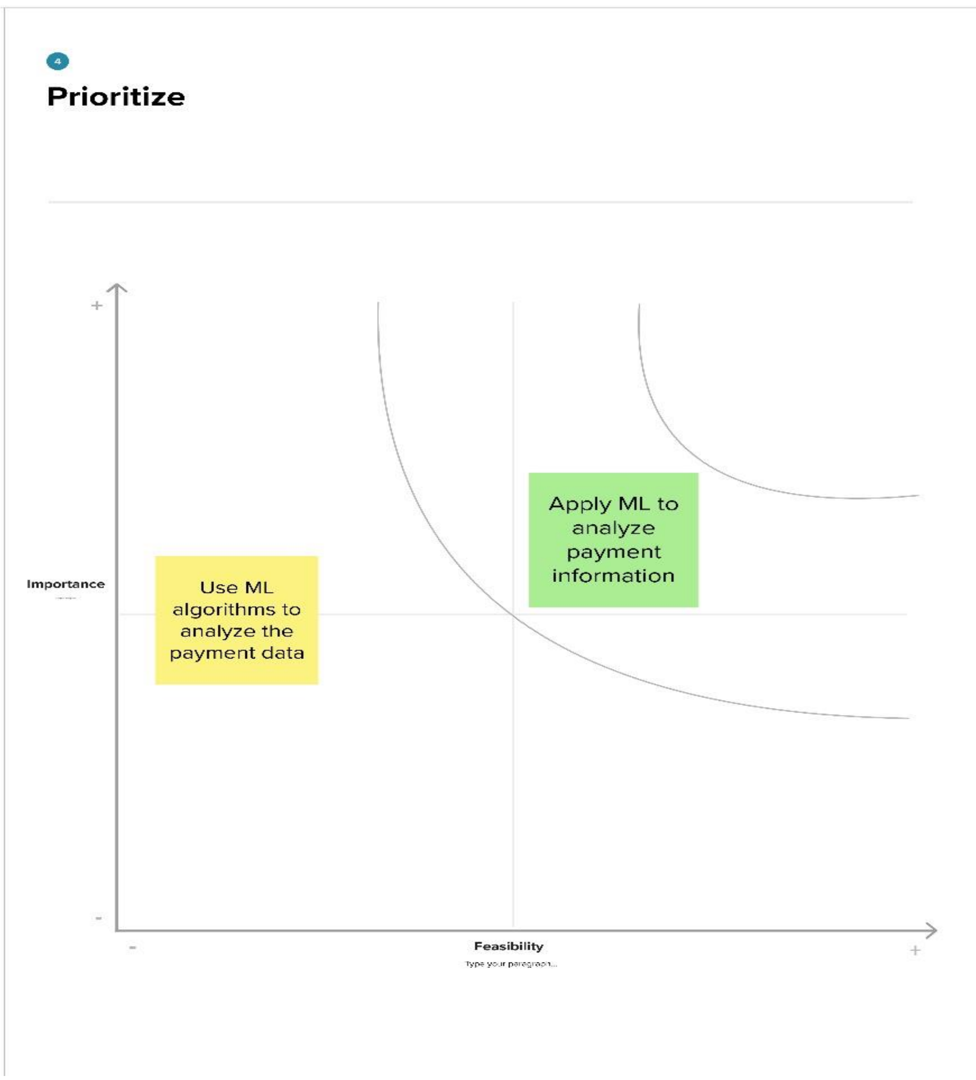
PROBLEM

Addressing the escalating issue of online credit/debit card fraud by developing a machine learning-based solution, utilizing classification algorithms, with the goal of significantly enhancing fraud detection accuracy and deploying it via a web application for real-time fraud prevention.

Step-2: Brainstorm, Idea Listing and Grouping



Step-3: Idea Prioritization



4. REQUIREMENT ANALYSIS

4.1 Functional Requirements

Real-time Transaction Monitoring:The system must continuously monitor incoming transactions in real-time. This includes the ability to analyze and process transaction data as it occurs, providing an immediate response to potential fraudulent activities.

Integration with Classification Algorithms:The system should integrate with various classification algorithms such as Decision Trees, Random Forest, SVM, Extra Trees, and XGBoost. This integration is crucial for effectively analyzing transaction patterns and identifying potential instances of fraud.

User Notification for Flagged Transactions:Upon the identification of a potentially fraudulent transaction, the system should generate and send notifications to users. These notifications should be timely and informative, allowing users to take appropriate actions to secure their accounts.

4.2 Non-Functional Requirements

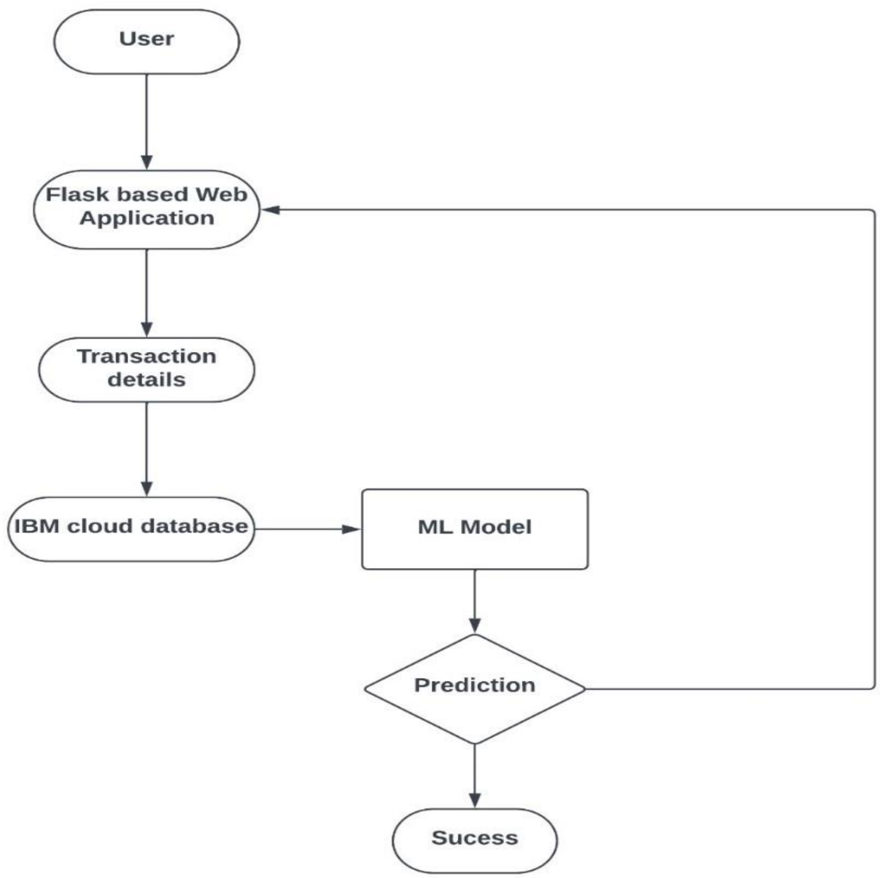
System Reliability:The system must exhibit high reliability, ensuring minimal downtime and consistent performance. Reliability is crucial for maintaining continuous monitoring and timely response to potential fraud, enhancing the overall trustworthiness of the system.

Data Security and Privacy Compliance:To protect sensitive financial information, the system must adhere to robust data security measures. This includes encryption of data in transit and at rest, secure storage practices, and compliance with relevant privacy regulations to safeguard user information.

User-Friendly Interface: The user interface should be intuitive and easy to navigate. Users, including both administrators and regular account holders, should be able to interact with the system effortlessly. A user-friendly interface contributes to effective monitoring, notification management, and overall user satisfaction.

5. PROJECT DESIGN

5.1 Data Flow Diagrams & User Stories



User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer	Fraud Alerts	USN-1	As a user I can Receive Real-time Fraud Alerts.	I can receive instant alerts via email and SMS for any suspicious transactions exceeding a certain threshold.	High	Sprint-1
	Transaction Monitoring	USN-2	As a user I can View Transaction History.	I can access and review a list of their recent transactions to identify any potential fraud.	High	Sprint-1
	Self-service Dispute Resolution	USN-3	As a user I can access and review a list of their recent transactions to identify any potential fraud.	I can initiate a dispute directly from the transaction history page if they suspect a fraudulent charge.	Low	Sprint-2
Customer support	Investigate Reported Fraud	USN-4	As a support agent I can investigate Fraud Reports.	I can access a list of transactions reported by customers as potentially fraudulent and investigate them further.	Medium	Sprint-1
	Flag Transactions for Review	USN-5	I can mark Transactions for Review.	As a support agent I can manually flag specific transactions for further review if they suspect fraudulent activity	High	Sprint-1
Fraud Analyst	Real-time Monitoring.	USN-6	I can monitor transactions in Real-time	As a fraud analysts I can view real-time transaction data, including those flagged as suspicious by automated systems.	Low	Sprinit-2
	Suspicious Transaction Analysis	USN-7	I can Analysis Suspicious Transactions.	As a fraud analysts can access detailed information about transactions flagged as suspicious and conduct in-depth analysis.	Medium	Sprint -1
Merchant	Transaction Verification	USN-8	As a user I can verify customer Transactions	As a merchant I can confirm the legitimacy of customer transactions, reducing false alarms and ensuring legitimate payments proceed without delay.	High	Sprint-1
Compliance Officer	Regulatory Reporting	USN-9	As a compliance officer I can Generate Compliance Reports.	As a Compliance officers can generate reports on detected fraud cases for regulatory compliance and auditing purposes.	Low	Sprint -2

5.2 Solution Architecture

1. Finding the Best Tech Solution:

- In our architecture, we are utilizing technology to address the business problem of online payment fraud detection.
- Machine Learning (Classical ML methods) is being used as the primary technology solution to detect fraud, showcasing a thoughtful choice of technology.

2. Describing the Structure and Characteristics:

- our architecture outlines the structure and behavior of the software components involved in the fraud detection process. It describes how data flows through various stages and checks.

3. Defining Features and Requirements:

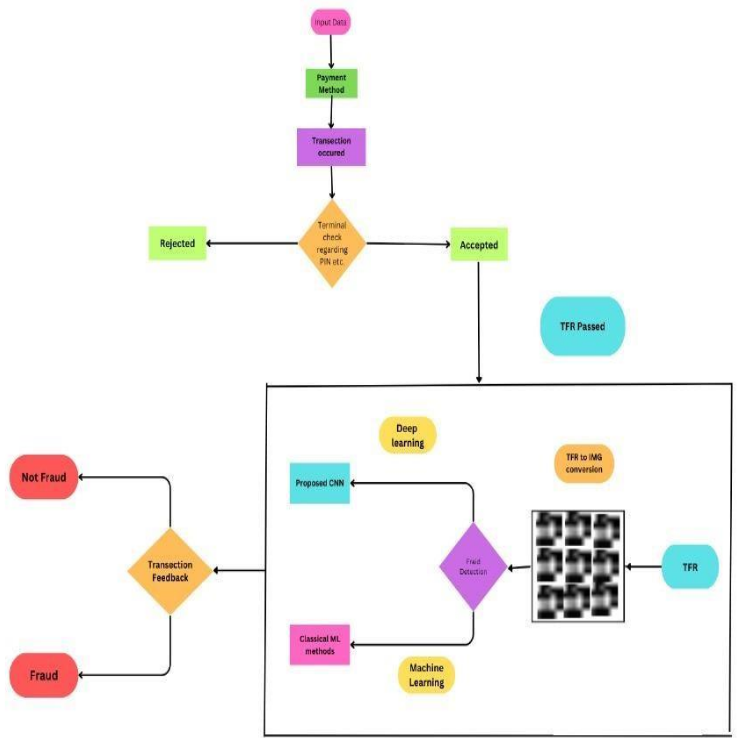
- The architecture defines various features, including data input, transaction processing, fraud detection, and transaction feedback.
- It also highlights key requirements, such as the need for real-time processing and fraud detection, as well as the conversion of transactions to images.

4. Providing Specifications:

- Our architecture provides specifications for how the solution is designed and managed, including the role of Machine Learning in fraud detection and the steps involved in handling transactions.

5. Communicating with Stakeholders:

- The architecture serves as a communication tool for project stakeholders by clearly illustrating how the technology solution addresses the business problem.
- It outlines the flow of data and decisions in a transparent manner, which aids stakeholders' understanding



Input Data
Payment Method
Transection occured
Terminal check regarding PIN etc.
Rejected
Accepted
TFR Passed
Deep learning
TFR to IMG conversion
Proposed CNN
Fraud Detection
TFR
Classical ML methods
Machine Learning
Not Fraud
Transection Feedback
Fraud

6. PROJECT PLANNING & SCHEDULING

6.1 Technical Architecture

Table-1: Components & Technologies

S.No	Component	Description	Technology
1	User Interface	Web-based interface for users to interact with fraud detection application	HTML, CSS, JavaScript / React Js
2	Application Logic-1	Implementation of machine learning models for fraud detection	Python, scikit-learn, XGBoost, TensorFlow
3	Application Logic-2	Integration with IBM Watson Speech to Text service for voice recognition	IBM Watson STT service
4	Application Logic-3	Integration with IBM Watson Assistant for chatbot-based interactions	IBM Watson Assistant
5	Database	Storage and management of transaction data	MySQL, NoSQL databases
6	Cloud Database	Cloud-based database service for scalability and reliability	IBM DB2, IBM Cloudant, AWS RDS
7	File Storage	Storing files, possibly for logs and model serialization	IBM Block Storage, Local Filesystem
8	External API1	Integration with external APIs like IBM Weather for additional data	IBM Weather API
9	External API2	Integration with external APIs, such as Aadhar for identity verification	Aadhar API

10	Machine Learning Model	Implementation of machine learning models for fraud detection	Decision Tree, Random Forest, SVM, Extra Tree, XGBoost
11	Infrastructure (Server /	Deployment of the application on cloud platforms for scalability	IBM Cloud, Kubernetes, AWS, Azure

Table-2: Application Characteristics

S.No	Characteristics	Description	Technology
1	Open-Source Frameworks	Utilization of open-source frameworks for machine learning.	Python (for machine learning)
2	Security	Implementation of security measures to protect financial data.	Encryption, anomaly detection

3	Scalable Architecture	Ensuring the architecture can scale to handle growing transaction volume.	Microservices architecture, load balancing
4	Availability	Ensuring high availability to prevent disruptions in online payments.	Load balancers, redundant servers
5	Performance	Optimizing for high performance to process numerous transactions.	Caching, high-performance computing

6.2 Sprint Planning & Estimation

Sprint	Functional requirement (Epic)	User story number	User Story / Task	story point	Priority	Team members
Sprint1	Fraud Alerts	USN-1	As a user I can Receive Real-time Fraud Alerts.	2	High	Kajal

Sprint 1		USN-2	As a user, I want the option to reply to a fraud alert to confirm if it is fraudulent or not so appropriate action can be taken.	2	High	Rani Kushwaha
Sprint1		USN-3	As a user, I want the fraud alert to provide clear details about the suspicious activity so I can evaluate if it is fraudulent or not.	2	Low	Sachin
Sprint1		USN-4	As a user, I want the fraud alert to guide me toward steps to take if the activity is fraudulent so I can act quickly.	2	Medium	Sachin
Sprint1		USN-5	As a user, I want to receive alerts about suspicious activity related to my account so I can take quick action to prevent fraud.	2	High	Rani kushwaha
Sprint2	Transaction monitoring	USN-6	I can monitor transactions in Real- time	6	High	Kajal
Sprint2		USN-7	As user I can view transaction history .	5	Medium	Rani
Sprint2		USN-8	As a user, I want access to transaction records and monitoring tools to ensure regulatory compliance and conduct audits as needed.	5	High	Rani Kushwaha

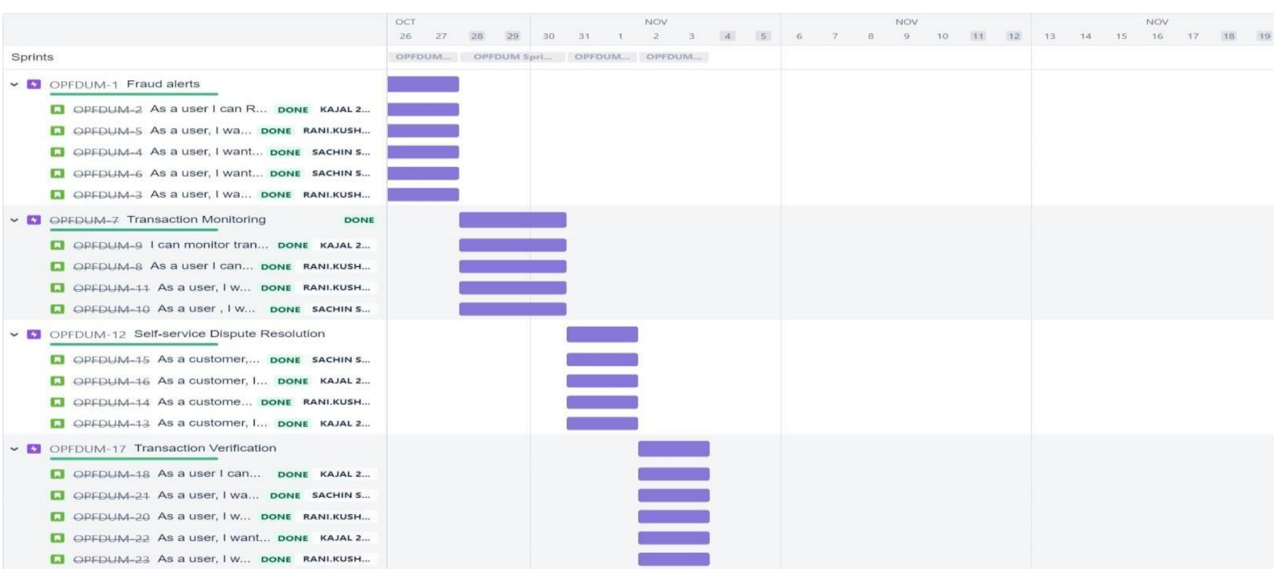
Sprint2		USN-9	As a user, I want a dashboard that provides an overview of transactions flagged as suspicious.	4	low	Sachin
Sprint3	Self-service	USN10	As a user , I want to be able to track the status of my dispute so that I know it is being worked on.	6	High	Sachin
Sprint 3		USN11	As a user I want to receive notifications when the status of my dispute changes so that I am informed.	4	Low	Kajal
Sprint3		USN12	As a user , I want to be able to upload documentation to support my dispute claim so that I can provide evidence.	4	Medium	Rani Kushwaha

Sprint3		USN-13	As a user , I want to be able to file a dispute online so that I don't have to call or email customer service.	6	High	Kajal
Sprint4	Transaction Verification	USN-14	As a user I can verify customer transactions.	2	High	Kajal
Sprint4		USN-15	As a user, I want to be prompted to confirm/authorize high-value transactions so I can avoid fraudulent ones.	2	High	Sachin
Sprint4		USN-16	As a user, I want to be able to view transaction details including amount, date, recipient etc.	2	Low	Rani Kushwaha

Sprint4		USN-17	As a user, I want to be able to report unrecognized or suspicious transactions for further investigation.	2	Medium	Kajal
Sprint4		USN-18	As a user, I want to be able to instantly freeze my account if I suspect unauthorized transactions so I can prevent further losses.	2	Medium	Rani Kushwaha

6.3 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release I (Actual)
Sprint-1	10	2 Days	25 Oct 2023	27 Oct 2023	10	28 Oct 2023
Sprint-2	20	2 Days	28 Oct 2023	30 Nov 2023	20	30 Nov 2023
Sprint-3	20	1 Days	31 Oct 2023	1 Nov 2023	20	1 Nov 2023
Sprint-4	10	1 Days	2 Nov 2022	3 Nov 2022	10	2 Nov 2022



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

7.1 Feature 1

Milestone 1: 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 create the dataset or Download the dataset:

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc.

In this project we have used PS_20174392719_1491204439457_logs.csv data. This data is downloaded from kaggle.com. Please refer to the link given below to download the dataset.

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

Milestone 2: 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.

Note: There are a number of techniques for understanding the data. But here we have used some of it. In an additional way, you can use multiple techniques.

Activity 1: Importing the libraries

Import the necessary libraries as shown in the image. (optional) Here we have used visualisation style as fivethirtyeight.

```
In [1]: # Activity 1
        # Importing libraries
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from scipy import stats
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import accuracy_score
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.ensemble import ExtraTreesClassifier
        from sklearn.svm import SVC
        import xgboost as xgb
        from sklearn.metrics import f1_score
        from sklearn.metrics import classification_report, confusion_matrix
        import warnings
        import pickle
```

Activity 2: 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.

Here, the input features in the dataset are known using the df.columns function.

In [3]:
```
# Activity 2: Read the dataset
df = pd.read_csv("PS_20174392719_1491204439457_log.csv")
```

In [4]:
```
df
```

Out[4]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	0.00	0	0
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	0.00	0	0
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	0.00	1	0
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	0.00	1	0
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	0.00	0	0
...	...	...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	339682.13	1	0
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	0.00	1	0
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	6379898.11	1	0
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	0.00	1	0
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	7360101.63	1	0

6362620 rows × 11 columns

In [5]:
```
df.columns
```

Out[5]:
```
Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

Here, the dataset's superfluous columns are being removed using the drop method.

In [6]:
```
df.drop(['isFlaggedFraud'],axis = 1, inplace = True)
```

In [7]:
```
df
```

Out[7]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	0.00	0
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	0.00	0
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	0.00	1
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	0.00	1
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	0.00	0
...	...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	339682.13	1
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	0.00	1
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	6379898.11	1
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	0.00	1
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	7360101.63	1

6362620 rows × 10 columns

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

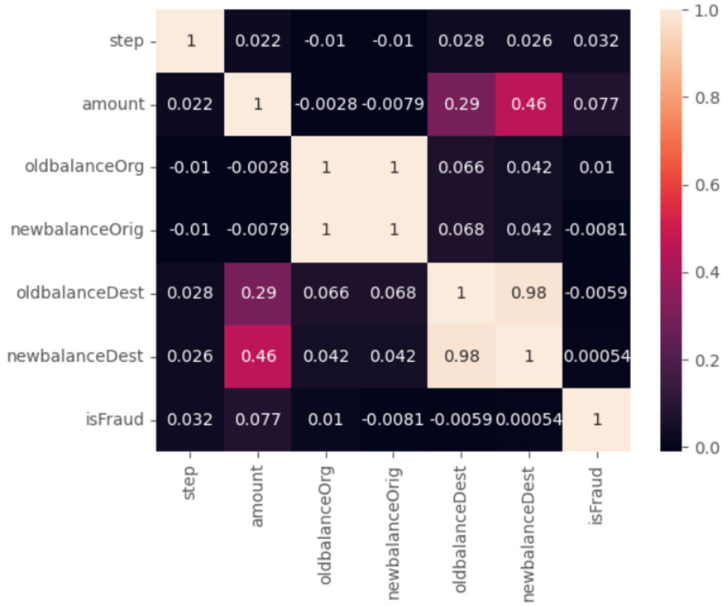
In [12]:
```
# Select only numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Calculate the correlation matrix
correlation_matrix = numeric_df.corr()

# Print the correlation matrix
print(correlation_matrix)
```

```
                    step    amount  oldbalanceOrg  newbalanceOrig  \
step            1.000000  0.022373      -0.010058       -0.010299
amount          0.022373  1.000000      -0.002762       -0.007861
oldbalanceOrg  -0.010058 -0.002762       1.000000        0.998803
newbalanceOrig -0.010299 -0.007861       0.998803        1.000000
oldbalanceDest  0.027665  0.294137       0.066243        0.067812
newbalanceDest  0.025888  0.459304       0.042029        0.041837
isFraud         0.031578  0.076688       0.010154       -0.008148

                oldbalanceDest  newbalanceDest   isFraud
step                  0.027665        0.025888  0.031578
amount                0.294137        0.459304  0.076688
oldbalanceOrg         0.066243        0.042029  0.010154
newbalanceOrig        0.067812        0.041837 -0.008148
oldbalanceDest        1.000000        0.976569 -0.005885
newbalanceDest        0.976569        1.000000  0.000535
isFraud              -0.005885        0.000535  1.000000
```

Utilising the corr function to examine the dataset's correlation

HEATMAP

```python
# Create a heatmap
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```

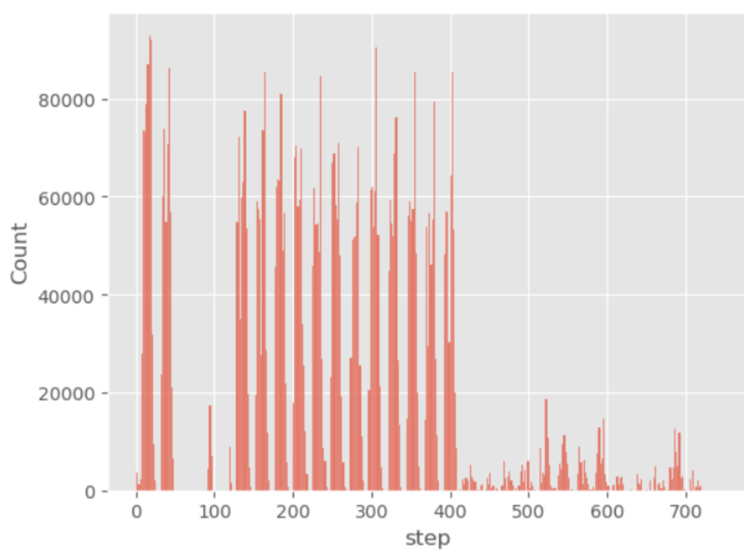


Here, a heatmap is used to understand the relationship between the input attributes and the anticipated goal value.

Activity 3: Univariate analysi

In simple words, univariate analysis is understanding the data with a single feature. Here I have displayed the graph such as histplot .

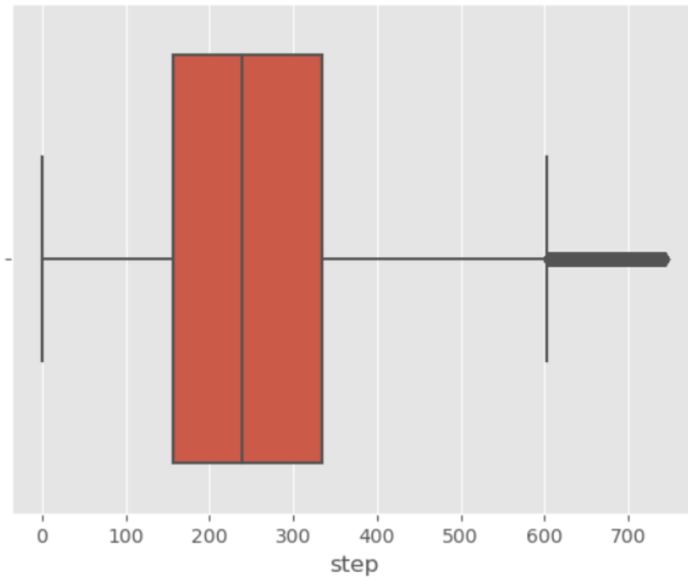
```python
In [15]: # step
         sns.histplot(data=df,x='step')

Out[15]: <Axes: xlabel='step', ylabel='Count'>
```



The distribution of one or more variables is represented by a histogram, a traditional visualisation tool, by counting the number of observations that fall within.

```
In [16]: sns.boxplot(data=df,x='step')
```

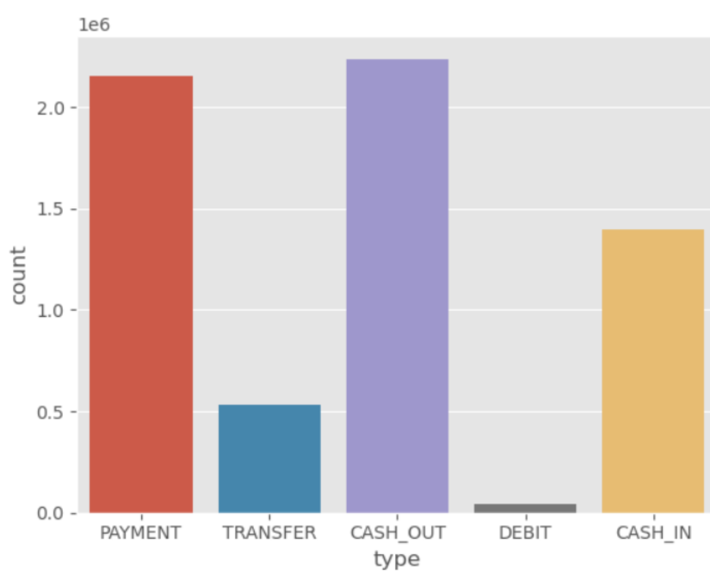
```
Out[16]: <Axes: xlabel='step'>
```



Here, the relationship between the step attribute and the boxplot is visualised.

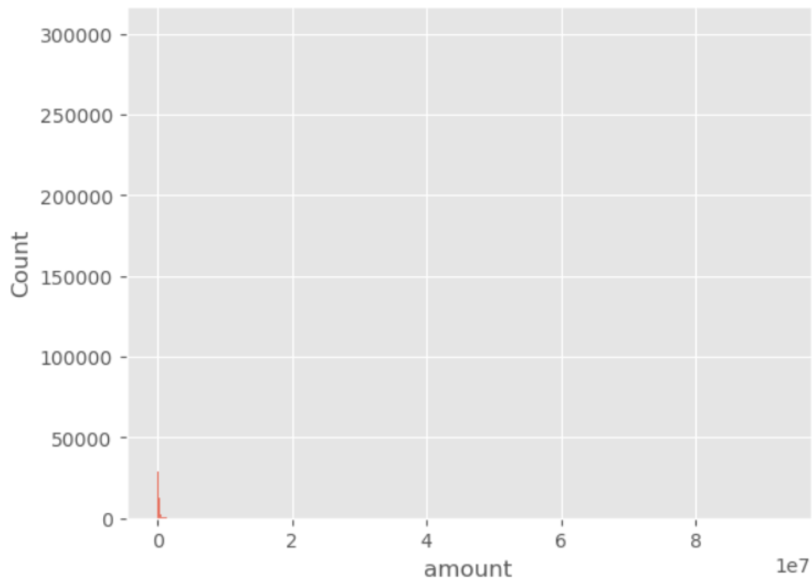
```
In [17]: # type
         sns.countplot(data=df,x='type')
```

```
Out[17]: <Axes: xlabel='type', ylabel='count'>
```



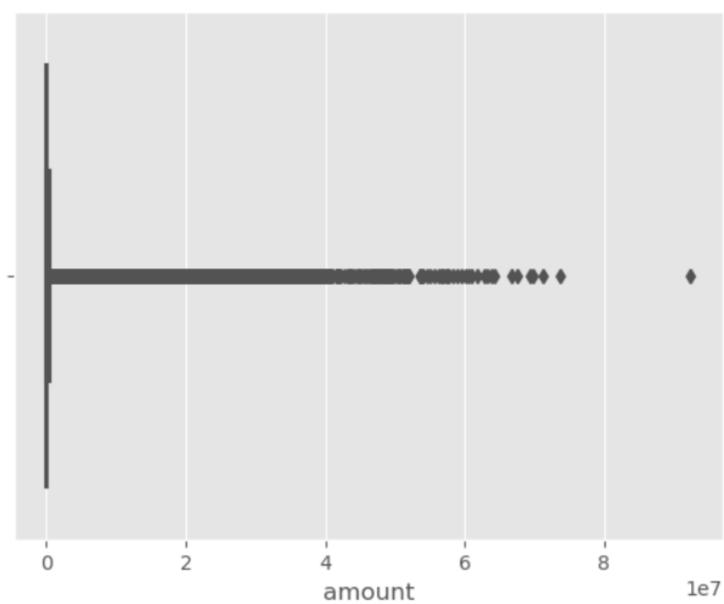
Here, the counts of observations in the type attribute of the dataset will be displayed using a countplot.

In [18]:
```
# amount
sns.histplot(data=df,x='amount')
```
Out[18]: <Axes: xlabel='amount', ylabel='Count'>



By creating bins along the data's range and then drawing bars to reflect the number of observations that fall within the amount attribute in the dataset.

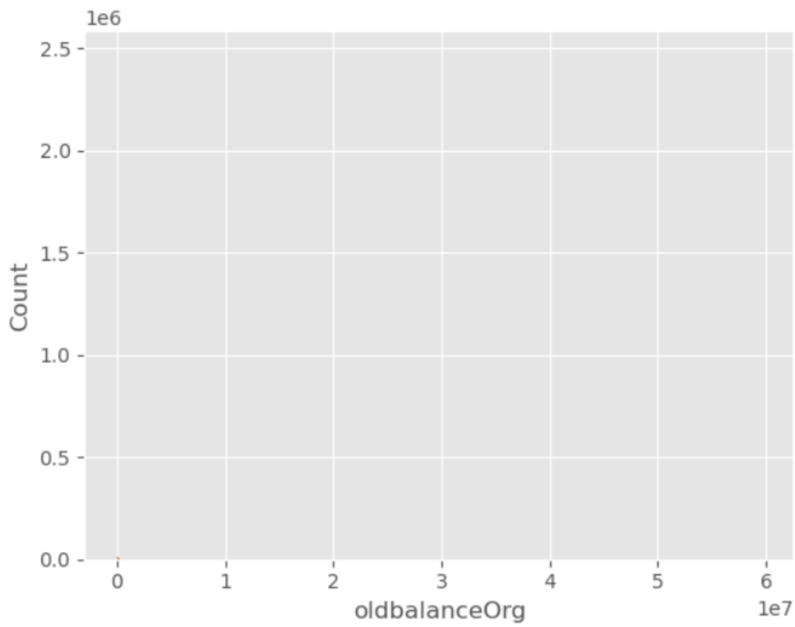
In [19]:
```
# amount
sns.boxplot(data=df,x='amount')
```
Out[19]: <Axes: xlabel='amount'>



Here, the relationship between the amount attribute and the boxplot is visualised.

In [20]:
```
# oldbalanceOrg
sns.histplot(data=df,x='oldbalanceOrg')
```

Out[20]: `<Axes: xlabel='oldbalanceOrg', ylabel='Count'>`



By creating bins along the data's range and then drawing bars to reflect the number of observations that fall within the oldbalanceOrg attribute in the dataset.

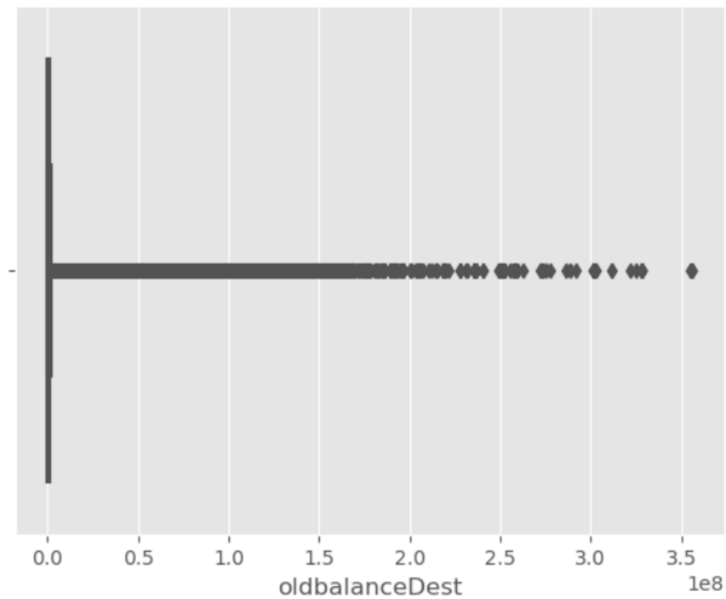
In [21]:
```
# nameDest
df['nameDest'].value_counts()
```

Out[21]:
```
nameDest
C1286084959    113
C985934102     109
C665576141     105
C2083562754    102
C248609774     101
              ...
M1470027725      1
M1330329251      1
M1784358659      1
M2081431099      1
C2080388513      1
Name: count, Length: 2722362, dtype: int64
```

Utilising the value counts() function here to determine how many times the nameDest column appears.

```
In [22]: # oldbalanceDest
sns.boxplot(data=df,x='oldbalanceDest')
```

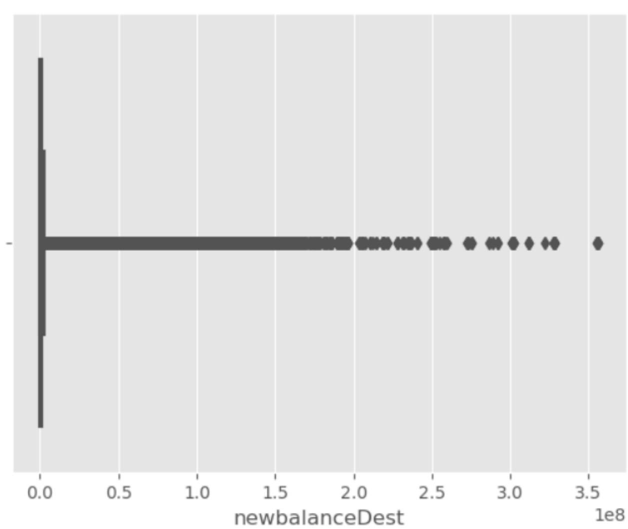
```
Out[22]: <Axes: xlabel='oldbalanceDest'>
```



Here, the relationship between the oldbalanceDest attribute and the boxplot is visualised.

```
In [23]: # newbalanceDest
sns.boxplot(data=df,x='newbalanceDest')
```

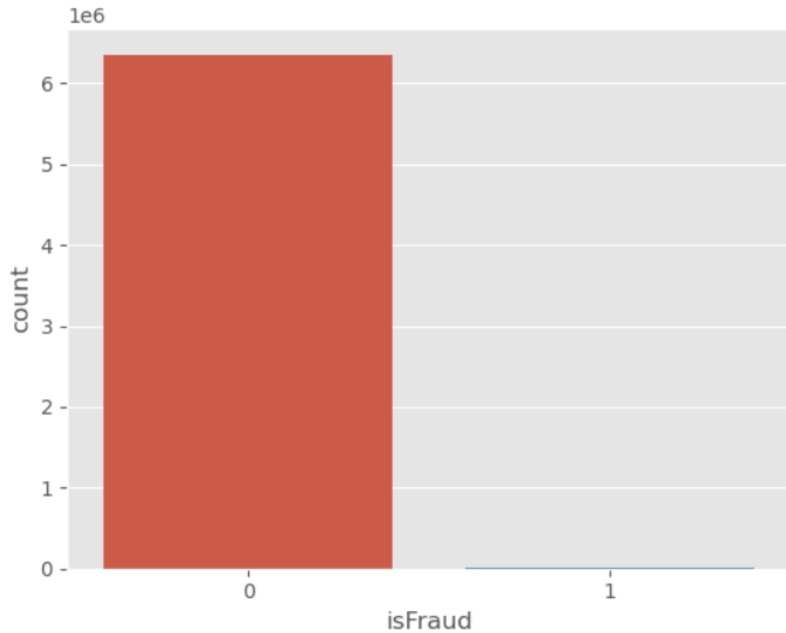
```
Out[23]: <Axes: xlabel='newbalanceDest'>
```



Here, the relationship between the newbalanceDest attribute and the boxplot is visualised.

```
In [24]: # isFraud:
         sns.countplot(data=df,x='isFraud')
```

```
Out[24]: <Axes: xlabel='isFraud', ylabel='count'>
```



Using the countplot approach here to count the number of instances in the dataset's target isFraud column.

```
In [25]: df['isFraud'].value_counts()
```

```
Out[25]: isFraud
         0    6354407
         1       8213
         Name: count, dtype: int64
```

Here, we're using the value counts method to figure out how many classes there are in the dataset's target isFraud column.

In [26]:
```
df.loc[df['isFraud']==0, 'isFraud'] = 'is not Fraud'
df.loc[df['isFraud']==1, 'isFraud'] == 'is Fraud'
```

Out[26]:
```
2          False
3          False
251        False
252        False
680        False
           ...  
6362615    False
6362616    False
6362617    False
6362618    False
6362619    False
Name: isFraud, Length: 8213, dtype: bool
```

In [27]:
```
df
```

Out[27]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	0.00	is not Fraud
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	0.00	is not Fraud
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	0.00	1
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	0.00	1
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	0.00	is not Fraud
...	...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	339682.13	1
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	0.00	1
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	6379898.11	1
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	0.00	1
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	7360101.63	1

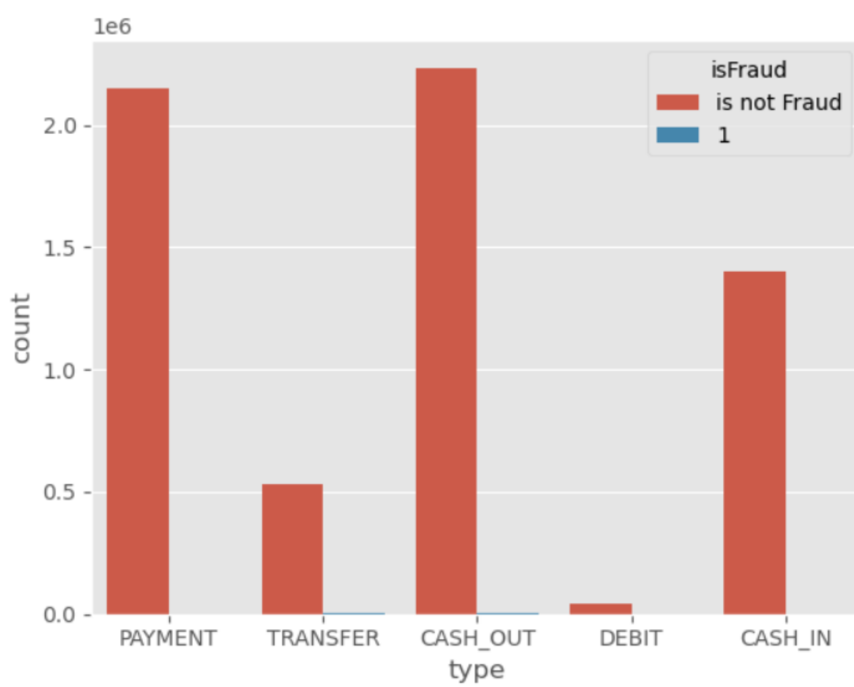
Converting 0-means: is not fraud and 1-means: is fraud using the loc technique here

Activity 4: Bivariate analysis

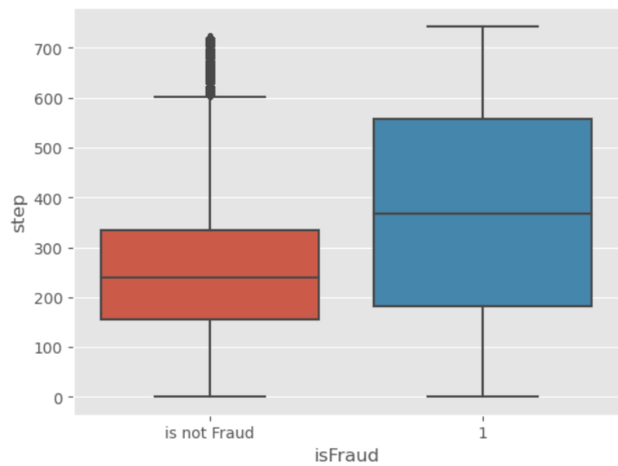
Here we are visualising the relationship between type and isFraud.countplot is used here. As a 1st parameter we are passing x value and as a 2nd parameter we are passing hue value.

In [30]:
```
sns.countplot(data=df,x='type',hue='isFraud')
```

Out[30]: <Axes: xlabel='type', ylabel='count'>



```
In [31]: sns.boxplot(data=df,x='isFraud',y='step')
Out[31]: <Axes: xlabel='isFraud', ylabel='step'>
```



Here we are visualising the relationship between isFraud and amount.boxtplot is used here. As a 1 st parameter we are passing x value and as a 2 nd parameter we are passing hue value.

Activity 5: 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.

```
In [38]: df.describe(include='all')
Out[38]:
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
count	6.362620e+06	6362620	6.362620e+06	6362620	6.362620e+06	6.362620e+06	6362620	6.362620e+06	6.362620e+06	6362620
unique	NaN	5	NaN	6353307	NaN	NaN	2722362	NaN	NaN	2
top	NaN	CASH_OUT	NaN	C1902386530	NaN	NaN	C1286084959	NaN	NaN	is not Fraud
freq	NaN	2237500	NaN	3	NaN	NaN	113	NaN	NaN	6354407
mean	2.433972e+02	NaN	1.798619e+05	NaN	8.338831e+05	8.551137e+05	NaN	1.100702e+06	1.224996e+06	NaN
std	1.423320e+02	NaN	6.038582e+05	NaN	2.888243e+06	2.924049e+06	NaN	3.399180e+06	3.674129e+06	NaN
min	1.000000e+00	NaN	0.000000e+00	NaN	0.000000e+00	0.000000e+00	NaN	0.000000e+00	0.000000e+00	NaN
25%	1.560000e+02	NaN	1.338957e+04	NaN	0.000000e+00	0.000000e+00	NaN	0.000000e+00	0.000000e+00	NaN
50%	2.390000e+02	NaN	7.487194e+04	NaN	1.420800e+04	0.000000e+00	NaN	1.327057e+05	2.146614e+05	NaN
75%	3.350000e+02	NaN	2.087215e+05	NaN	1.073152e+05	1.442584e+05	NaN	9.430367e+05	1.111909e+06	NaN
max	7.430000e+02	NaN	9.244552e+07	NaN	5.958504e+07	4.958504e+07	NaN	3.560159e+08	3.561793e+08	NaN

Milestone 3: 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

In [40]:
```
# shape of csv data
df.shape
```

Out[40]:
```
(6362620, 10)
```

Here, I'm using the shape approach to figure out how big my dataset is

In [41]:
```
df.drop(['nameOrig', 'nameDest'],axis=1,inplace=True)
df.columns
```

Out[41]:
```
Index(['step', 'type', 'amount', 'oldbalanceOrg', 'newbalanceOrig',
       'oldbalanceDest', 'newbalanceDest', 'isFraud'],
      dtype='object')
```

In [42]:
```
df.head()
```

Out[42]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
0	1	PAYMENT	9839.64	170136.0	160296.36	0.0	0.0	is not Fraud
1	1	PAYMENT	1864.28	21249.0	19384.72	0.0	0.0	is not Fraud
2	1	TRANSFER	181.00	181.0	0.00	0.0	0.0	1
3	1	CASH_OUT	181.00	181.0	0.00	21182.0	0.0	1
4	1	PAYMENT	11668.14	41554.0	29885.86	0.0	0.0	is not Fraud

Here, the dataset's superfluous columns (nameOrig,nameDest) are being removed using the drop method.

Activity 1: Checking for null values

Isnull is used (). sum() to check your database for null values. Using the df.info() function, the data type can be determined.

In [44]:
```
# Finding null values
df.isnull().sum()
```

Out[44]:
```
step              0
type              0
amount            0
oldbalanceOrg     0
newbalanceOrig    0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
dtype: int64
```

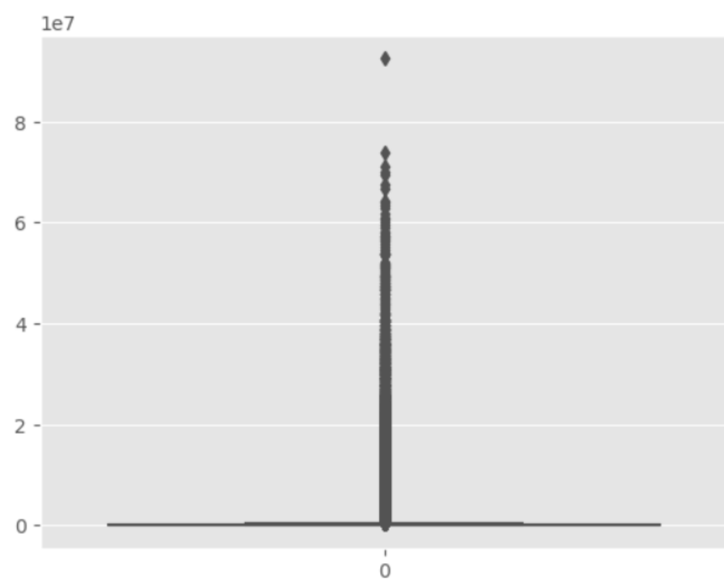
For checking the null values, data.isnull() function is used. To sum those null values we use the .sum() function to it. From the above image we found that there are no null values present in our dataset.So we can skip handling of missing values step.

```
In [45]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 8 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   oldbalanceOrg   float64
 4   newbalanceOrig  float64
 5   oldbalanceDest  float64
 6   newbalanceDest  float64
 7   isFraud         object
dtypes: float64(5), int64(1), object(2)
memory usage: 388.3+ MB
```

Determining the types of each attribute in the dataset using the info() function.

Activity 2: Handling outliers

```
In [47]: sns.boxplot(df['amount'])
Out[47]: <Axes: >
```



Here, a boxplot is used to identify outliers in the dataset's amount attribute.

In [49]:
```
from scipy import stats
print(stats.mode(df['amount']))
print(np.mean(df['amount']))
```

```
ModeResult(mode=10000000.0, count=3207)
179861.90354913071
```

In [50]:
```
q1 = np.quantile(df['amount'],0.25)
q3 = np.quantile(df['amount'], 0.75)

IQR = q3-q1

upper_bound = q3+ (1.5*IQR)
lower_bound = q1-(1.5*IQR)

print('q1 :',q1)
print('q3 :',43)
print('IQR :' ,IQR)
print('Upper Bound :',upper_bound)
print('Lower Bound :',lower_bound)
print('Skewed data:',len (df[df['amount']>upper_bound]))
print('Skewed data:',len(df[df['amount']<lower_bound]))
```

```
q1 : 13389.57
q3 : 43
IQR : 195331.9075
Upper Bound : 501719.33875
Lower Bound : -279608.29125
Skewed data: 338078
Skewed data: 0
```

Activity 3: Object data labelencoding

In [56]:
```
from sklearn.preprocessing import LabelEncoder

la = LabelEncoder()
df['type'] = la.fit_transform(df['type'])
```

In [57]:
```
df['type'].value_counts()
```

Out[57]:
```
type
1    2237500
3    2151495
0    1399284
4     532909
2      41432
Name: count, dtype: int64
```

Using labelencoder to encode the dataset's object type

X & Y Split and Scaling Columns

```
In [58]: x = df.drop('isFraud',axis=1)
         y = df['isFraud']
```

```
In [59]: x
```

Out[59]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	1	3	9.194174	170136.00	160296.36	0.00	0.00
1	1	3	7.530630	21249.00	19384.72	0.00	0.00
2	1	4	5.198497	181.00	0.00	0.00	0.00
3	1	1	5.198497	181.00	0.00	21182.00	0.00
4	1	3	9.364617	41554.00	29885.86	0.00	0.00
...	...	...	...	...	...	...	...
6362615	743	1	12.735766	339682.13	0.00	0.00	339682.13
6362616	743	4	15.657870	6311409.28	0.00	0.00	0.00
6362617	743	1	15.657870	6311409.28	0.00	68488.84	6379898.11
6362618	743	4	13.652995	850002.52	0.00	0.00	0.00
6362619	743	1	13.652995	850002.52	0.00	6510099.11	7360101.63

6362620 rows × 7 columns

```
In [60]: y
```

```
Out[60]: 0          is not Fraud
         1          is not Fraud
         2                     1
         3                     1
         4          is not Fraud
                        ...
         6362615               1
         6362616               1
         6362617               1
         6362618               1
         6362619               1
         Name: isFraud, Length: 6362620, dtype: object
```

Activity 4: Splitting data into train and test

Now let’s split the Dataset into train and test setsChanges: first split the dataset into x and y and then split the data set.

Here x and y variables are created. On x variable, df is passed with dropping the target variable. And my target variable is passed. For splitting training and testing data we are using the train_test_split() function from sklearn. As parameters, we are passing x, y, test_size, random_state.

```
In [62]: # Train test split
         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)

In [63]: print(x_train.shape)
         print(x_test.shape)
         print(y_test.shape)
         print(y_train.shape)

         (5090096, 7)
         (1272524, 7)
         (1272524,)
         (5090096,)
```

Milestone 4: Model Building

Now our data is cleaned and it's time to build the model. We can train our data on different algorithms. For this project we are applying four classification algorithms. The best model is saved based on its performance

Activity 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.

```
In [110]: rfc = RandomForestClassifier()
          rfc.fit(X_train, y_train)

Out[110]: RandomForestClassifier()

In [111]: y_test_pred_1 = rfc.predict(X_test)

In [112]: accuracy_test_1 = accuracy_score(y_test, y_test_pred_1)
          accuracy_test_1

Out[112]: 0.9996898545774217

In [113]: pd.crosstab(y_test, y_test_pred_1)

Out[113]:
```

col_0	is Fraud	is not Fraud
isFraud		
is Fraud	1889	552
is not Fraud	40	1906301

Activity 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.

```
In [114]: from sklearn.tree import DecisionTreeClassifier
          dtc = DecisionTreeClassifier()

In [115]: dtc.fit(X_train, y_train)

Out[115]: DecisionTreeClassifier()

In [116]: y_test_pred_2 = dtc.predict(X_test)

In [117]: accuracy_test_2 = accuracy_score(y_test, y_test_pred_2)
          accuracy_test_2

Out[117]: 0.9996662793341513

In [118]: pd.crosstab(y_test, y_test_pred_2)

Out[118]:
```

col_0	is Fraud	is not Fraud
isFraud		
is Fraud	2079	362
is not Fraud	275	1906066

Activity 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.

```
In [119]: from sklearn.ensemble import ExtraTreesClassifier
          etc = ExtraTreesClassifier()

In [120]: etc.fit(X_train, y_train)

Out[120]: ExtraTreesClassifier()
```

```
In [121]: y_test_pred_3 = etc.predict(X_test)
```

```
In [122]: accuracy_test_3 = accuracy_score(y_test, y_test_pred_3)
          accuracy_test_3
```

```
Out[122]: 0.9996767572200492
```

```
In [123]: pd.crosstab(y_test, y_test_pred_3)
```

Out[123]:

col_0 / isFraud	is Fraud	is not Fraud
is Fraud	1849	592
is not Fraud	25	1906316

Activity 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.

```
In [38]: from sklearn.svm import SVC
         svc = SVC()
```

```
In [ ]: svc.fit(X_train, y_train)
```

```
In [ ]: y_test_pred_4 = svc.predict(X_test)
```

```
In [ ]: accuracy_test_4 = accuracy_score(y_test, y_test_pred_4)
        accuracy_test_4
```

```
In [ ]: pd.crosstab(y_test, y_test_pred_4)
```

Activity 5: Evaluating performance of the model and saving the model

Our model is performing well. So, we are saving the model is svc by pickle.dump().

```
In [ ]: import pickle
```

```
In [ ]: pickle.dump(svc, open('model.pkl', 'wb'))
```

7.2 Feature 2

Milestone 5: Application Building

In this section, we will be building a web application that is integrated to the model we built. A UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

• Building HTML Pages

• Building server side script

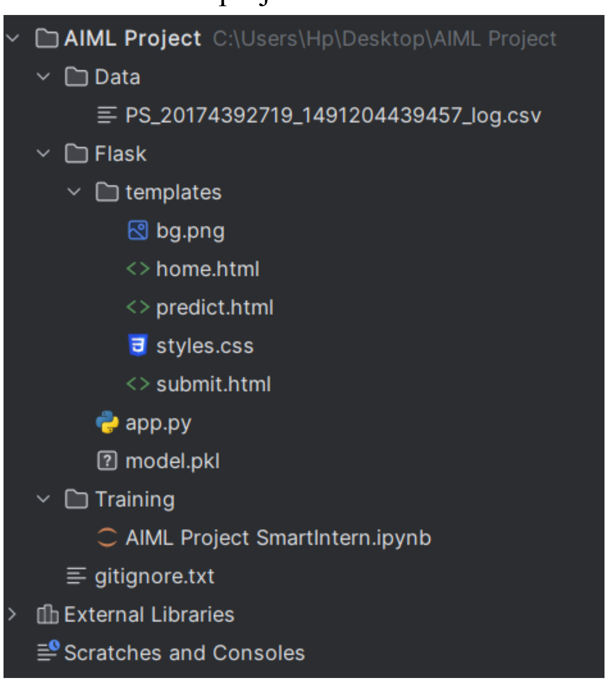
Activity1: Building Html Pages:

For this project create three HTML files namely

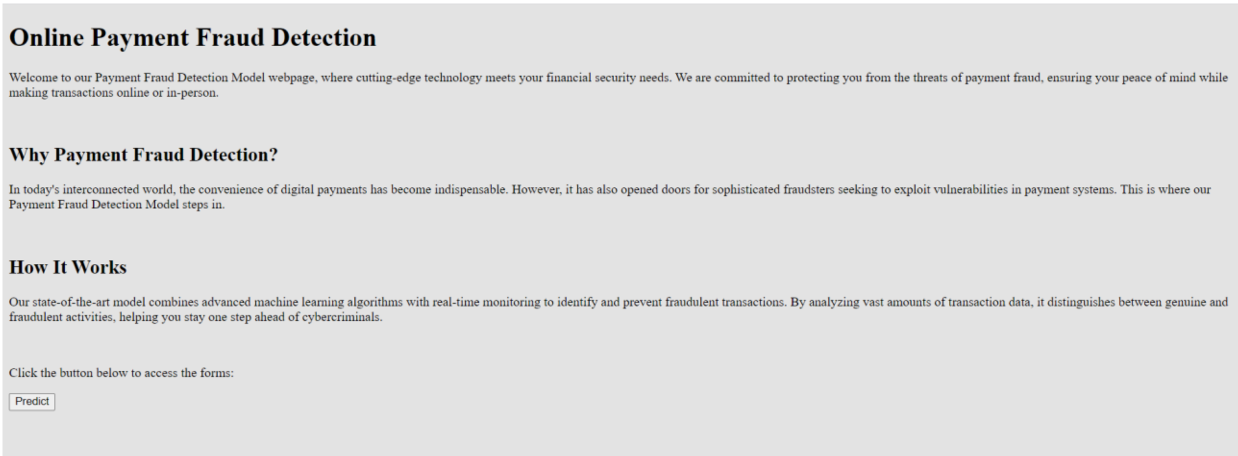
- index.html
- predict.html
- submit.html

and save them in the templates folder.

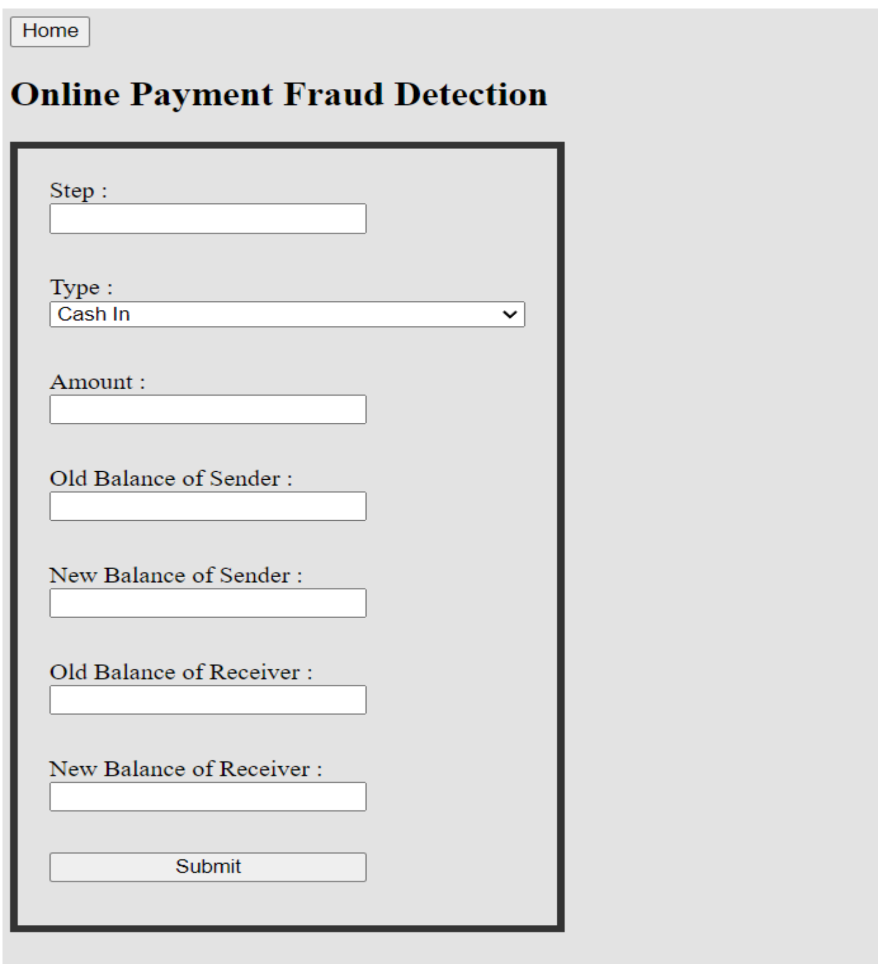
As shown in the project structure



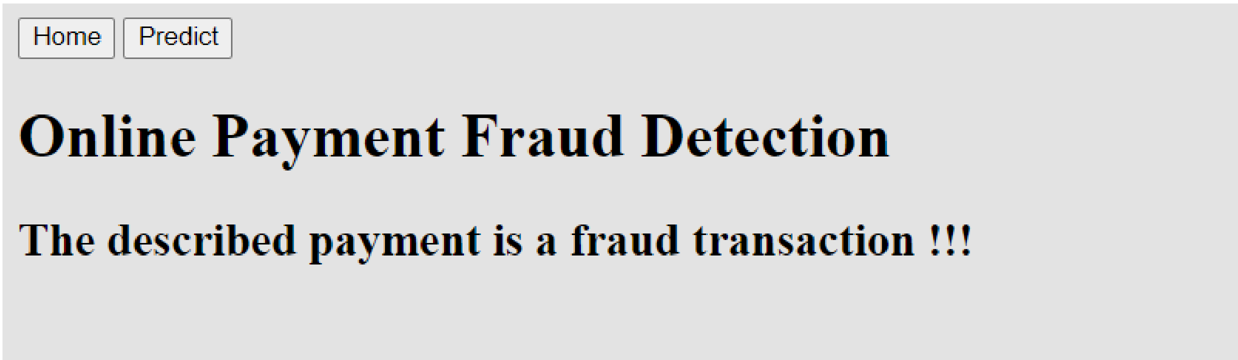
Let’s see how our home.html page looks like:



Now when you click on predict button you will get redirected to predict.html
Let's look how our predict.html file looks like:



Now when you click on submit button you will get redirected to submit.htm
Let's look how our submit.html file looks like:



Activity 2: Build Python code:

Import the libraries
Load the saved model. Importing the flask module in the project is mandatory. An object of Flask class is our WSGI application. Flask constructor takes the name of the current module (__name__) as argument.

```
from flask import Flask, request, render_template
import pickle as pkl

model = pkl.load(open("model.pkl", 'rb'))

app = Flask(__name__)
```

Render HTML page:

```
@app.route("/home.html")
def home1():
    return render_template("home.html")


@app.route("/")
def home():
    return render_template("home.html")
```

Here we will be using a declared constructor to route to the HTML page which we have created earlier.

In the above example, '/' URL is bound with the home.html function. Hence, when the home page of the web server is opened in the browser, the html page will be rendered. Whenever you enter the values from the html page the values can be retrieved using POST Method.

Retrieves the value from UI:

```
@app.route('/predict.html')
def predict_page():
    return render_template('predict.html')

1 usage (1 dynamic)
@app.route( rule: '/submit.html', methods=['POST'])
def predict():
    # Get user input from the form
    feature1 = float(request.form['step'])
    feature2 = float(request.form['type'])
    feature3 = float(request.form['amount'])
    feature4 = float(request.form['oldbalanceOrg'])
    feature5 = float(request.form['newbalanceOrg'])
    feature6 = float(request.form['oldbalanceDest'])
    feature7 = float(request.form['newbalanceDest'])
```

Here we are routing our app to predict() function. This function retrieves all the values from the HTML page using Post request. That is stored in an array. This array is passed to the model.predict() function. This function returns the prediction. And this prediction value will be rendered to the text that we have mentioned in the submit.html page earlier.

Main Function:

```
if __name__ == "__main__":
    app.run(debug=True)
```

Activity 3: Run the application

- Open VSCODE prompt from the start menu
- Navigate to the folder where your python script is.
- Now type "python app.py" command
- Navigate to the localhost where you can view your web page.

● Click on the predict button from the top right corner, enter the inputs, click on the submit button, and see the result/prediction on the web

```
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
  warnings.warn(
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with watchdog (windowsapi)
```

8.PERFORMANCE TESTING

8.1 Performance Metrics

Model Performance Testing:

Since the outcome of our project needed to be predicted as either "is a fraud" or "is not a fraud," a classification-based model was necessary.

Random Forest classifier, Decision Tree classifier, Extra Tree classifier, SVM classifier were the models utilized in the projects.

The metrics reports for each model are as follows:

Random Forest classifier:

1. Test accuracy

```
y_pred=rfc.predict(X_test)
print("Training Score",accuracy_score(y_train_smote,rfc.predict(x_train_smote)))
print("Testing Accuracy",accuracy_score(y_test,y_pred))
print(X_test.shape)
```

```
Testing Accuracy 0.9837896584810781
```

2. Train accuracy

```
y_pred=rfc.predict(X_test)
print("Training Score",accuracy_score(y_train_smote,rfc.predict(x_train_smote)))
print("Testing Accuracy",accuracy_score(y_test,y_pred))
print(X_test.shape)
```

```
Training Score 0.9386852256321613
```

3.Confusion Matrix

```
pd.crosstab(y_test,y_pred)
```

col_0	is Fraud	is not Fraud
isFraud		
is Fraud	1439	148
is not Fraud	20480	1250454

3. Classification Report

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

    is Fraud       0.07      0.91      0.12      1587
is not Fraud       1.00      0.98      0.99   1270934

    accuracy                           0.98   1272521
   macro avg       0.53      0.95      0.56   1272521
weighted avg       1.00      0.98      0.99   1272521
```

Decision tree Classifier:

1. Test accuracy

```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
```

```
y_test_pred_2 = dtc.predict(X_test)
```

```
accuracy_test_2 = accuracy_score(y_test, y_test_pred_2)
accuracy_test_2
```

```
0.9997053093819277
```

2. Train accuracy

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

```
1.0
```

3. Confusion Matrix

```
pd.crosstab(y_test, y_test_pred_2)
```

col_0	is Fraud	is not Fraud
isFraud		
is Fraud	1403	184
is not Fraud	191	1270743

4. Classification Report

ExtraTrees Classifier

1. Test accuracy

```
from sklearn.ensemble import ExtraTreesClassifier
etc=ExtraTreesClassifier()
etc.fit(x_train_smote,y_train_smote)
y_pred=etc.predict(X_test)
print("Training Score",accuracy_score(y_train_smote,etc.predict(x_train_smote)))
print("Testing Accuracy",accuracy_score(y_test,y_pred))
```

```
Testing Accuracy 0.9994451957963758
```

2. Train accuracy

```
Training Score 1.0
```

3. Confusion Matrix

```
pd.crosstab(y_test,y_pred)
```

col_0	is Fraud	is not Fraud
isFraud		
is Fraud	1426	161
is not Fraud	545	1270389

4. Classification Report

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

    is Fraud       0.72      0.90      0.80      1587
is not Fraud       1.00      1.00      1.00   1270934

    accuracy                           1.00   1272521
   macro avg       0.86      0.95      0.90   1272521
weighted avg       1.00      1.00      1.00   1272521
```

Final Prediction:

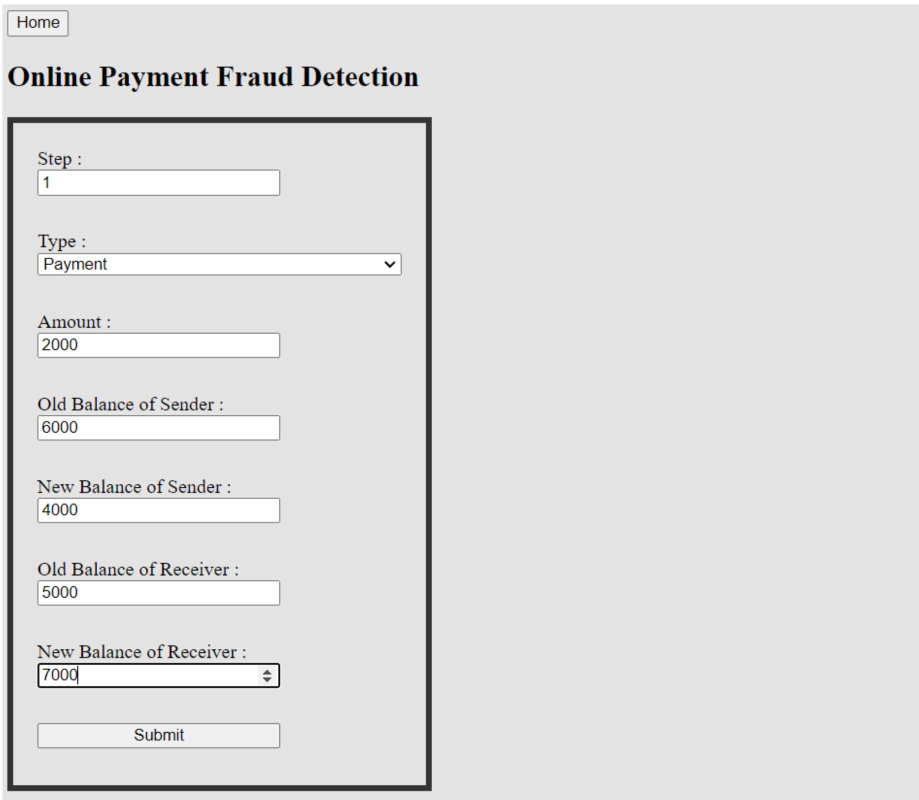
```
etc.predict([[0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 1.00000000e+00,0.00000000e+00, 0.00000000e+00, 1.00000000e+00
```

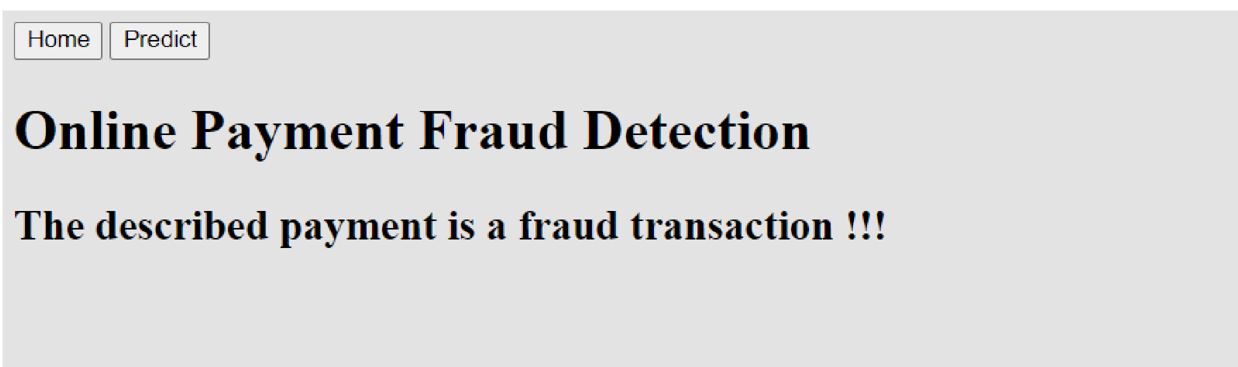
```
array(['is not Fraud'], dtype=object)
```

9.RESULTS

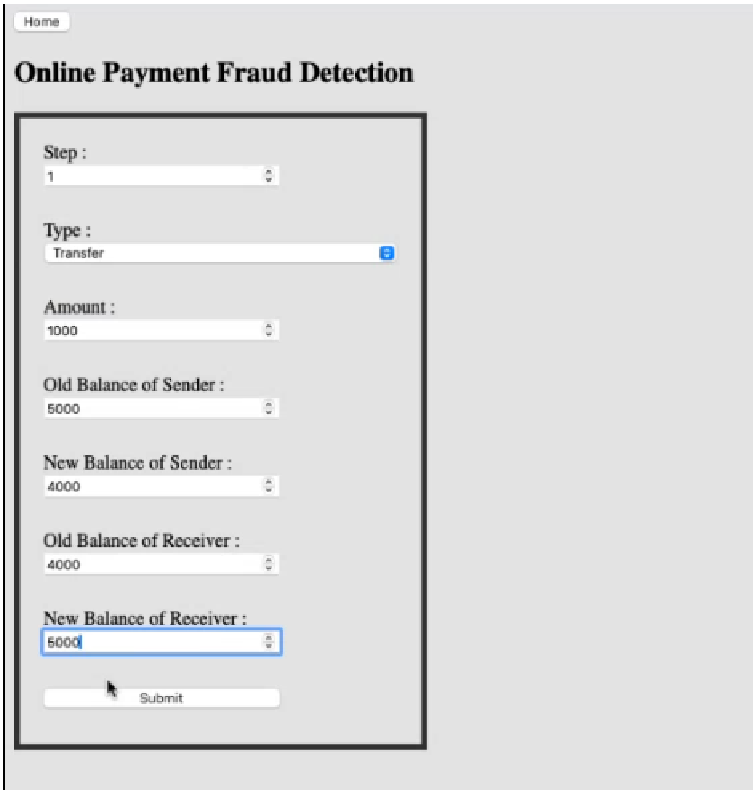
9.1Output Screenshots

When transaction is fraud





When transaction is not fraud


Home
Online Payment Fraud Detection
Step :
1
Type :
Transfer
Amount :
1000
Old Balance of Sender :
5000
New Balance of Sender :
4000
Old Balance of Receiver :
4000
New Balance of Receiver :
5000
Submit


Home
Predict
Online Payment Fraud Detection
The described payment is not a fraud transaction !!!

10.ADVANTAGES & DISADVANTAGES

Advantages:

1. Improved Fraud Detection Accuracy:
The utilization of classification algorithms such as Decision Trees, Random Forest, SVM, Extra Trees, and XGBoost enhances the accuracy of fraud detection, leading to a more robust and reliable system.

2. Real-time Monitoring
The implementation of real-time transaction monitoring ensures prompt identification of potentially fraudulent activities, allowing for immediate intervention and mitigation.

3. Adaptive System:
The integration of multiple classification algorithms makes the system adaptive to evolving patterns of fraudulent behavior. This adaptability is crucial in addressing the dynamic nature of online fraud.

4. User Notifications
Users receive timely notifications for flagged transactions, empowering them to take quick actions to secure their accounts. This proactive approach contributes to user trust and engagement.

5**. Compliance with Data Security Standards**
Adherence to robust data security measures ensures the protection of sensitive financial information, maintaining the confidentiality and integrity of user data.

Disadvantages:

1.**Computational Resource Requirements**
The integration of multiple classification algorithms may demand significant computational resources, potentially leading to higher infrastructure costs.

2**. Complex Implementation:**
The complexity of implementing and maintaining a system with various classification algorithms could pose challenges in terms of development and ongoing system management.

3. Algorithmic Sensitivity :
The effectiveness of the system heavily relies on the accuracy of the chosen classification algorithms. Sensitivity to the quality and diversity of data used for training could impact overall performance.

4.**False Positives/Negatives:**

Like any fraud detection system, there is a possibility of false positives (flagging non-fraudulent transactions) or false negatives (missing actual fraudulent transactions). Striking the right balance is a continuous challenge.

5.User Notification Management:

Managing user notifications effectively requires careful consideration to avoid overwhelming users with alerts. Striking the right balance between informative notifications and avoiding user fatigue is essential.

6.Dependency on Training Data Quality:

The accuracy of the system is heavily dependent on the quality and representativeness of the training data. Insufficient or biased training data may impact the model's ability to generalize effectively.

11.CONCLUSION

In conclusion, the development and implementation of our project online payment fraud detection system using machine learning algorithms represent a significant stride toward enhancing the security and trustworthiness of online transactions. The project, focusing on real-time monitoring and integration with multiple classification algorithms, has demonstrated several notable outcomes.

The incorporation of Decision Trees, Random Forest, SVM, Extra Trees, and XGBoost classifiers has substantially improved the accuracy and adaptability of the system. This comprehensive approach ensures the system's capability to identify and respond to a diverse range of fraudulent patterns in real-time, contributing to a more secure online financial environment.

The project's user-centric design, coupled with timely notifications for flagged transactions, addresses the end-users' concerns and fosters a sense of confidence in online transactions. The user-friendly interface facilitates efficient interaction, empowering users to respond promptly to potential threats.

However, it is essential to acknowledge the project's limitations and challenges. The complexity associated with implementing and maintaining a system with multiple algorithms requires ongoing attention. The potential for false positives or false negatives, dependency on training data quality, and the need for careful user notification management are aspects that warrant continual refinement and optimization.

Despite these challenges, the overall advantages of improved accuracy, real-time monitoring, and user empowerment position the developed system as a valuable tool in the ongoing battle against online payment fraud. The commitment to data security standards and user privacy compliance further reinforces the project's contribution to building a trustworthy online financial ecosystem.

As the digital landscape continues to evolve, the system's adaptability becomes crucial. Ongoing efforts should be directed towards monitoring algorithmic performance, refining models based on emerging trends, and addressing any evolving challenges in the online fraud landscape.

12.FUTURE SCOPE:

The successful implementation of the online payment fraud detection system has laid a solid foundation for future advancements and enhancements. Moving forward, the project holds significant potential for growth and refinement. One avenue for exploration involves integrating more advanced machine learning models and algorithms to further improve the accuracy of fraud detection. Big data analytics can be leveraged to efficiently handle large volumes of transaction data, enhancing the system's scalability. Behavioral analytics offers another promising direction, allowing for a deeper understanding of user behavior patterns over time. The integration of blockchain technology can enhance the security and transparency of transactions, providing an immutable ledger for added trust. Real-time machine learning updates ensure that the system remains adaptive to evolving fraud patterns, and expanding the system's scope to address cross-border fraud can significantly enhance its effectiveness in a broader context. Collaboration with financial institutions, continuous user education, and a focus on explainability and interpretability contribute to the system's ongoing improvement and user trust. Additionally, exploring mobile application integration and international collaboration will extend the system's reach and effectiveness. By venturing into these future avenues, the online payment fraud detection system has the potential to evolve into a comprehensive, adaptive, and globally impactful solution for securing online financial transactions.

13. **APPENDIX** Source Code

GitHub Link

https://github.com/smartinternz02/SI-GuidedProject-601123-1697605244

Project Demo Link

https://drive.google.com/drive/folders/1nDQUnOos1y3ZpB_zQIvu-mo9LZwIjw1O