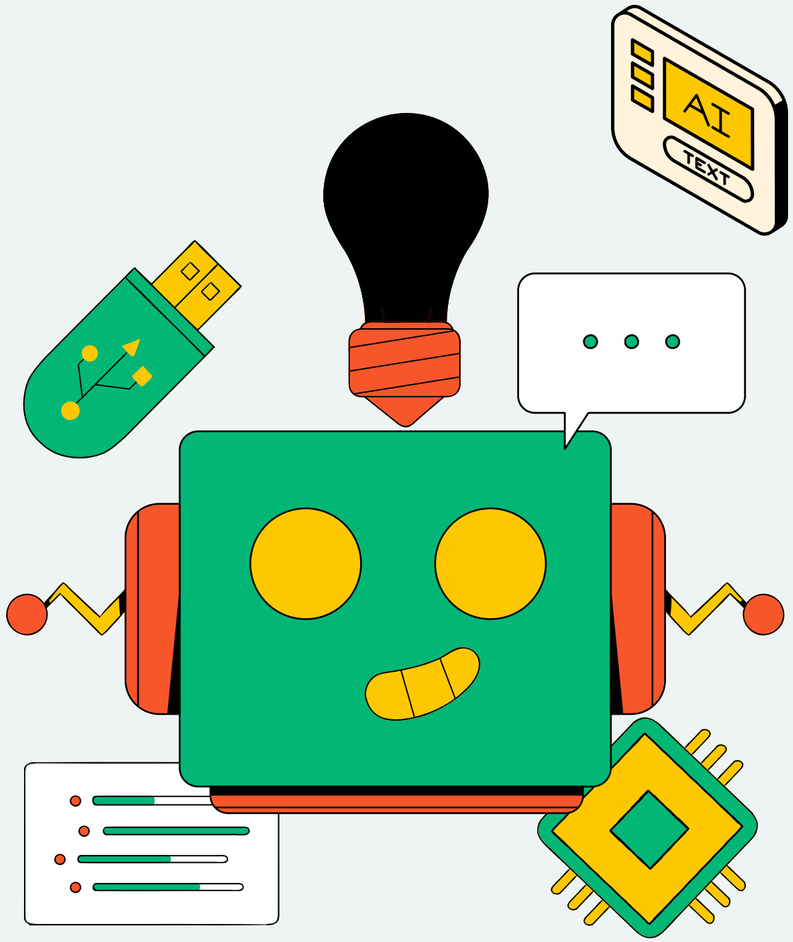
MENTORNESS

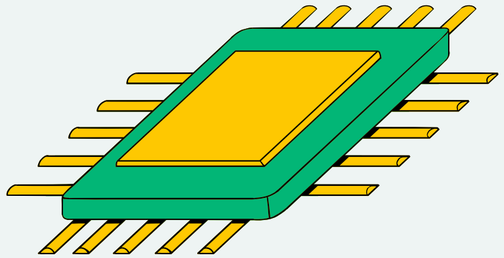


FAST TAG FRAUD DETECTION

USING MACHINE LEARNING

PRESENTED BY:

RISHABH KOSTA



PRESENTATION OUTLINE

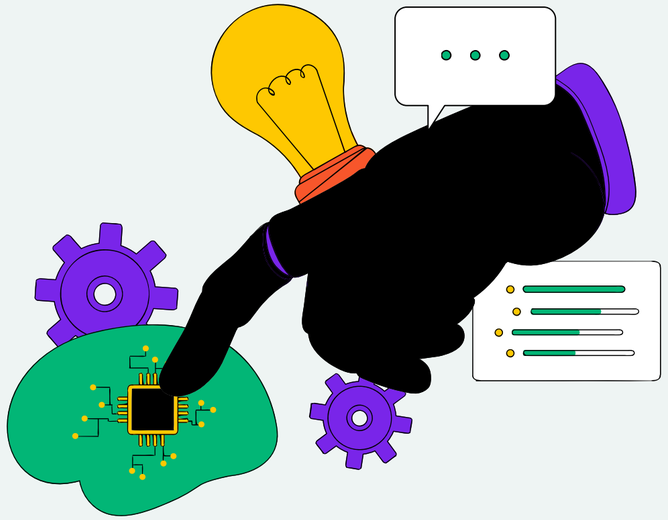
- Problem Statement
- Data Description
- Project Objective
- Data Exploration
- Exploratory Data Analysis
- Feature Engineering
- Model Development
- Real – Time Fraud Detection
- Deliverables
- Expected Outcomes
- References

PROBLEM STATEMENT

This project focuses on leveraging machine learning classification techniques to develop an effective fraud detection system for Fastag transactions. The dataset comprises key features such as transaction details, vehicle information, geographical location, and transaction amounts. The goal is to create a robust model that can accurately identify instances of fraudulent activity, ensuring the integrity and security of Fastag transactions.

DATASET DESCRIPTION

- **Transaction_ID:** Unique identifier for each transaction.
- **Timestamp:** Date and time of the transaction.
- **Vehicle_Type:** Type of vehicle involved in the transaction.
- **FastagID:** Unique identifier for Fastag.
- **TollBoothID:** Identifier for the toll booth.
- **Lane_Type:** Type of lane used for the transaction.
- **Vehicle_Dimensions:** Dimensions of the vehicle.
- **Transaction_Amount:** Amount associated with the transaction.
- **Amount_paid:** Amount paid for the transaction.
- **Geographical_Location:** Location details of the transaction.
- **Vehicle_Speed:** Speed of the vehicle during the transaction.
- **Vehicle_Plate_Number:** License plate number of the vehicle.
- **Fraud_indicator:** Binary indicator of fraudulent activity (target variable).



PROJECT OBJECTIVE

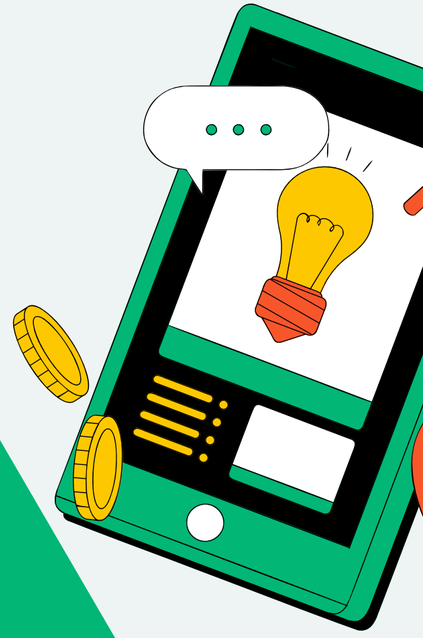
Model Development

Feature Engineering

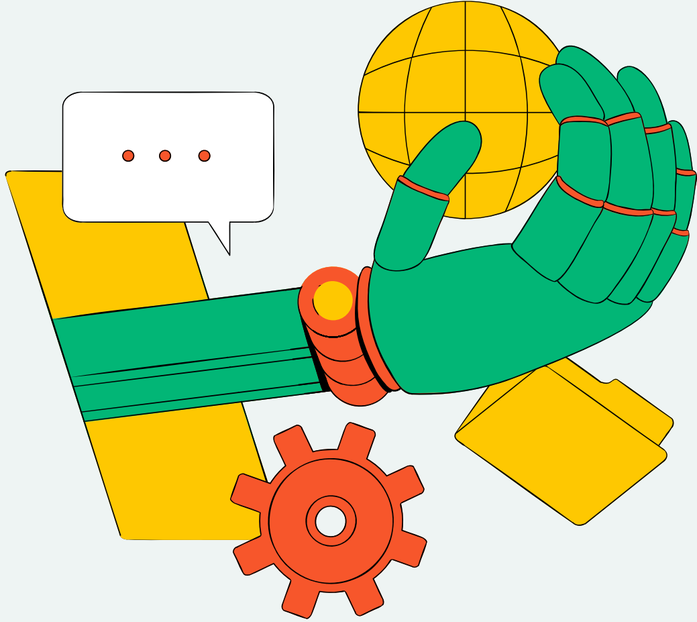
Explanatory Analysis

Data Exploration

Real-Time Fraud Detection



DATA EXPLORATION



DATA PREPARATION

- Data collection, cleaning, and preprocessing
- Ensuring data quality and reliability
- Data labeling and annotation

The main goal of data exploration are to identify potential relationship between variables, detect outliers or anomalies, understand the distribution of data, and gain insights that can guide further analysis or modelling tasks.

DATA SUMMARY

Importing CSV File

[1]:
```
import pandas as pd

#Load theb dataset
data = pd.read_csv("FastagFraudDetection.csv")

print("Datatset loaded successfully")
```

```
Datatset loaded successfully
```

[2]:
```
#Display first few rows of dataset
print("First few rows of the dataset: ")
print(data.head())
```

```
First few rows of the dataset:
   Transaction_ID       Timestamp Vehicle_Type         FastagID TollBoothID  \
0               1  1/6/2023 11:20         Bus   FTG-001-ABC-121       A-101
1               2  1/7/2023 14:55         Car   FTG-002-XYZ-451       B-102
2               3  1/8/2023 18:25  Motorcycle               NaN       D-104
3               4   1/9/2023 2:05       Truck   FTG-044-LMN-322       C-103
4               5  1/10/2023 6:35         Van   FTG-505-DEF-652       B-102

  Lane_Type Vehicle_Dimensions  Transaction_Amount  Amount_paid  \
0   Express              Large                350          120
1   Regular              Small                120          100
2   Regular              Small                  0            0
3   Regular              Large                350          120
4   Express             Medium                140          100

                  Geographical_Location  Vehicle_Speed Vehicle_Plate_Number  \
0  13.059816123454882, 77.77068662374292             65           KA11AB1234
1  13.059816123454882, 77.77068662374292             78           KA66CD5678
2  13.059816123454882, 77.77068662374292             53           KA88EF9012
3  13.059816123454882, 77.77068662374292             92           KA11GH3456
4  13.059816123454882, 77.77068662374292             60           KA44IJ6789

  Fraud_indicator
```

Summary Statistics/ Missing Values

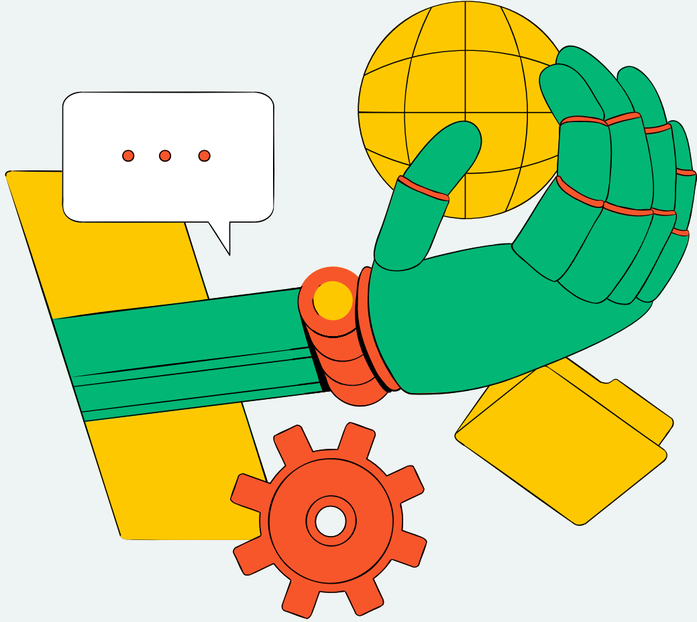
[4]:
```
# Summary statistics of numerical columns
print("\nSummary statistics:")
print(data.describe())
```

```
Summary statistics:
       Transaction_ID  Transaction_Amount  Amount_paid  Vehicle_Speed
count     5000.000000         5000.00000  5000.000000    5000.000000
mean      2500.500000          161.06200   141.261000      67.851200
std       1443.520003          112.44995   106.480996      16.597547
min          1.000000            0.00000     0.000000      10.000000
25%       1250.750000          100.00000    90.000000      54.000000
50%       2500.500000          130.00000   120.000000      67.000000
75%       3750.250000          290.00000   160.000000      82.000000
max       5000.000000          350.00000   350.000000     118.000000
```

[5]:
```
#check for missing values
print("\n Missing Values")
print(data.isnull().sum())
```

```
 Missing Values
Transaction_ID            0
Timestamp                 0
Vehicle_Type              0
FastagID                549
TollBoothID               0
Lane_Type                 0
Vehicle_Dimensions        0
Transaction_Amount        0
Amount_paid               0
Geographical_Location     0
Vehicle_Speed             0
Vehicle_Plate_Number      0
Fraud_indicator           0
dtype: int64
```

EXPLANATORY ANALYSIS



EXPLANATORY ANALYSIS

- Provide insights into factors contributing to fraudulent transactions.

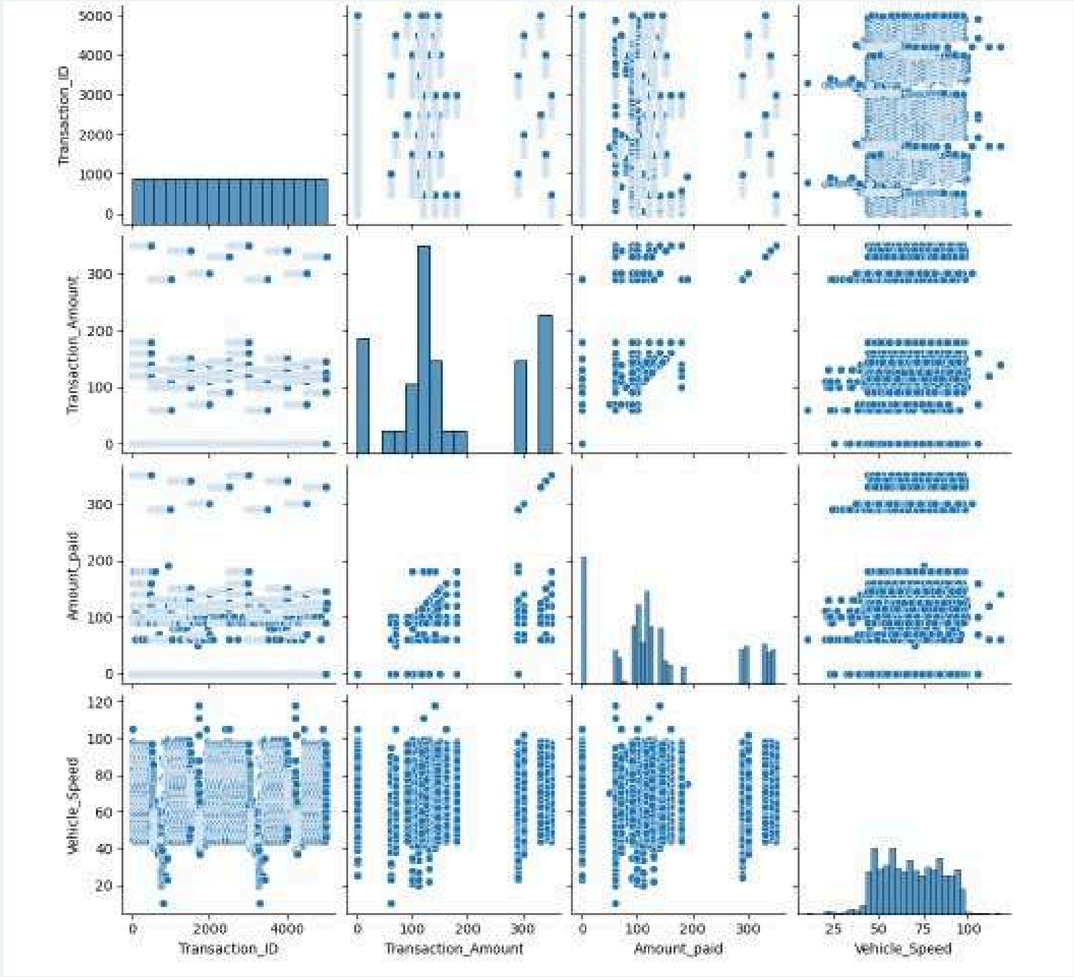
Explanatory anlysis involves exploring and understanding data to gain insights into patterns, relationships, and trends. Unlike predictive analysis. which focuses on making predictions or classifications, explanatory analysis aims to explain the underlying structure and characteristics of the data.

DATA VISUALIZATION

Pairwise Scatter plots for Numerical Values

```
#unique values in categorical columns
print("\nUnique values in categorical columns:")
for col in data.select_dtypes(include='object').columns:
        print(f"{col}: {data[col].unique()}")

#Visualize distribution of numerical columns
import matplotlib.pyplot as plt
import seaborn as sns

sns.pairplot(data)
plt.show()
```

```
Unique values in categorical columns:
(col): ['1/6/2023 11:20' '1/7/2023 14:55' '1/8/2023 18:25' ... '2/5/2023 5:08'
 '2/20/2023 20:34' '3/10/2023 0:59']
(col): ['Bus ' 'Car' 'Motorcycle' 'Truck' 'Van' 'Sedan' 'SUV']
(col): ['FTG-001-ABC-121' 'FTG-002-XYZ-451' nan ... 'FTG-447-PLN-109'
 'FTG-458-VFR-876' 'FTG-459-WSX-543']
(col): ['A-101' 'B-102' 'D-104' 'C-103' 'D-105' 'D-106']
(col): ['Express' 'Regular']
(col): ['Large' 'Small' 'Medium']
(col): ['13.059816123454882, 77.77068662374292'
 '13.042660878688794, 77.47580097259879'
 '12.84197701525119, 77.67547528176169'
 '12.936687032945434, 77.53113977439017'
 '13.21331620748757, 77.55413526894684']
(col): ['KA11AB1234' 'KA66CD5678' 'KA88EF9012' ... 'KA33WX6789' 'KA35YZ0123'
 'KA37AB3456']
(col): ['Fraud' 'Not Fraud']
```



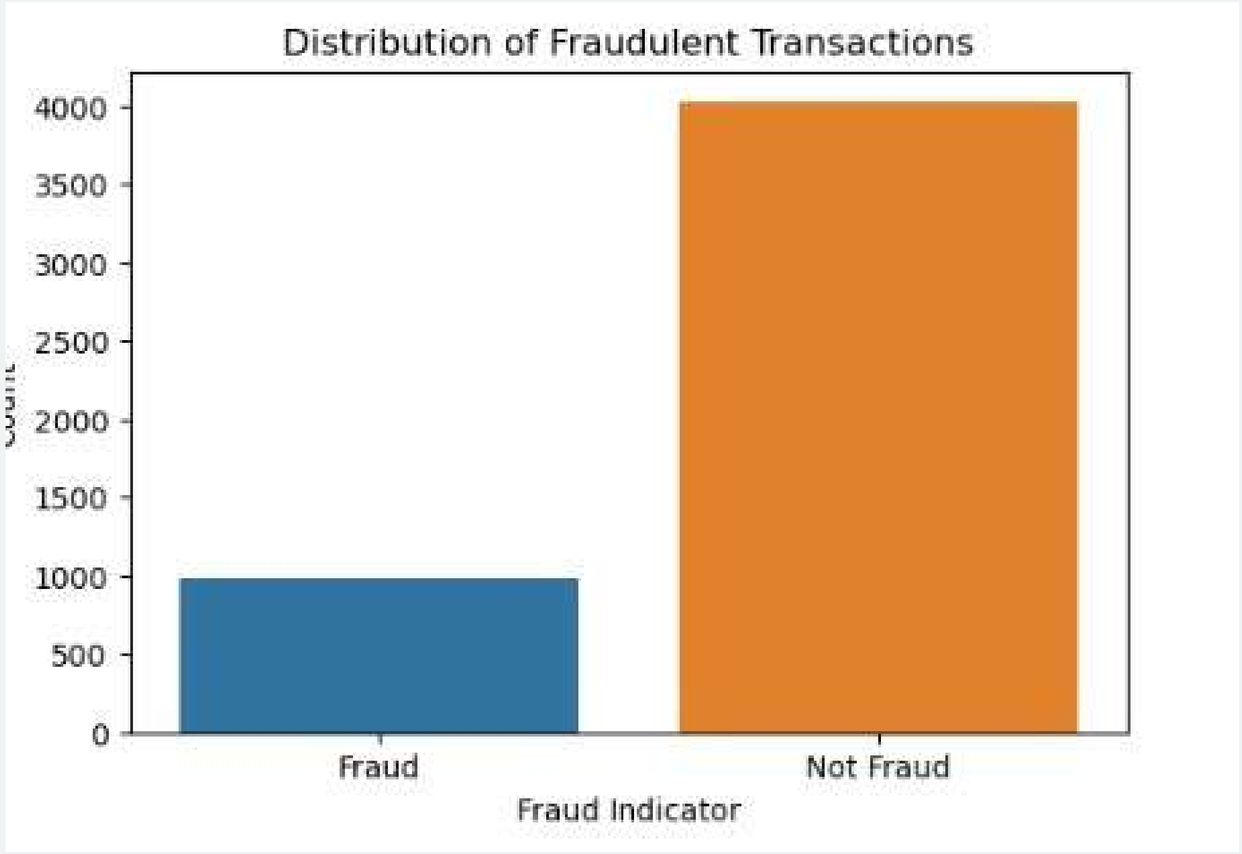
DATA VISUALIZATION

Bar plots for Categorical Features

```
# Summary statistics
print("\nSummary statistics:")
print(data.describe())
```

```
Summary statistics:
       Transaction_ID  Transaction_Amount  Amount_paid  Vehicle_Speed
count     5000.000000         5000.00000  5000.000000    5000.000000
mean      2500.500000          161.06200   141.261000      67.851200
std       1443.520003          112.44995   106.480996      16.597547
min          1.000000            0.00000     0.000000      10.000000
25%       1250.750000          100.00000    90.000000      54.000000
50%       2500.500000          130.00000   120.000000      67.000000
75%       3750.250000          290.00000   160.000000      82.000000
max       5000.000000          350.00000   350.000000     118.000000
```

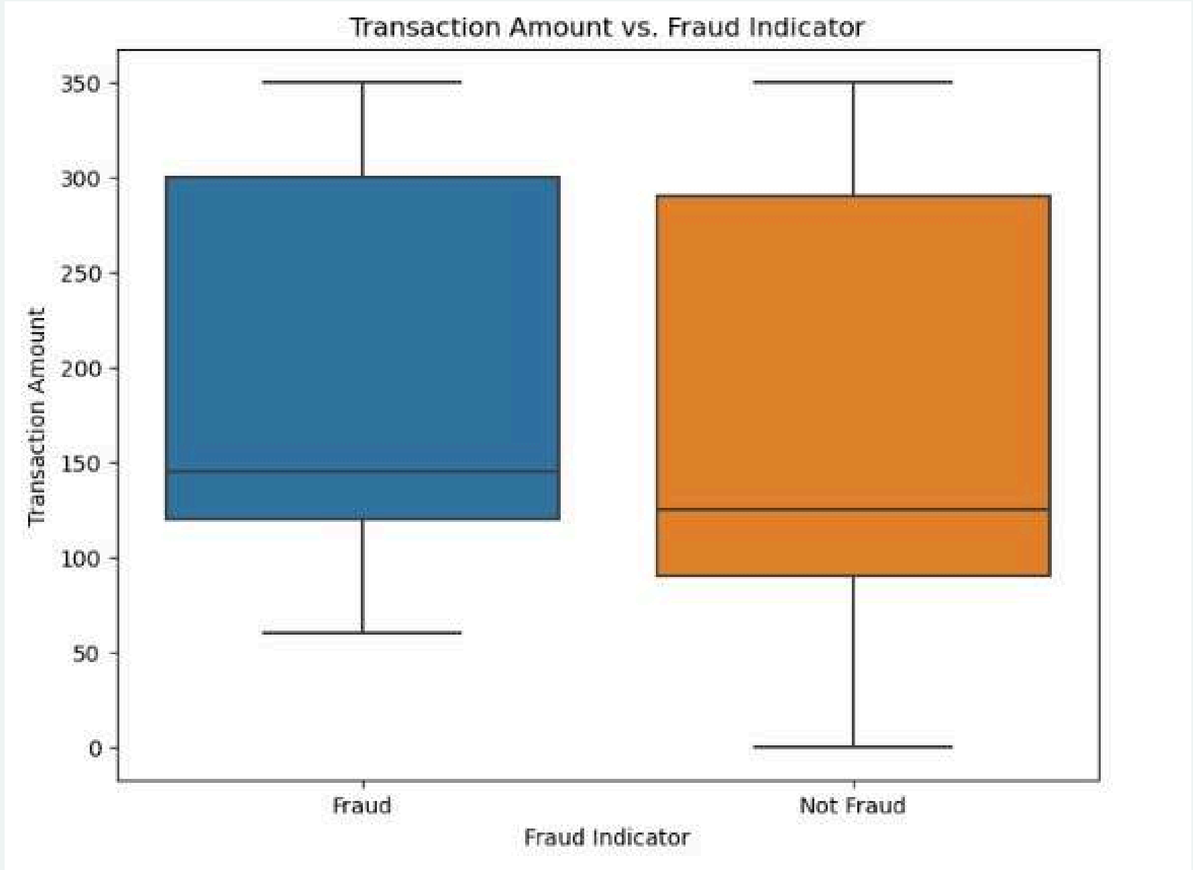
```
import seaborn as sns
import matplotlib.pyplot as plt

# Visualize the distribution of the target variable (Fraud_indicator)
plt.figure(figsize=(6, 4))
sns.countplot(x='Fraud_indicator', data=data)
plt.title('Distribution of Fraudulent Transactions')
plt.xlabel('Fraud Indicator')
plt.ylabel('Count')
plt.show()
```



DATA VISUALIZATION

Box plots for Numerical Features

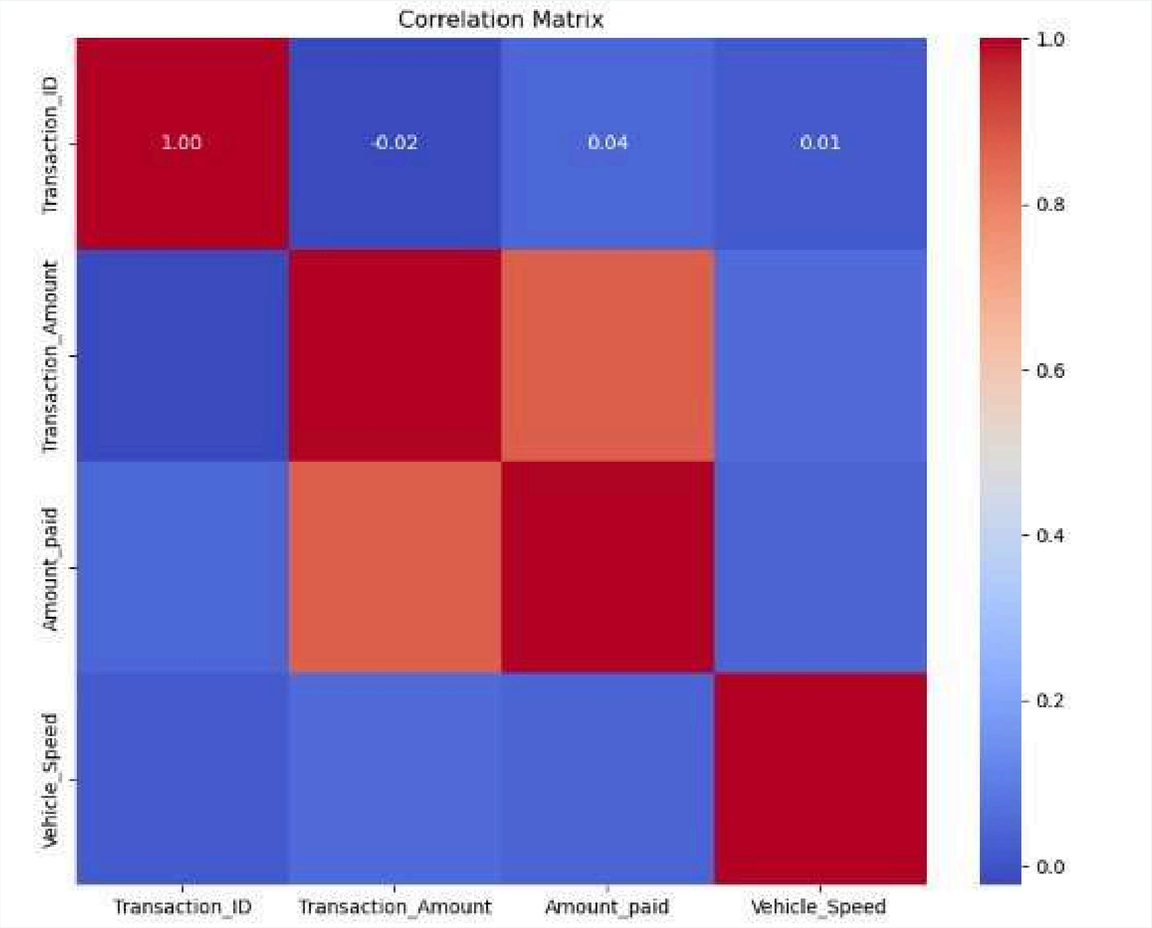
```
# Visualize the relationship between Transaction_Amount and Fraud_indicator
plt.figure(figsize=(8, 6))
sns.boxplot(x='Fraud_indicator', y='Transaction_Amount', data=data)
plt.title('Transaction Amount vs. Fraud Indicator')
plt.xlabel('Fraud Indicator')
plt.ylabel('Transaction Amount')
plt.show()
```



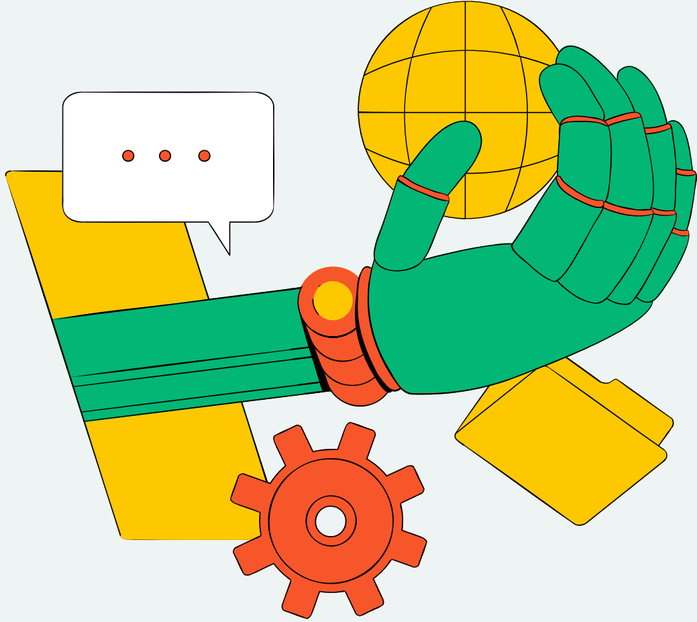
DATA VISUALIZATION

Correlation Analysis

```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only numerical columns for correlation matrix
numerical_data = data.select_dtypes(include=['float64', 'int64'])

# Visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(numerical_data.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



FEATURE ENGINEERING



FEATURE ENGINEERING

- Identify and engineer relevant features that contribute to fraud detection accuracy.

Feature engineering is the process of creating new features or modifying existing one in a dataset to improve the performance of machine learning models. It involves selecting, transforming and creating features that are relevant and informative for the task at hand.

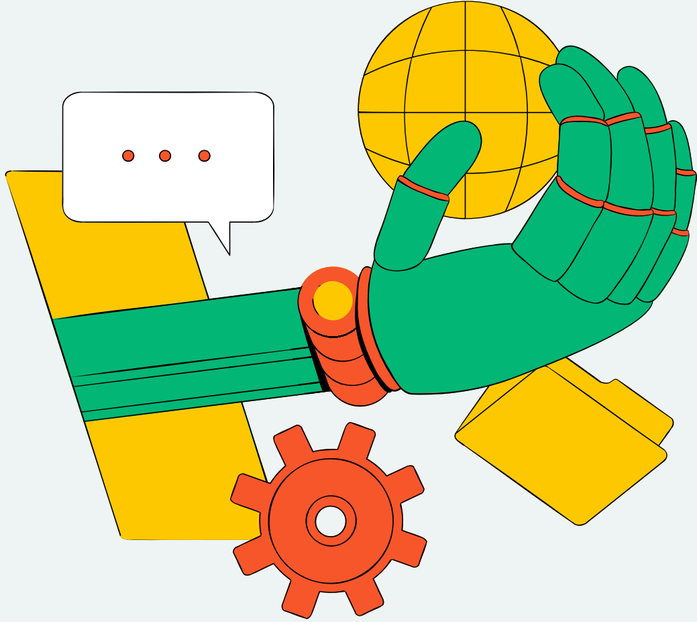
FEATURE ENGINEERING

FEATURE ENGINEERING

```
from sklearn.preprocessing import LabelEncoder

# Load the dataset
fastag_data = pd.read_csv('FastagFraudDetection.csv')

# Feature engineering

# Convert Timestamp to datetime
fastag_data['Timestamp'] = pd.to_datetime(fastag_data['Timestamp'])

# Extract date and time features
fastag_data['Day'] = fastag_data['Timestamp'].dt.day
fastag_data['Month'] = fastag_data['Timestamp'].dt.month
fastag_data['Year'] = fastag_data['Timestamp'].dt.year
fastag_data['Hour'] = fastag_data['Timestamp'].dt.hour
fastag_data['Minute'] = fastag_data['Timestamp'].dt.minute

# Encode categorical variables using LabelEncoder
label_encoder = LabelEncoder()
fastag_data['Vehicle_Type'] = label_encoder.fit_transform(fastag_data['Vehicle_Type'])
fastag_data['Lane_Type'] = label_encoder.fit_transform(fastag_data['Lane_Type'])
fastag_data['Geographical_Location'] = label_encoder.fit_transform(fastag_data['Geographical_Location'])

# Extract features from Vehicle_Plate_Number
# For example, extracting the state code or vehicle category

# Drop unnecessary columns
fastag_data.drop(['Transaction_ID', 'Timestamp', 'FastagID', 'TollBoothID', 'Vehicle_Dimensions', 'Vehicle_Plate_Number'], axis=1, inplace=True)

# Save the engineered dataset
fastag_data.to_csv('engineered_fastag_data.csv', index=False)
```

- Converting timestamp to datetime
- Encoding categorical variables
- Dropping unnecessary columns
- saved the engineered dataset

MODEL DEVELOPMENT



MODEL DEVELOPMENT

- Build a machine learning classification model to predict and fast tag transaction fraud.
- Evaluate and fine-tune model performance using appropriate metrics.

Model development is the process of creating, training, and evaluating machine learning models to solve specific problem or tasks. It involves selecting the appropriate algorithm, preprocessing the data, tuning model parameters and assessing the model's performance using various evaluation metrics.

MODEL DEVELOPMENT

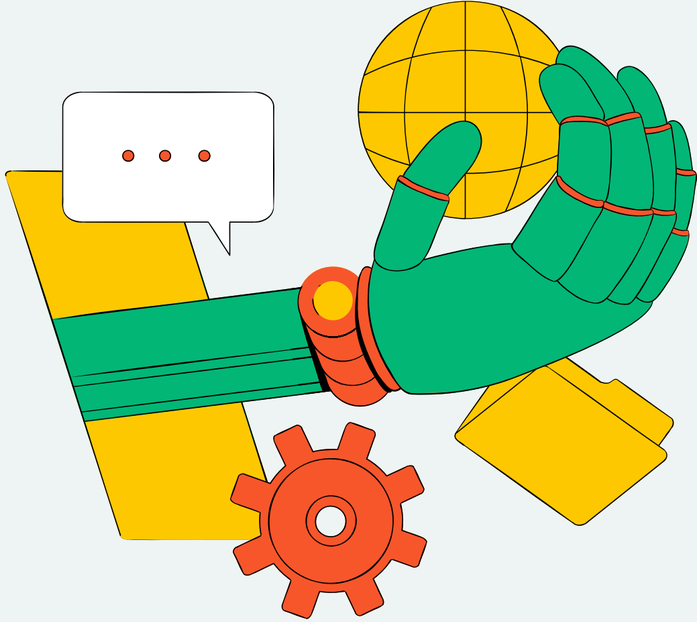
MODEL DEVELOPMENT

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# Split the dataset into features (X) and target variable (y)
X = fastag_data.drop('Fraud_indicator', axis=1)
y = fastag_data['Fraud_indicator']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Random Forest classifier
clf = RandomForestClassifier()

# Train the classifier on the training data
clf.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = clf.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Convert accuracy to percentage
accuracy_percentage = accuracy * 100

# Print the evaluation metrics
print(f"Accuracy: {accuracy_percentage:.2f}%")
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

Evaluation Metrics Results

```
Accuracy: 98.00%
Confusion Matrix:
 [[197  20]
 [  0 783]]
Classification Report:
              precision    recall  f1-score   support

       Fraud       1.00      0.91      0.95       217
   Not Fraud       0.98      1.00      0.99       783

    accuracy                           0.98      1000
   macro avg       0.99      0.95      0.97      1000
weighted avg       0.98      0.98      0.98      1000
```

REAL-TIME FRAUD DETECTION



REAL-TIME FRAUD DETETCION

- Explore the feasibility of implementing the model for real-time fraud detection.

Real-Time fraud detection is the process of identifying and preventing fraudulent activities as they occur in a timely manner.

The goal is to detect fraud as quickly as possible to minimize financial losses and protect against security threats.

REAL-TIME FRAUD DETECTION

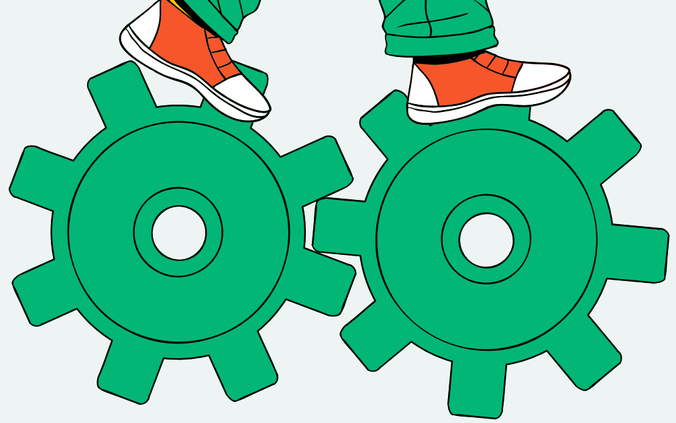
REAL - TIME FRAUD DETECTION

```python
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
import joblib
import time

# Load the historical dataset
historical_data = pd.read_csv('engineered_fastag_data.csv')

# Feature engineering (if necessary)

# Separate features and target variable
X = historical_data.drop('Fraud_indicator', axis=1)
y = historical_data['Fraud_indicator']

# Initialize the model
model = RandomForestClassifier()

# Train the model on historical data
model.fit(X, y)

# Save the trained model
joblib.dump(model, 'fastag_fraud_detection_model.pkl')

# Simulate real-time data arrival
while True:
    # Get new data (replace this with code to receive real-time data)
    new_data = pd.read_csv('engineered_fastag_data.csv')

    # Separate features from the new data
    X_new = new_data.drop('Fraud_indicator', axis=1)

    # Predict fraud for the new data
    fraud_predictions = model.predict(X_new)

    # Print the predictions (or take further action)
    print("New data processed. Predicted fraud status:", fraud_predictions)

    # Wait for a specified time interval before processing next batch of data
    time.sleep(60)  # wait for 1 minute
```

Result Analysis

```
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
New data processed. Predicted fraud status: ['Fraud' 'Fraud' 'Not Fraud' ... 'Not Fraud' 'Not Fraud' 'Fraud']
```

DELIVERABLES



01

- **Trained machine learning model for Fastag fraud detection.**

02

- **Evaluation metrics and analysis report.**

03

- **Documentation on relevant features and their impact on fraud detection.**

EXPECTED OUTCOME

An effective and scalable Fastag fraud detectio system capable of minimizing financial losses and ensuring the security of digital toll transactions.

THANKYOU

For joining me on this journey of exploring Real-Time Fast tag Fraud Detection.
Our knowledge and skills will continue to evolve with practice and experimentation.

FOLLOW ME

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https://github.com/Rishabhk-20