Prject Overview:-

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.

Principle Aim:-

The main goal is to develop a robust fraud detection system for Fastag transactions using machine learning. By analyzing transaction details, vehicle information, location, and amounts, the system aims to accurately identify fraudulent activities, ensuring the security and integrity of Fastag transactions.

```
# Data Loading
from google.colab import drive
import pandas as pd
drive.mount('/content/drive')
file_path = '/content/drive/My Drive/FastagFraudDetection.csv'
df = pd.read_csv(file_path)
```

```
Mounted at /content/drive
```

```
df.head()
```

	Transaction_ID	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Type
0	1	1/6/2023 11:20	Bus	FTG-001-ABC-121	A-101	Express
1	2	1/7/2023	Car	FTG-002-	B-102	Regular

1	2	14:55	Car	XYZ-451	B-102	Regular
2	3	1/8/2023 18:25	Motorcycle	NaN	D-104	Regular
3	4	1/9/2023 2:05	Truck	FTG-044-LMN-322	C-103	Regular
4	5	1/10/2023 6:35	Van	FTG-505-DEF-652	B-102	Express

Next steps: Generate code with df View recommended plots

```
df.head(20)
```

	Transaction_ID	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Type
0	1	1/6/2023 11:20	Bus	FTG-001-ABC-121	A-101	Express
1	2	1/7/2023 14:55	Car	FTG-002-XYZ-451	B-102	Regula
2	3	1/8/2023 18:25	Motorcycle	NaN	D-104	Regula
3	4	1/9/2023 2:05	Truck	FTG-044-LMN-322	C-103	Regula
4	5	1/10/2023 6:35	Van	FTG-505-DEF-652	B-102	Express
5	6	1/11/2023 10:00	Sedan	FTG-066-GHI-987	A-101	Regula
6	7	1/12/2023 15:40	SUV	FTG-707-JKL-210	B-102	Express
7	8	1/13/2023 20:15	Bus	FTG-088-UVW-543	C-103	Regula
8	9	1/14/2023 1:55	Car	FTG-909-RST-876	A-101	Express
9	10	1/15/2023 7:30	Motorcycle	NaN	D-104	Regula
10	11	1/16/2023 12:10	Truck	FTG-021-QWE-765	C-103	Express
11	12	1/17/2023 17:45	Van	FTG-011-ZXC-431	B-102	Regula
12	13	1/18/2023 22:20	Sedan	FTG-013-POI-104	A-101	Express
13	14	1/19/2023 4:00	SUV	FTG-014-KJH-872	B-102	Regula
14	15	1/20/2023 8:30	Bus	FTG-055-DCV-543	A-101	Express
		1/21/2023		FTG-066-		

15	16	13:10	Car	NBH-210	B-102	Regula
16	17	1/22/2023 16:45	Motorcycle	NaN	D-104	Regula
17	18	1/23/2023 22:25	Truck	FTG-088-EYT-654	C-103	Regula
18	19	1/24/2023 2:55	Van	FTG-099-FTD-321	B-102	Express
19	20	1/25/2023 7:35	Sedan	FTG-120-TTU-098	A-101	Regula

Next steps: Generate code with df View recommended plots

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Transaction_ID        5000 non-null   int64 
 1   Timestamp             5000 non-null   object
 2   Vehicle_Type          5000 non-null   object
 3   FastagID              4451 non-null   object
 4   TollBoothID           5000 non-null   object
 5   Lane_Type             5000 non-null   object
 6   Vehicle_Dimensions    5000 non-null   object
 7   Transaction_Amount    5000 non-null   int64 
 8   Amount_paid           5000 non-null   int64 
 9   Geographical_Location 5000 non-null   object
 10  Vehicle_Speed         5000 non-null   int64 
 11  Vehicle_Plate_Number  5000 non-null   object
 12  Fraud_indicator       5000 non-null   object
dtypes: int64(4), object(9)
memory usage: 507.9+ KB
```

```
df.describe()
```

	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

```
df.shape
```

```
(5000, 13)
```

```
print(df.columns)
```

```
Index(['Timestamp', 'FastagID', 'TollBoothID', 'Transaction_Amount',
       'Amount_paid', 'Vehicle_Speed', 'Vehicle_Plate_Number',
       'Fraud_indicator', 'Hour', 'Day', 'Month', 'Amount_Difference',
       'Payment_Ratio', 'Vehicle_Type_Bus ', 'Vehicle_Type_Car',
       'Vehicle_Type_Motorcycle', 'Vehicle_Type_SUV', 'Vehicle_Type_Sedan',
       'Vehicle_Type_Truck', 'Vehicle_Type_Van', 'Lane_Type_Express',
       'Lane_Type_Regular', 'Vehicle_Dimensions_Large',
       'Vehicle_Dimensions_Medium', 'Vehicle_Dimensions_Small', 'Latitude',
       'Longitude'],
      dtype='object')
```

```
df['Timestamp'] = pd.to_datetime(df['Timestamp'])
df.isnull()
```

	Transaction_ID	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Ty
0	False	False	False	False	False	Fa
1	False	False	False	False	False	Fa
2	False	False	False	True	False	Fa
3	False	False	False	False	False	Fa
4	False	False	False	False	False	Fa
...	...	...	...	...	...	
4995	False	False	False	False	False	Fa
4996	False	False	False	False	False	Fa
4997	False	False	False	False	False	Fa

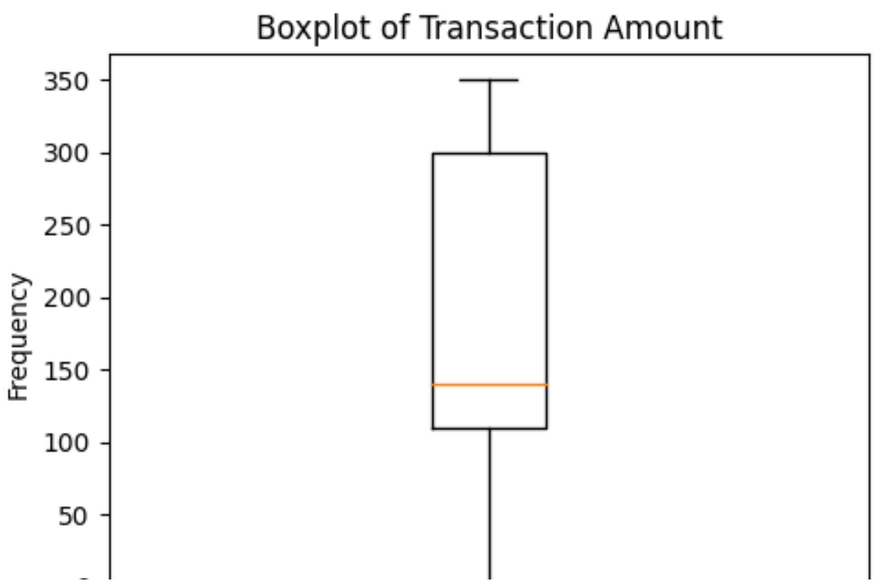
4997	False	False	False	False	False	Fa
4998	False	False	False	False	False	Fa
4999	False	False	False	False	False	Fa

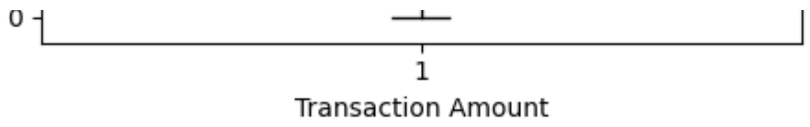
5000 rows × 13 columns

```
df=df.set_index('Transaction_ID')
df.describe().T
```

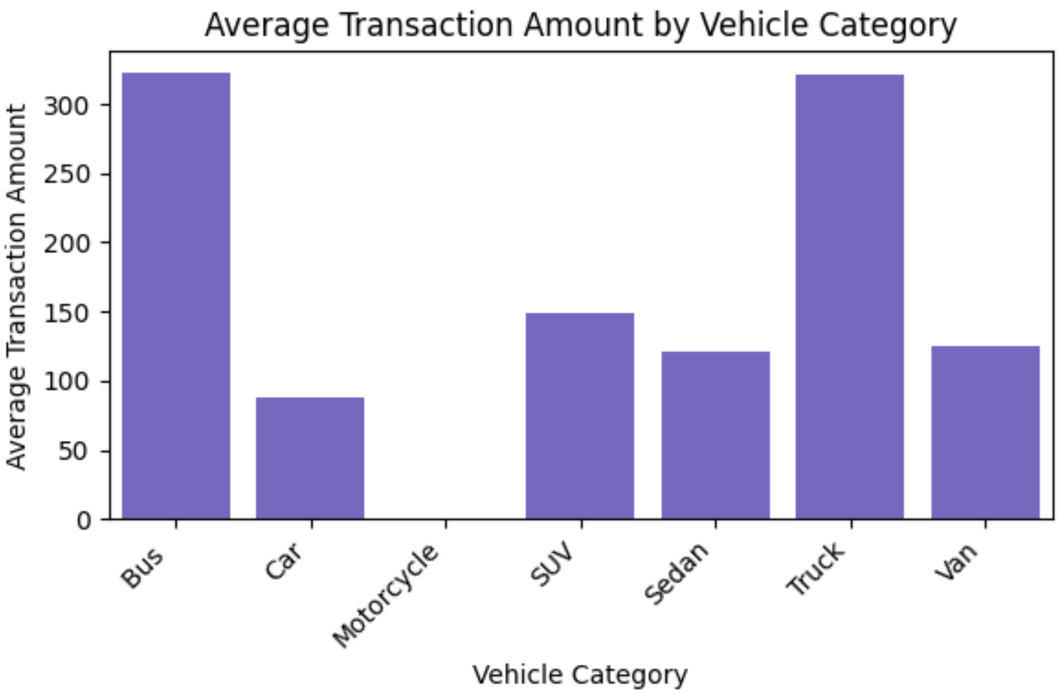
	count	mean	std	min	25%	50%	75%	max
Transaction_Amount	4451.0	180.927881	103.004437	0.0	110.0	140.0	300.0	350.0
Amount_paid	4451.0	158.684565	99.857565	0.0	100.0	120.0	180.0	350.0
Vehicle_Speed	4451.0	67.884745	16.632295	10.0	55.0	67.0	82.0	118.0

```
plt.figure(figsize=(5,4))

plt.boxplot(df['Transaction_Amount'])
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.title('Boxplot of Transaction Amount')


plt.tight_layout()
plt.show()
```

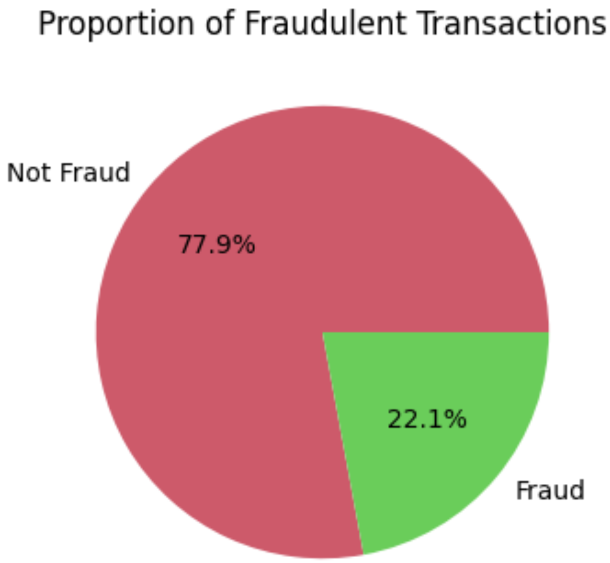





```
avg_transaction_amounts = df.groupby('Vehicle_Type')['Transaction_Amount'].mear

plt.figure(figsize=(6, 4))
sns.barplot(x='Vehicle_Type', y='Transaction_Amount', data=avg_transaction_amou
plt.xlabel('Vehicle Category')
plt.ylabel('Average Transaction Amount')
plt.title('Average Transaction Amount by Vehicle Category')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

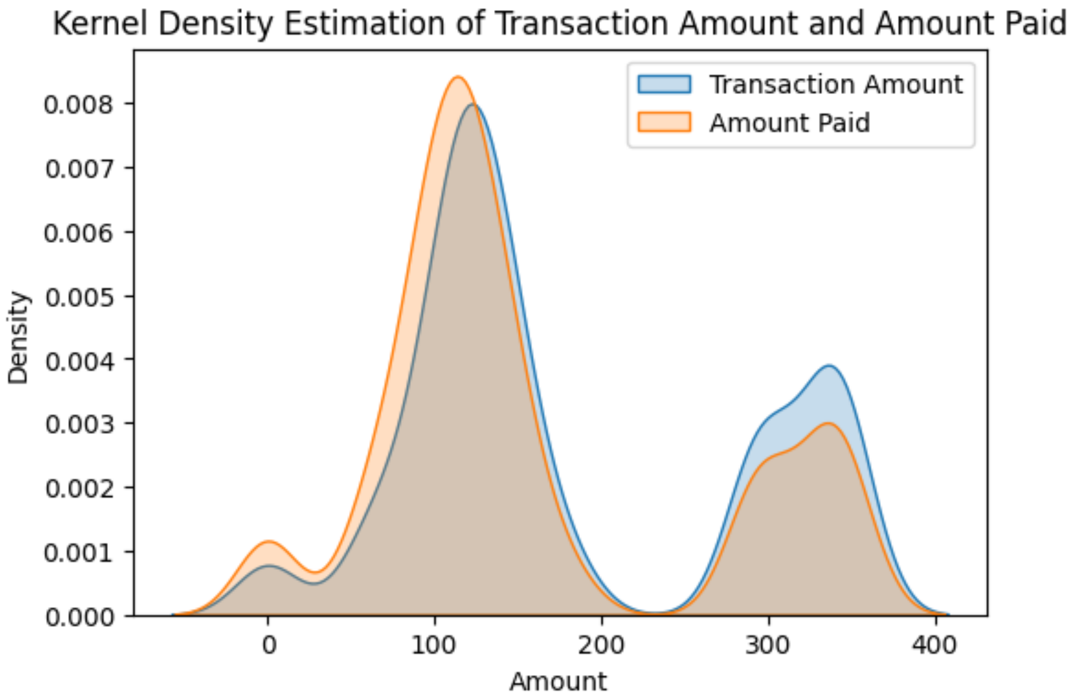


```
plt.figure(figsize=(6,4))
df['Fraud_indicator'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors
plt.title('Proportion of Fraudulent Transactions')
plt.ylabel('')
plt.show()
```



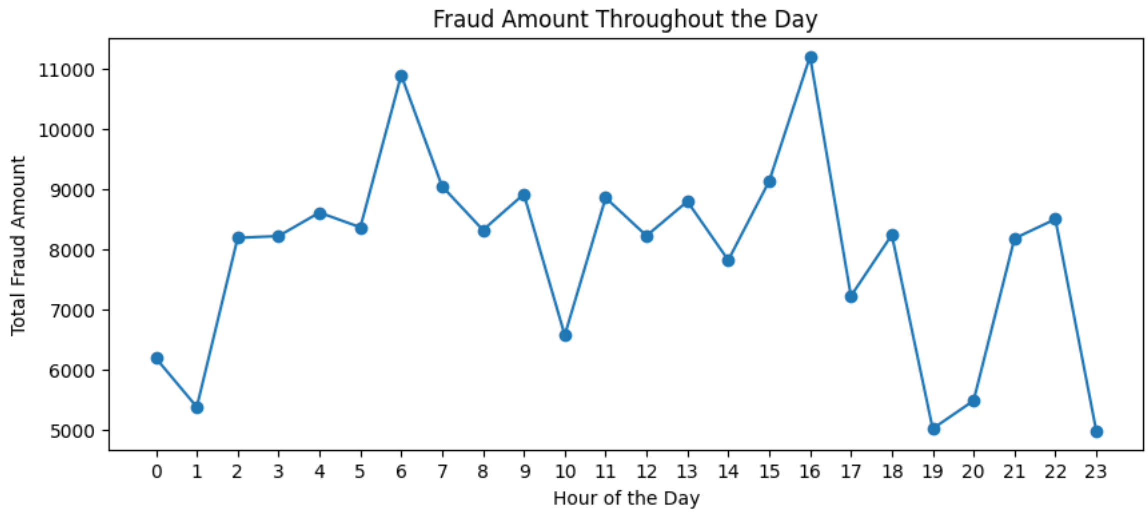

```
plt.figure(figsize=(6,4))
sns.kdeplot(data=df['Transaction_Amount'], fill=True, label='Transaction Amount
sns.kdeplot(data=df['Amount_paid'], fill=True, label='Amount Paid')
plt.xlabel('Amount')
plt.ylabel('Density')
plt.title('Kernel Density Estimation of Transaction Amount and Amount Paid')
```

```
plt.legend()
plt.show()
```




```
df['Timestamp'] = pd.to_datetime(df['Timestamp'])

# Extract hour from the timestamp
df['Hour'] = df['Timestamp'].dt.hour

# Filter fraudulent transactions
fraudulent_transactions = df[df['Fraud_indicator'] == 'Fraud']

# Group by hour and sum transaction amount
fraudulent_amount_by_hour = fraudulent_transactions.groupby('Hour')['Transactic

plt.figure(figsize=(10, 4))
fraudulent_amount_by_hour.plot(marker='o', linestyle='-')
plt.title('Fraud Amount Throughout the Day')
```

```
plt.xlabel('Hour of the Day')
plt.ylabel('Total Fraud Amount')
plt.xticks(range(24))
plt.show()
```




```
print("Missing values in 'FastagID':", df['FastagID'].isnull().sum())
```

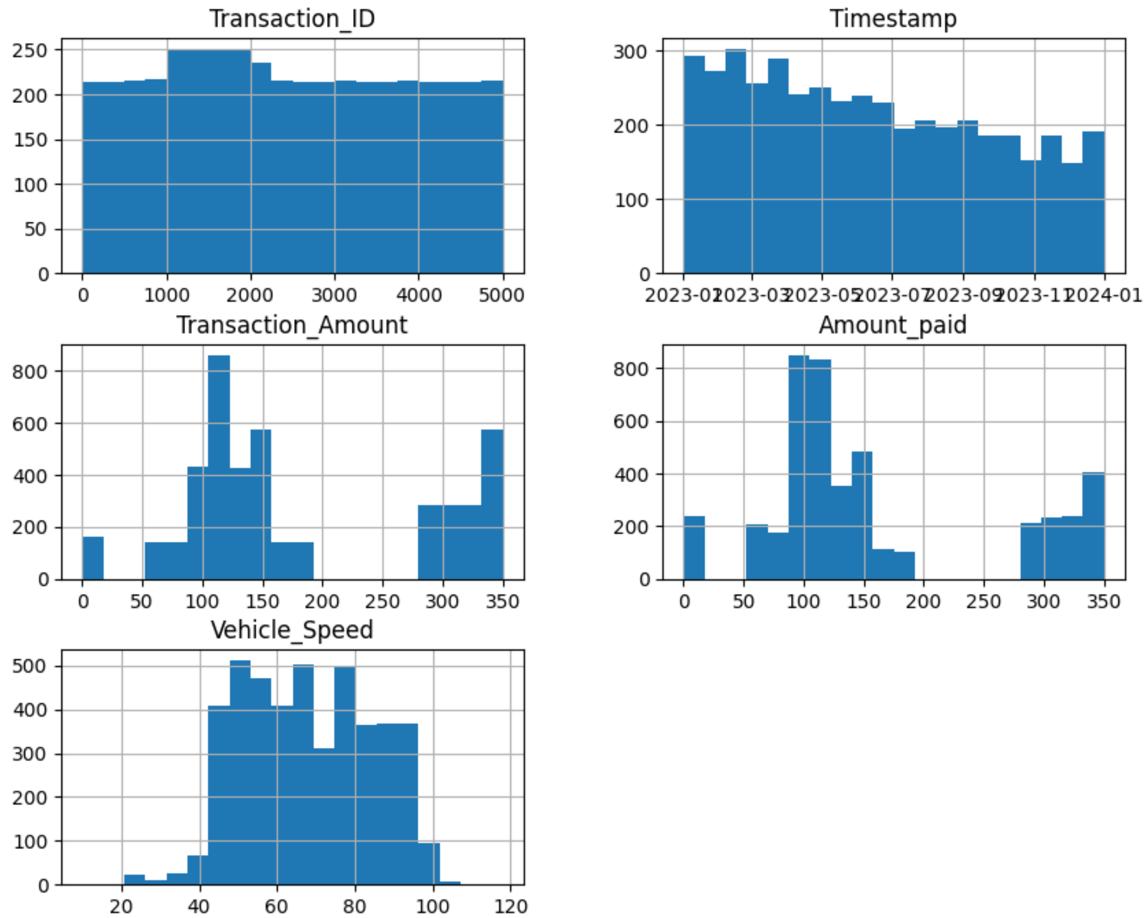
```
Missing values in 'FastagID': 549
```

```
df = df.dropna(subset=['FastagID'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4451 entries, 0 to 4999
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Transaction_ID        4451 non-null   int64
 1   Timestamp             4451 non-null   datetime64[ns]
 2   Vehicle_Type          4451 non-null   object
 3   FastagID              4451 non-null   object
 4   TollBoothID           4451 non-null   object
 5   Lane_Type             4451 non-null   object
 6   Vehicle_Dimensions    4451 non-null   object
 7   Transaction_Amount    4451 non-null   int64
 8   Amount_paid           4451 non-null   int64
 9   Geographical_Location 4451 non-null   object
 10  Vehicle_Speed         4451 non-null   int64
 11  Vehicle_Plate_Number  4451 non-null   object
 12  Fraud_indicator       4451 non-null   object
dtypes: datetime64[ns](1), int64(4), object(8)
memory usage: 486.8+ KB
```

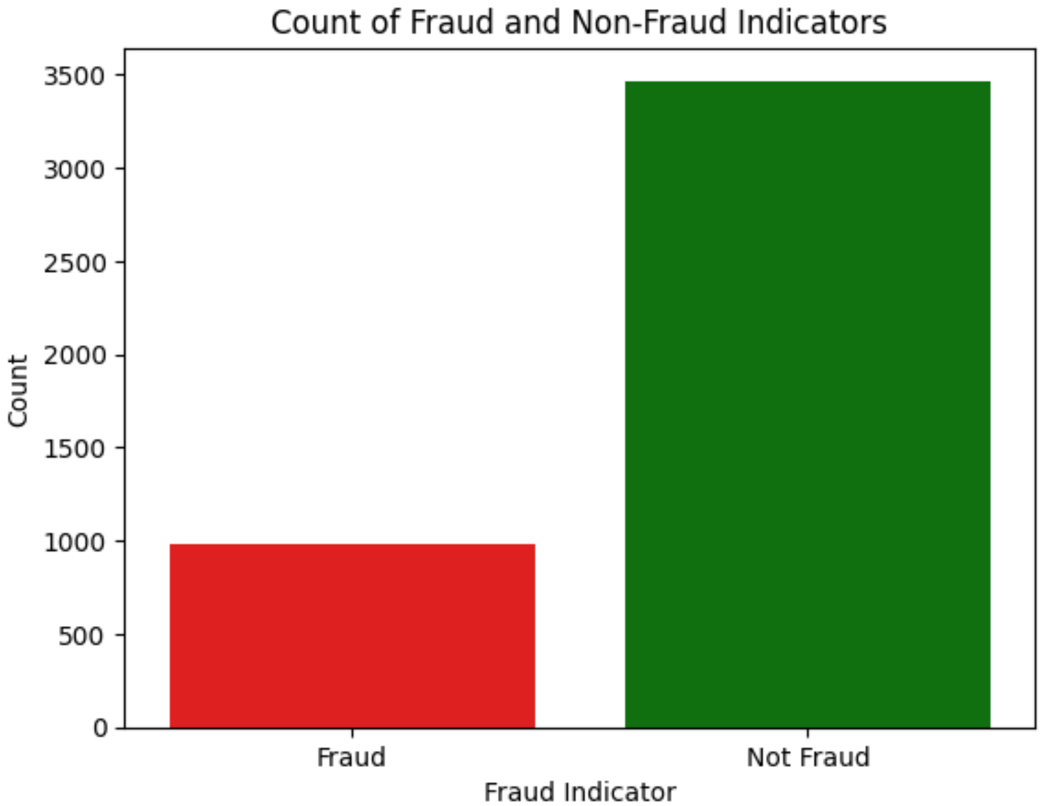
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
import pandas as pd
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report
import tensorflow as tf
```

```
df.hist(figsize=(10, 8), bins=20)
plt.show()
```

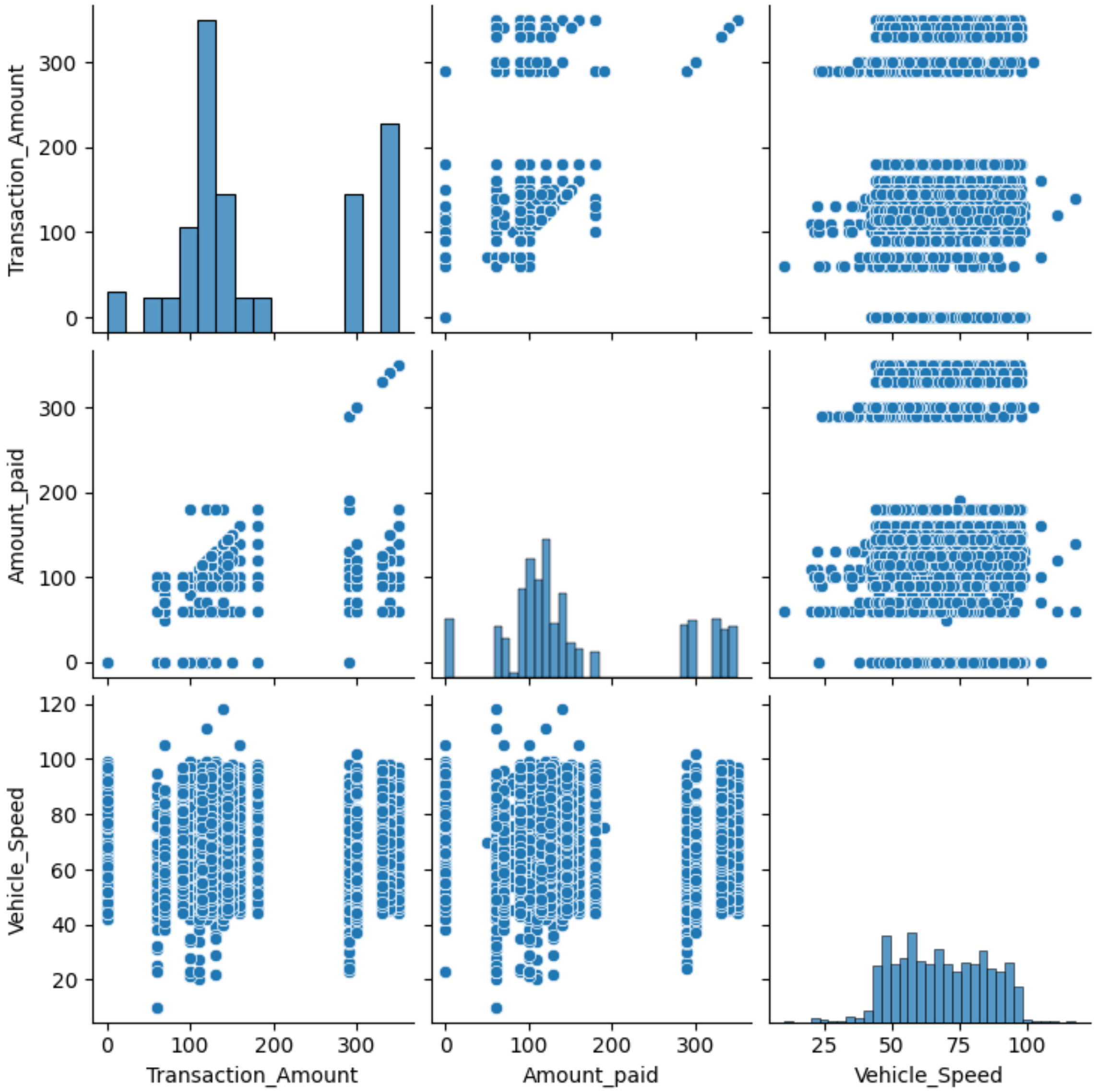


```
sns.countplot(x='Fraud_indicator', data=df, palette=['red', 'green'])
plt.xlabel('Fraud Indicator')
plt.ylabel('Count')
plt.title('Count of Fraud and Non-Fraud Indicators')
plt.show()
```

```
<ipython-input-13-a0b8bf54ff9b>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed

  sns.countplot(x='Fraud_indicator', data=df, palette=['red', 'green'])
```



```
sns.pairplot(df, vars=['Transaction_Amount', 'Amount_paid', 'Vehicle_Speed'])
plt.show()
```

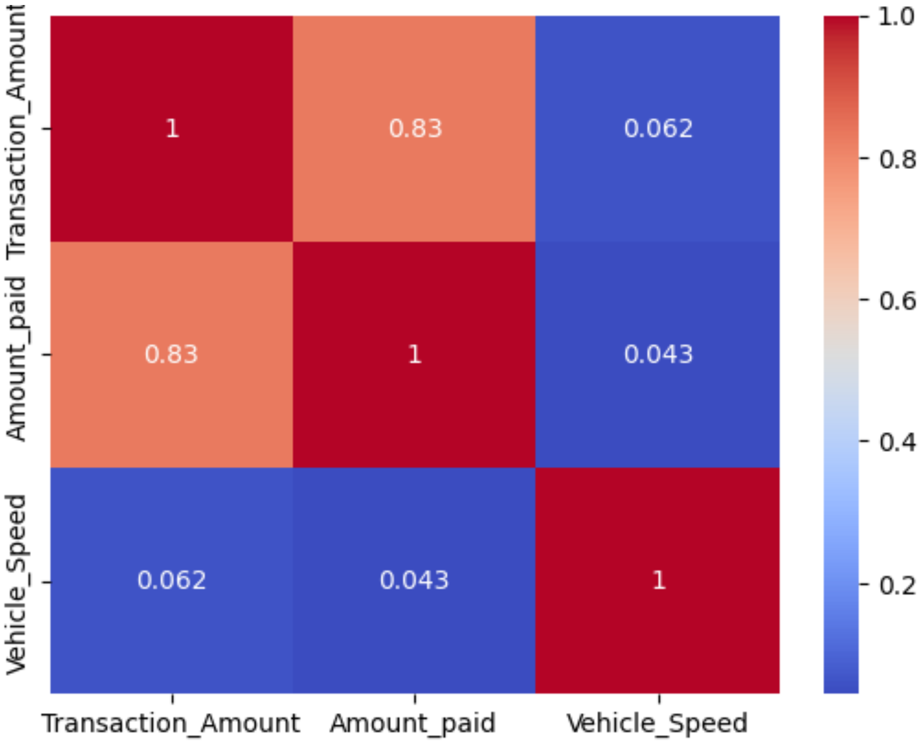


```
sns.boxplot(
    x = "Fraud_indicator",
    y = "Transaction_Amount",
    showmeans=True,
    data=df,
    palette=["red", "green"]
)

plt.xlabel("Fraud Indicator")
plt.ylabel("Transaction Amount")
plt.title("Distribution of Transaction Amount by Fraud Indicator")
plt.xticks(rotation=45)
plt.show()
```

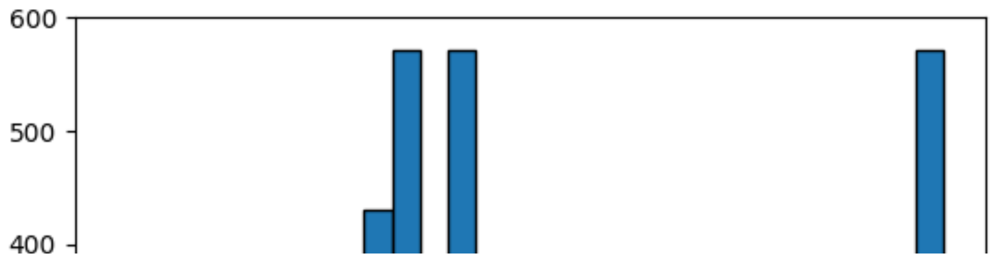
```
<ipython-input-15-b6b2f11221a9>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed

  sns.boxplot(
```

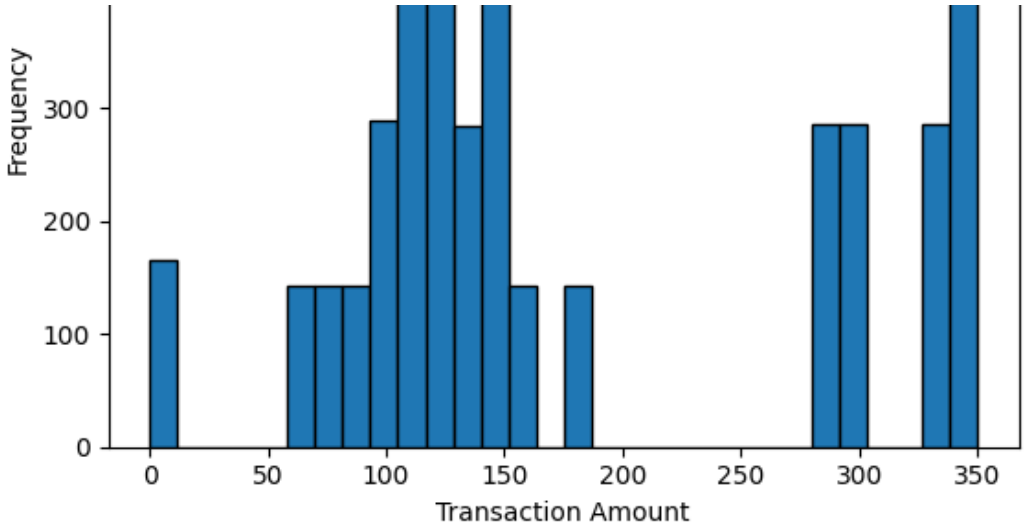

```
correlation_matrix = df[['Transaction_Amount', 'Amount_paid', 'Vehicle_Speed']]
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
```

..

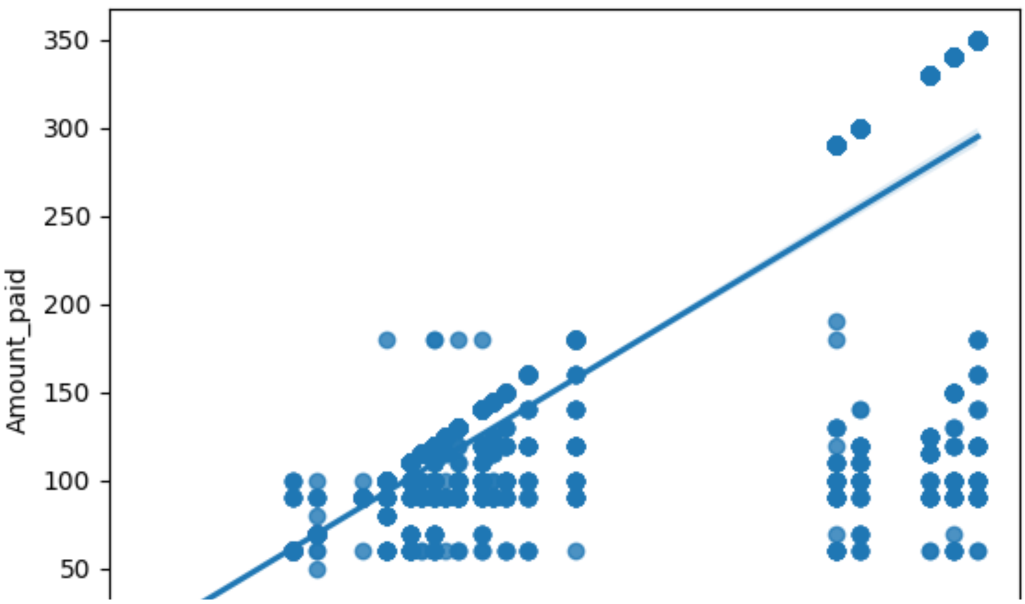


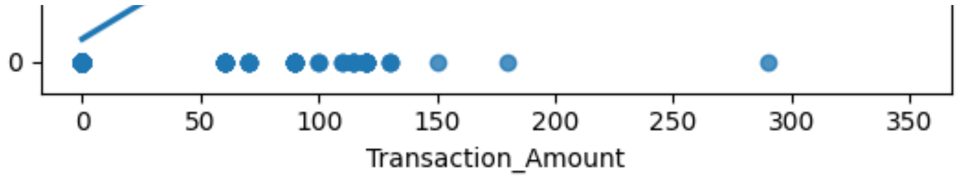

```
plt.hist(df['Transaction_Amount'], bins=30, edgecolor='black')
plt.xlabel('Transaction Amount')
plt.ylabel('Frequency')
plt.show()
```



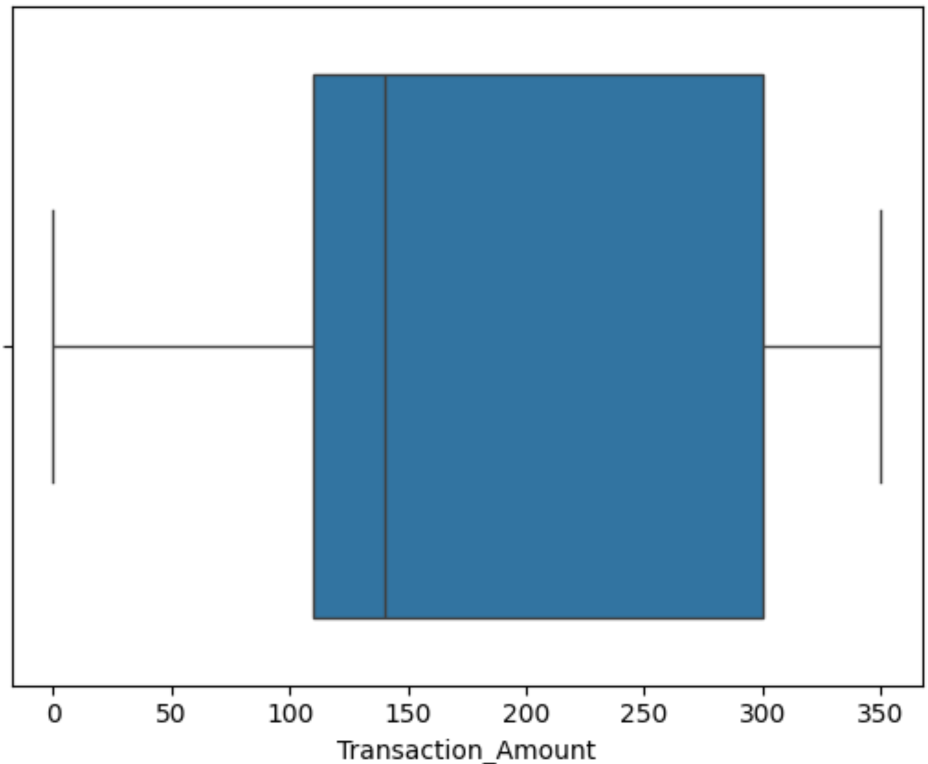



```
sns.regplot(x='Transaction_Amount', y='Amount_paid', data=df)
plt.show()
```






```
sns.boxplot(x='Transaction_Amount', data=df)
plt.show()
```




```
selected_features = ['Transaction_Amount', 'Amount_paid']
```

```
X = df[selected_features]
y = df['Fraud_indicator']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random
```

```
from sklearn.preprocessing import LabelEncoder
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)
```

```
from tensorflow.keras import models, layers

model = models.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(X_train_scaled.shape
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
model.summary()
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 32)                96

 dense_1 (Dense)             (None, 16)                528

 dense_2 (Dense)             (None, 1)                 17

=================================================================
Total params: 641 (2.50 KB)
Trainable params: 641 (2.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model.fit(X_train_scaled, y_train_encoded, epochs=40, batch_size=32, validatior
```

```
Epoch 12/40
89/89 [==============================] - 0s 4ms/step - loss: 0.0444 - accur
Epoch 13/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0434 - accur
Epoch 14/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0426 - accur
Epoch 15/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0413 - accur
Epoch 16/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0403 - accur
```

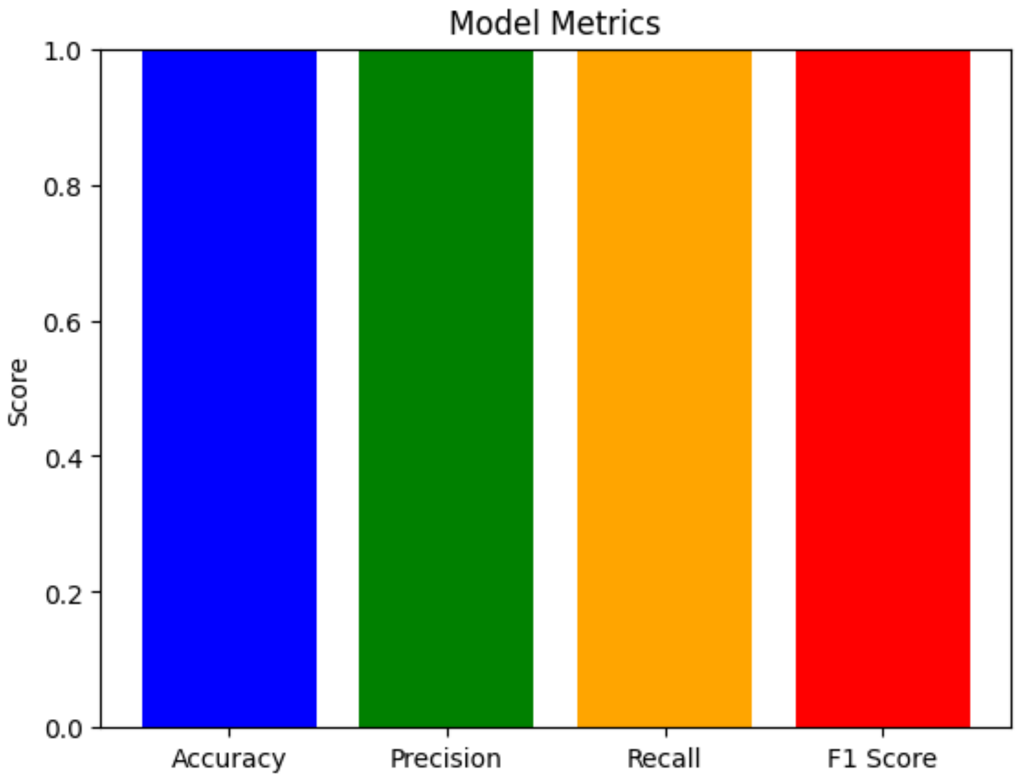
```
Epoch 17/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0394 - accur
Epoch 18/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0383 - accur
Epoch 19/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0375 - accur
Epoch 20/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0366 - accur
Epoch 21/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0359 - accur
Epoch 22/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0347 - accur
Epoch 23/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0338 - accur
Epoch 24/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0331 - accur
Epoch 25/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0320 - accur
Epoch 26/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0311 - accur
Epoch 27/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0304 - accur
Epoch 28/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0292 - accur
Epoch 29/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0281 - accur
Epoch 30/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0274 - accur
Epoch 31/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0263 - accur
Epoch 32/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0256 - accur
Epoch 33/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0243 - accur
Epoch 34/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0228 - accur
Epoch 35/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0216 - accur
Epoch 36/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0202 - accur
Epoch 37/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0188 - accur
Epoch 38/40
89/89 [==============================] - 0s 2ms/step - loss: 0.0172 - accur
Epoch 39/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0160 - accur
Epoch 40/40
89/89 [==============================] - 0s 3ms/step - loss: 0.0144 - accur
<keras.src.callbacks.History at 0x7f733c2954e0>
```

```
y_pred_prob = model.predict(X_test_scaled)
# Convert probabilities to binary predictions
y_pred = np.round(y_pred_prob)
# Print accuracy metrics
accuracy = accuracy_score(y_test_encoded, y_pred)
precision = precision_score(y_test_encoded, y_pred)
recall = recall_score(y_test_encoded, y_pred)
f1 = f1_score(y_test_encoded, y_pred)
# Print accuracy metrics
print("Accuracy: {:.2f}%".format(accuracy * 100))
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1 Score: {:.2f}%".format(f1 * 100))
```

```
28/28 [==============================] - 0s 5ms/step
Accuracy: 99.66%
Precision: 99.57%
Recall: 100.00%
F1 Score: 99.79%
```

```
import matplotlib.pyplot as plt
```

```
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
values = [99.66 ,99.57, 100.00 , 99.79]

plt.bar(metrics, values, color=['blue', 'green', 'orange', 'red'])
plt.ylabel('Score')
plt.title('Model Metrics')
plt.ylim(0, 1)
plt.show()
```




```
df['Day']=df['Timestamp'].dt.dayofweek

df['Month']=df['Timestamp'].dt.month
```

```
# Calculate the difference between "Transaction_Amount" and "Amount_paid"
df['Amount_Difference'] = df['Transaction_Amount'] - df['Amount_paid']

# Calculate the ratio of "Amount_paid" to "Transaction_Amount"
df['Payment_Ratio'] = df['Amount_paid'] / df['Transaction_Amount']
```

```
df.head(2)
```

	Timestamp	Vehicle_Type	FastagID	TollBoothID	Lane_Type	V
Transaction_ID						
1	2023-01-06 11:20:00	Bus	FTG-001-ABC-121	A-101	Express	
2	2023-01-07 14:55:00	Car	FTG-002-XYZ-451	B-102	Regular	

Next steps: Generate code with df View recommended plots

```
df = pd.get_dummies(df, columns=['Vehicle_Type', 'Lane_Type', 'Vehicle_Dimensic
```

```
label_encoder = LabelEncoder()
df['Fraud_indicator'] = label_encoder.fit_transform(df['Fraud_indicator'])
```

```
df.head(3)
```

	Timestamp	FastagID	TollBoothID	Transaction_Amount	Amount
Transaction_ID					
1	2023-01-06 11:20:00	FTG-001-ABC-121	A-101	350	
2	2023-01-07 14:55:00	FTG-002-XYZ-451	B-102	120	
4	2023-01-09 02:05:00	FTG-044-LMN-322	C-103	350	

3 rows × 26 columns

```
# Extract latitude and longitude from 'Geographical_Location'
df['Latitude'] = df['Geographical_Location'].apply(lambda x: float(x.split(',')
df['Longitude'] = df['Geographical_Location'].apply(lambda x: float(x.split(','

# Drop the original 'Geographical_Location' column
df.drop(columns=['Geographical_Location'], inplace=True)
```

```
df.head(3)
```

	Timestamp	FastagID	TollBoothID	Transaction_Amount	Amount
Transaction_ID					
1	2023-01-06 11:20:00	FTG-001-ABC-121	A-101	350	
2	2023-01-07 14:55:00	FTG-002-XYZ-451	B-102	120	
4	2023-01-09 02:05:00	FTG-044-LMN-322	C-103	350	

3 rows × 27 columns

```
df.Fraud_indicator.value_counts()
```

```
1    3468
0     983
Name: Fraud_indicator, dtype: int64
```

```
# Separate features and target variable
X = df.drop(columns=['Fraud_indicator', 'Timestamp', 'FastagID', 'TollBoothID',
X
```

	Transaction_Amount	Amount_paid	Vehicle_Speed	Hour	Day	M
Transaction_ID						
1	350	120	65	11	4	
2	120	100	78	14	5	
4	350	120	92	2	0	
5	140	100	60	6	1	
6	160	100	105	10	2	
...	...	...	...	...	...	
4996	330	330	81	22	6	
4997	125	125	64	13	1	
4998	115	115	93	5	6	
4999	145	145	57	20	0	
5000	330	125	86	0	4	

4451 rows × 22 columns

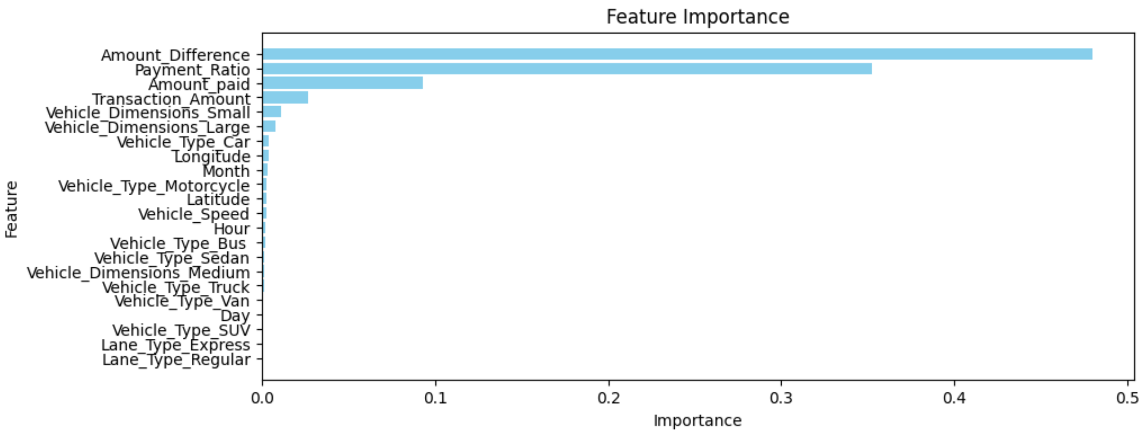
```
y = df['Fraud_indicator']
y
```

```
Transaction_ID
1       0
2       0
4       0
5       0
6       0
       ..
4996    1
4997    1
4998    1
4999    1
5000    0
Name: Fraud_indicator, Length: 4451, dtype: int64
```

```
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
imputer = SimpleImputer(strategy='mean')

# Fit the imputer on the features and transform the features
X_imputed = imputer.fit_transform(X)

rf_classifier = RandomForestClassifier()

rf_classifier.fit(X_imputed, y)

feature_importances = rf_classifier.feature_importances_

feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
})

# Sort the DataFrame by feature importance
feature_importance_df = feature_importance_df.sort_values(by='Importance', asce

# Print the top 5 important features
top_n = 5
print(f"Top {top_n} Important Features:")
print(feature_importance_df.head(top_n))
```

```
Top 5 Important Features:
                    Feature  Importance
6         Amount_Difference    0.479879
7             Payment_Ratio    0.352243
1               Amount_paid    0.092946
0        Transaction_Amount    0.026552
19  Vehicle_Dimensions_Small    0.010919
```

```
plt.figure(figsize=(10, 4))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'],
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance')
plt.gca().invert_yaxis()
plt.show()
```




```
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.metrics import confusion_matrix, roc_curve, auc
```

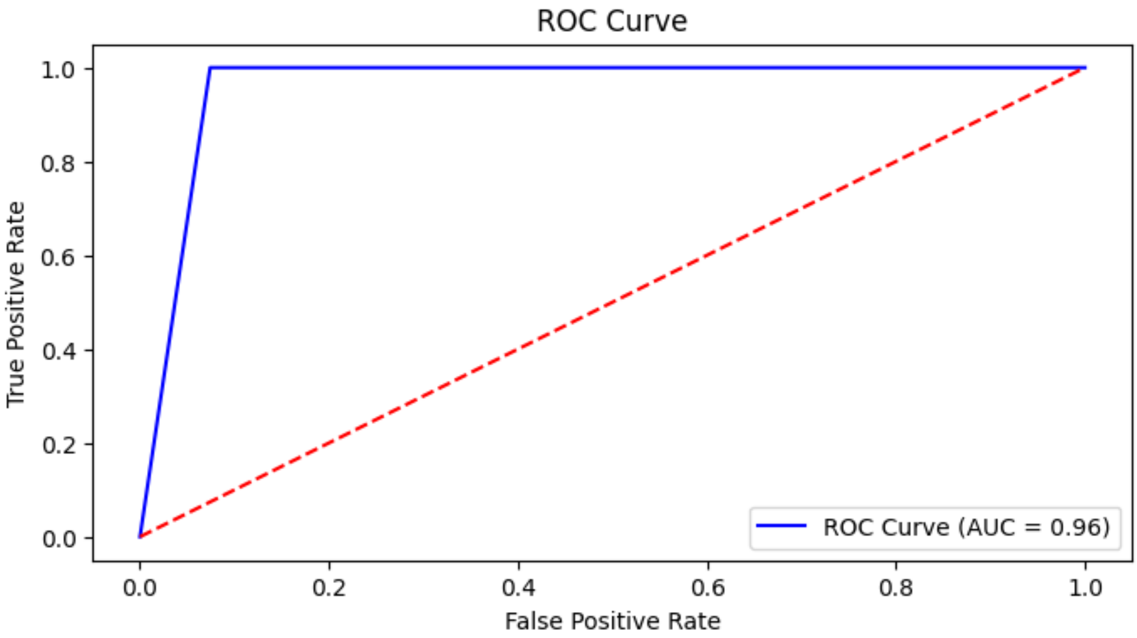
```
top_features = feature_importance_df.head(5)['Feature'].tolist()
X_top_features = X[top_features]
y = df['Fraud_indicator']

# StratifiedKFold
```

```
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

logistic_model = LogisticRegression()

# Initialize lists to store evaluation metrics
accuracies = []

# Perform cross-validation
for train_index, test_index in skf.split(X_top_features, y):
    X_train, X_test = X_top_features.iloc[train_index], X_top_features.iloc[tes
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Impute missing values
    imputer = SimpleImputer(strategy='mean')
    X_train_imputed = imputer.fit_transform(X_train)
    X_test_imputed = imputer.transform(X_test)

    # Fit the model
    logistic_model.fit(X_train_imputed, y_train)

    # Make predictions
    y_pred = logistic_model.predict(X_test_imputed)

    # Calculate accuracy and store it
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)

# Calculate mean accuracy
mean_accuracy = np.mean(accuracies)
print("Mean Accuracy of stratified cross validation:", mean_accuracy)

# Display classification report using the entire dataset
X_imputed = imputer.fit_transform(X_top_features)
logistic_model.fit(X_imputed, y)
y_pred = logistic_model.predict(X_imputed)
print("Classification Report:")
print(classification_report(y, y_pred))
```

```
Mean Accuracy of stratified cross validation: 0.9836002976077882
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.93      0.96       983
           1       0.98      1.00      0.99      3468

    accuracy                           0.98      4451
   macro avg       0.99      0.96      0.98      4451
weighted avg       0.98      0.98      0.98      4451
```

```
# Calculate ROC curve and AUC
fpr, tpr, _ = roc_curve(y, y_pred)
```

```
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 4))
plt.plot(fpr, tpr, color='b', label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='r', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```




```
# Calculate confusion matrix
cm = confusion_matrix(y, y_pred)

# Normalize confusion matrix
cm_norm = cm / cm.sum(axis=1)[:, np.newaxis]  # Normalize along the true labels

# Define class labels
class_labels = ['Non-Fraudulent', 'Fraudulent']

# Plot confusion matrix with probabilities
```

```
plt.figure(figsize=(8, 4))
sns.heatmap(cm_norm, annot=True, cmap='Blues', fmt='.2%', cbar=False, xticklabe
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```