fraud-prediction

April 25, 2025

[1]:
```python
# DATA PREPROCESSING
```

[2]:
```python
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
import tensorflow
```

[3]:
```python
df=pd.read_csv("Fraud.csv")
```

[4]:
```python
data=pd.DataFrame(df)
```

[5]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

[6]:
```python
data.head(10)
```

[6]:
```
   step     type   amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
0     1  PAYMENT  9839.64  C1231006815      170136.00       160296.36
1     1  PAYMENT  1864.28  C1666544295       21249.00        19384.72
```

```
2     1  TRANSFER    181.00  C1305486145         181.00            0.00
3     1  CASH_OUT    181.00   C840083671         181.00            0.00
4     1   PAYMENT  11668.14  C2048537720       41554.00        29885.86
5     1   PAYMENT   7817.71    C90045638       53860.00        46042.29
6     1   PAYMENT   7107.77   C154988899      183195.00       176087.23
7     1   PAYMENT   7861.64  C1912850431      176087.23       168225.59
8     1   PAYMENT   4024.36  C1265012928        2671.00            0.00
9     1     DEBIT   5337.77   C712410124       41720.00        36382.23

      nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0  M1979787155             0.0            0.00        0               0
1  M2044282225             0.0            0.00        0               0
2   C553264065             0.0            0.00        1               0
3    C38997010         21182.0            0.00        1               0
4  M1230701703             0.0            0.00        0               0
5   M573487274             0.0            0.00        0               0
6   M408069119             0.0            0.00        0               0
7   M633326333             0.0            0.00        0               0
8  M1176932104             0.0            0.00        0               0
9   C195600860         41898.0        40348.79        0               0
```

[7]:
```
data["isFlaggedFraud"].value_counts()
```

[7]:
```
isFlaggedFraud
0    6362604
1         16
Name: count, dtype: int64
```

[8]:
```
# MISSING VALUES
```

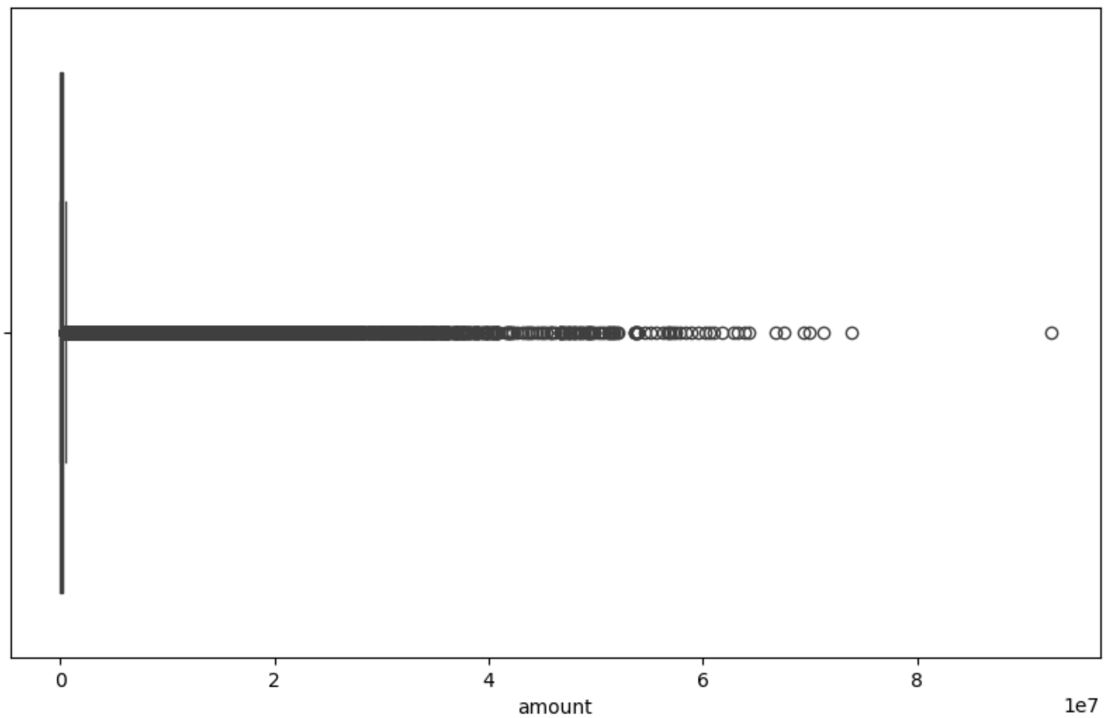
[9]:
```
missing_values = data.isnull().sum()
print(missing_values)
```

```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

[10]:
```
# Their are no Missing values
```

[11]:
```
# OUTLIERS
```

[12]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.boxplot(x=data['amount'])
plt.show()
```



[13]:
```
# Their are outliers in the amount column but, in transaction data it is true␣
↪that most of the transactions are in less amount.
# The outlier in this is also important in predicting fraud
```

[14]:
```
data["amount"].max()
```

[14]: 92445516.64

[15]:
```
# FEATURE ENGINEERING
```

[16]:
```
# FEATURE CREATION
data['netChangeOrig'] = data['newbalanceOrig'] - data['oldbalanceOrg']
data['netChangeDest'] = data['newbalanceDest'] - data['oldbalanceDest']
```

[17]:
```
# Creating new features of transaction frequency
data['origFreq'] = data.groupby('nameOrig')['nameOrig'].transform('count')
data['destFreq'] = data.groupby('nameDest')['nameDest'].transform('count')
```

[18]:
```
# FEARURE DELETION
data.drop(["nameOrig","nameDest"], axis=1, inplace=True)
data.head()
```

[18]:
```
   step      type    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0     1   PAYMENT   9839.64       170136.0       160296.36             0.0
1     1   PAYMENT   1864.28        21249.0        19384.72             0.0
2     1  TRANSFER    181.00          181.0            0.00             0.0
3     1  CASH_OUT    181.00          181.0            0.00         21182.0
4     1   PAYMENT  11668.14        41554.0        29885.86             0.0

   newbalanceDest  isFraud  isFlaggedFraud  netChangeOrig  netChangeDest  \
0             0.0        0               0       -9839.64            0.0
1             0.0        0               0       -1864.28            0.0
2             0.0        1               0        -181.00            0.0
3             0.0        1               0        -181.00       -21182.0
4             0.0        0               0      -11668.14            0.0

   origFreq  destFreq
0         1         1
1         1         1
2         1        44
3         1        41
4         1         1
```

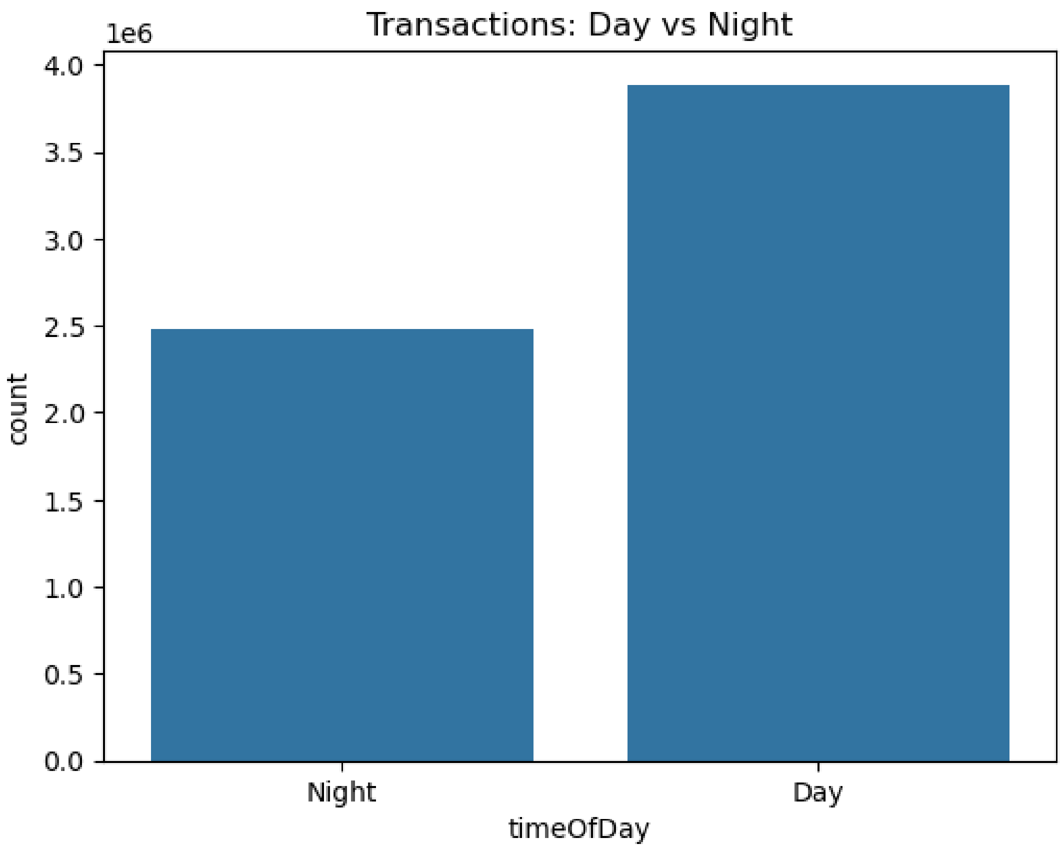
[19]:
```
# Classifying transaction in day/night and business/off-hours
def categorize_day_night(step):
    hour_of_day = step % 24
    if 6 <= hour_of_day < 18:
        return 'Day'
    else:
        return 'Night'

data['timeOfDay'] = data['step'].apply(categorize_day_night)

def categorize_business_hours(step):
    hour_of_day = step % 24
    if 9 <= hour_of_day < 18:
        return 'Business'
    else:
        return 'Off-hours'

data['businessHours'] = data['step'].apply(categorize_business_hours)
```

```
data[['step', 'timeOfDay', 'businessHours']].head()
```

[19]:

	step	timeOfDay	businessHours
0	1	Night	Off-hours
1	1	Night	Off-hours
2	1	Night	Off-hours
3	1	Night	Off-hours
4	1	Night	Off-hours

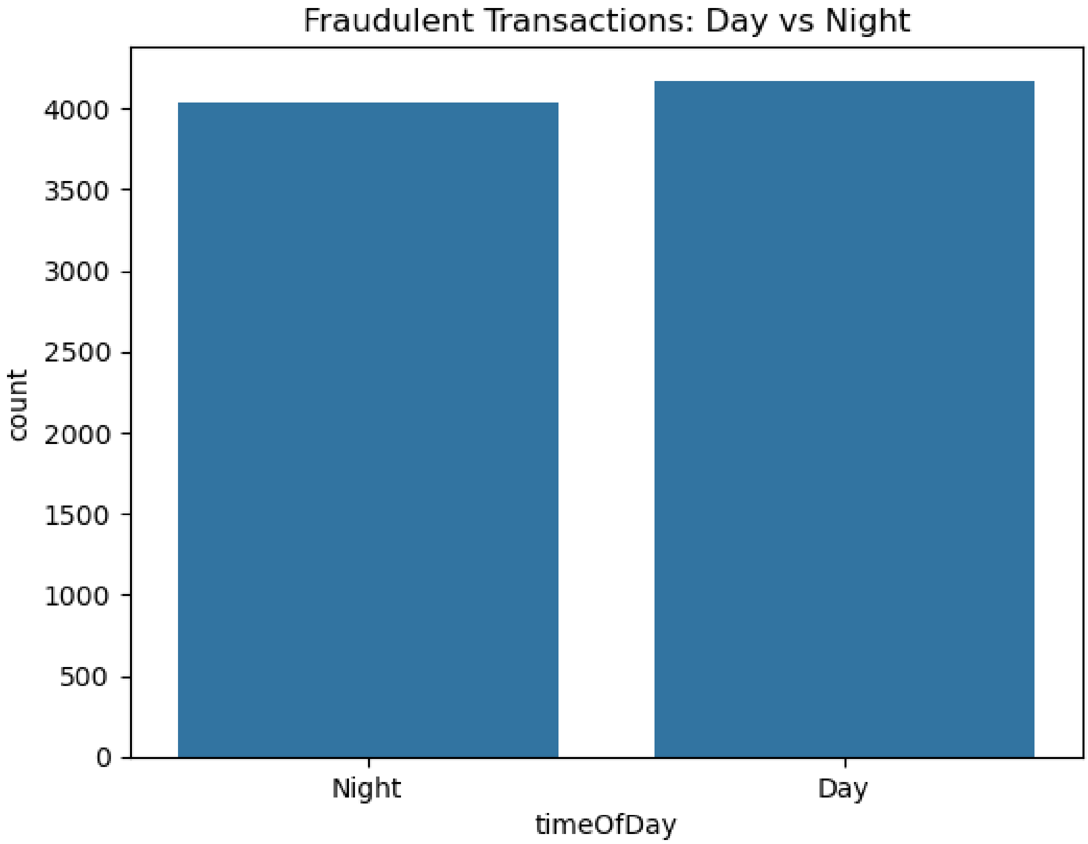
[20]:
```
import seaborn as sns
sns.countplot(data=data, x='timeOfDay')
plt.title('Transactions: Day vs Night')
plt.show()
```



[21]:
```
# In this we can see that the transaction is around in ratio 2(night):3(day)
```

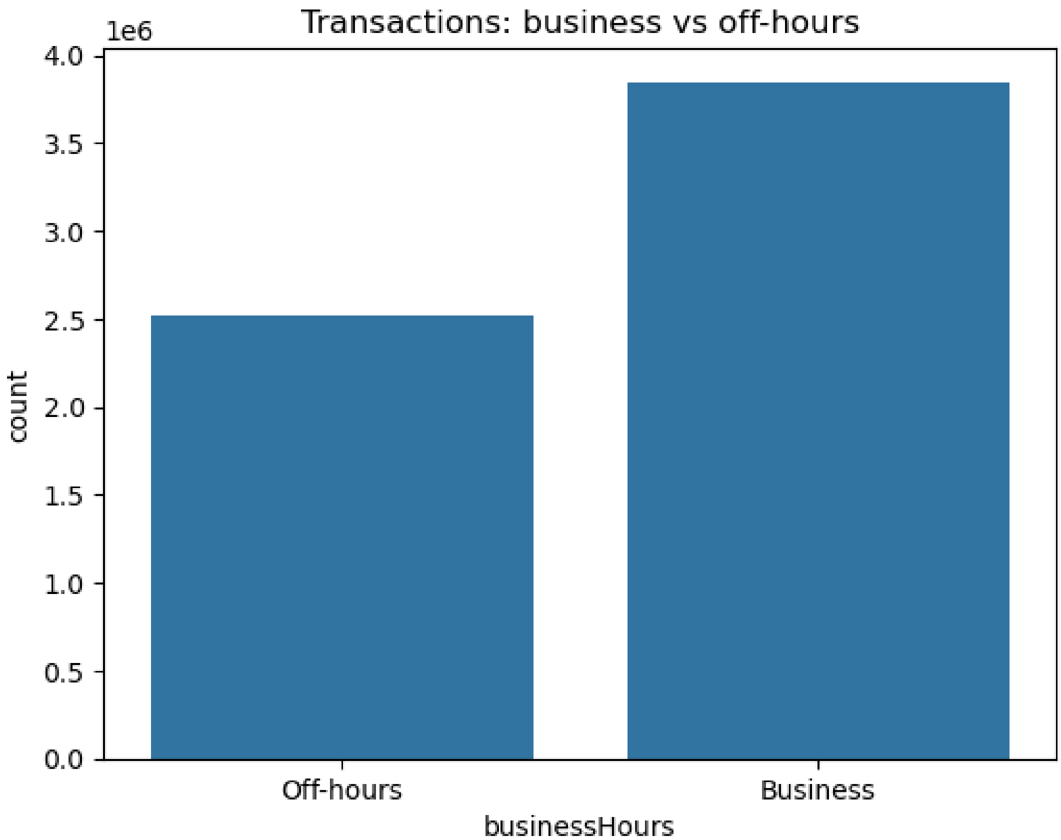
[22]:
```
# Visualising the relation between Fraud and time of Day
import seaborn as sns
sns.countplot(data=data[data['isFraud'] == 1], x='timeOfDay')
```

```
plt.title('Fraudulent Transactions: Day vs Night')
plt.show()
```



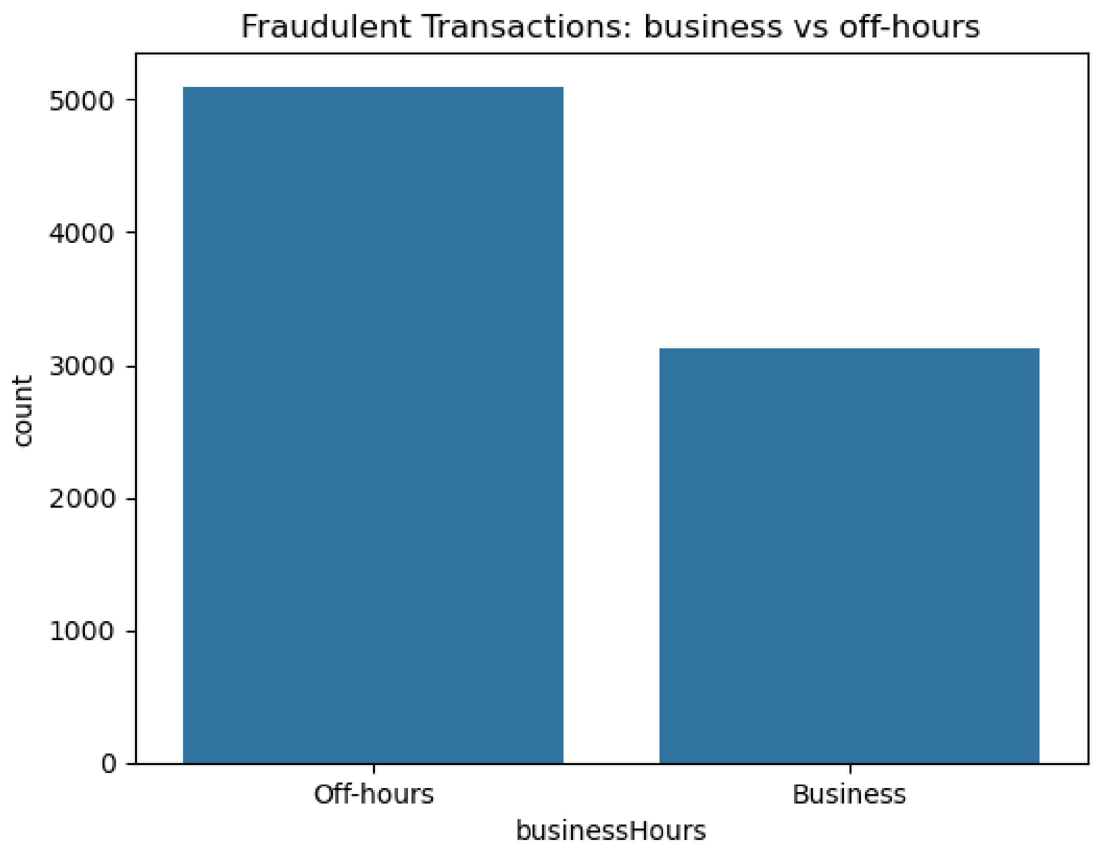
[23]:
```
# In this we see that difference between frauds at day and night are not much
data.drop(["timeOfDay"], axis=1, inplace=True)
```

[24]:
```
import seaborn as sns
sns.countplot(data=data, x='businessHours')
plt.title('Transactions: business vs off-hours')
plt.show()
```



[25]:
```
# We can see that more transactions are done in business-hours compared to
↪off-hours
```

[26]:
```
# Visualising the relation between Fraud and business hours
import seaborn as sns
sns.countplot(data=data[data['isFraud'] == 1], x='businessHours')
plt.title('Fraudulent Transactions: business vs off-hours')
plt.show()
```



[27]:
```python
# But in case of fraud more frauds occur in off-hours compared to business
```

[28]:
```python
data.drop('step',axis=1,inplace=True)
data = pd.get_dummies(data, columns=['businessHours'])
```

[29]:
```python
data.iloc[:,-1:]=data.iloc[:,-1:].astype(int)
```

[30]:
```python
data.head()
```

[30]:
```
       type    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0   PAYMENT   9839.64       170136.0       160296.36             0.0
1   PAYMENT   1864.28        21249.0        19384.72             0.0
2  TRANSFER    181.00          181.0            0.00             0.0
3  CASH_OUT    181.00          181.0            0.00         21182.0
4   PAYMENT  11668.14        41554.0        29885.86             0.0

   newbalanceDest  isFraud  isFlaggedFraud  netChangeOrig  netChangeDest  \
0             0.0        0               0       -9839.64            0.0
1             0.0        0               0       -1864.28            0.0
2             0.0        1               0        -181.00            0.0
```

```
3           0.0       1              0       -181.00      -21182.0
4           0.0       0              0     -11668.14           0.0

   origFreq  destFreq  businessHours_Business  businessHours_Off-hours
0         1         1                   False                       1
1         1         1                   False                       1
2         1        44                   False                       1
3         1        41                   False                       1
4         1         1                   False                       1
```

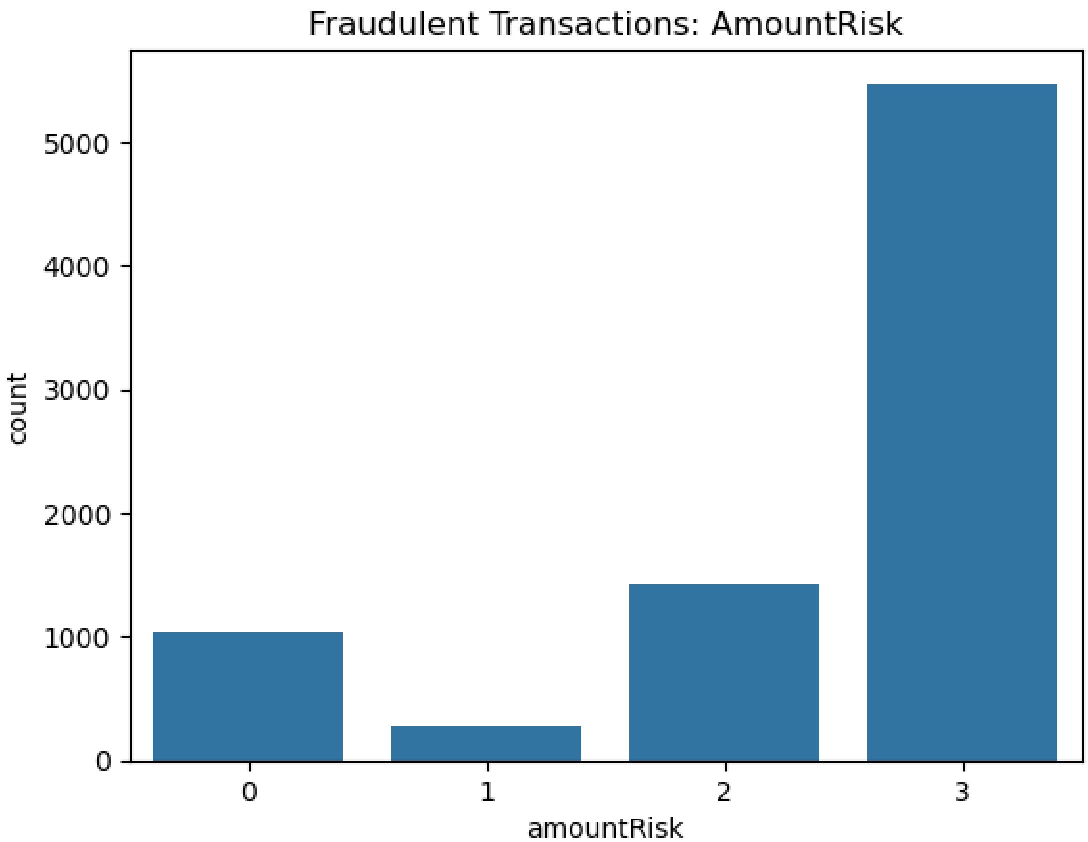
[31]:
```python
# Clissifying amount into risks
bins = [0, 10000, 100000, 200000, float('inf')]
labels = ['Low', 'Medium', 'High', 'Very High']

data['amountRisk'] = pd.cut(data['amount'], bins=bins, labels=labels,
 ↪include_lowest=True)
```

[32]:
```python
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
data['amountRisk'] = le.fit_transform(data['amountRisk'])
data.head()
```

[32]:
```
       type    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0   PAYMENT   9839.64       170136.0       160296.36             0.0
1   PAYMENT   1864.28        21249.0        19384.72             0.0
2  TRANSFER    181.00          181.0            0.00             0.0
3  CASH_OUT    181.00          181.0            0.00         21182.0
4   PAYMENT  11668.14        41554.0        29885.86             0.0

   newbalanceDest  isFraud  isFlaggedFraud  netChangeOrig  netChangeDest  \
0             0.0        0               0       -9839.64            0.0
1             0.0        0               0       -1864.28            0.0
2             0.0        1               0        -181.00            0.0
3             0.0        1               0        -181.00       -21182.0
4             0.0        0               0      -11668.14            0.0

   origFreq  destFreq  businessHours_Business  businessHours_Off-hours  \
0         1         1                   False                       1
1         1         1                   False                       1
2         1        44                   False                       1
3         1        41                   False                       1
4         1         1                   False                       1

   amountRisk
0           1
1           1
```

```
2             1
3             1
4             2
```

[33]:
```
import seaborn as sns
sns.countplot(data=data[data['isFraud'] == 1], x='amountRisk')
plt.title('Fraudulent Transactions: AmountRisk')
plt.show()
```



[34]:
```
# We can see that the number of Transaction tagged as Very High in risk are␣
↪most likely to be a fraud transaction
```

[35]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
data['type'] = le.fit_transform(data['type'])
```

[36]:
```
data1=data
data1.head()
```

[36]:
```
   type    amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
0     3   9839.64       170136.0       160296.36             0.0
1     3   1864.28        21249.0        19384.72             0.0
2     4    181.00          181.0            0.00             0.0
3     1    181.00          181.0            0.00         21182.0
4     3  11668.14        41554.0        29885.86             0.0

   newbalanceDest  isFraud  isFlaggedFraud  netChangeOrig  netChangeDest  \
0             0.0        0               0       -9839.64            0.0
1             0.0        0               0       -1864.28            0.0
2             0.0        1               0        -181.00            0.0
3             0.0        1               0        -181.00       -21182.0
4             0.0        0               0      -11668.14            0.0

   origFreq  destFreq  businessHours_Business  businessHours_Off-hours  \
0         1         1                   False                        1
1         1         1                   False                        1
2         1        44                   False                        1
3         1        41                   False                        1
4         1         1                   False                        1

   amountRisk
0           1
1           1
2           1
3           1
4           2
```

[41]:
```
# ML MODEL for understanding the Feature Importance
```

[46]:
```
from sklearn.ensemble import RandomForestClassifier

X = data1.drop('isFraud', axis=1)
y = data1['isFraud']

model = RandomForestClassifier(n_estimators=20,n_jobs=-1)
%time model.fit(X, y)

importances = model.feature_importances_

feature_importance_data = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

print(feature_importance_data)
```

```
CPU times: total: 15min 36s
Wall time: 2min 45s
                    Feature  Importance
7             netChangeOrig    0.285625
8             netChangeDest    0.171017
5            newbalanceDest    0.154705
2             oldbalanceOrg    0.119573
1                    amount    0.095548
4            oldbalanceDest    0.063396
10                 destFreq    0.038811
0                      type    0.031491
3            newbalanceOrig    0.021281
11   businessHours_Business    0.006543
12  businessHours_Off-hours    0.005700
13               amountRisk    0.005363
6            isFlaggedFraud    0.000739
9                  origFreq    0.000209
```

[65]:
```
# ML MODEL
# RANDOM FOREST
```

[49]:
```
# train test split
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪25,random_state=42)
rf=RandomForestClassifier(n_estimators=20,n_jobs=-1)
%time rf.fit(X_train,y_train)

accuracy_rf=rf.score(X_test,y_test)*100
print(accuracy_rf)
```

```
CPU times: total: 10min 38s
Wall time: 1min 51s
99.97020095495252
```

[50]:
```
# Accuracy is very high that may be because there are very less transactions␣
↪marked as fraud
# We will also consider other matrics for this dataset
```

[51]:
```
from sklearn.metrics import classification_report, confusion_matrix

y_pred = rf.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
```

```
              precision    recall  f1-score   support
```

```
           0       1.00      1.00      1.00   1588610
           1       0.98      0.79      0.87      2045

    accuracy                           1.00   1590655
   macro avg       0.99      0.89      0.94   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588572      38]
 [    436    1609]]
```

[ ]:
```
# In this we can see that 436 transactions are fraud which are categorised as␣
↪non fraud
# We can drop some features that does not have much importance
```

[53]:
```
from sklearn.ensemble import RandomForestClassifier

X1 = data1.
↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
↪axis=1)
y1 = data1['isFraud']
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X1,y1,test_size=0.
↪25,random_state=42)
rf1=RandomForestClassifier(n_estimators=20,n_jobs=-1)
%time rf1.fit(X_train,y_train)

accuracy_rf1=rf1.score(X_test,y_test)*100
print(accuracy_rf1)
from sklearn.metrics import classification_report, confusion_matrix

y_pred = rf1.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
```

```
CPU times: total: 15min 22s
Wall time: 2min 33s
99.97347004850204
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.97      0.82      0.89      2045

    accuracy                           1.00   1590655
   macro avg       0.98      0.91      0.94   1590655
weighted avg       1.00      1.00      1.00   1590655
```

```
[[1588555      55]
 [    367    1678]]
```

[ ]:
```
# Still we can see that 367 transactions are fraud but are classified as not␣
↪fraud
# Lets increase the number of Trees
```

[54]:
```
from sklearn.ensemble import RandomForestClassifier

X2 = data1.
↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
↪axis=1)
y2 = data1['isFraud']
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X2,y2,test_size=0.
↪25,random_state=42)
rf2=RandomForestClassifier(n_estimators=50,n_jobs=-1)
%time rf2.fit(X_train,y_train)

accuracy_rf2=rf2.score(X_test,y_test)*100
print(accuracy_rf2)
from sklearn.metrics import classification_report, confusion_matrix

y_pred = rf2.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
```

```
CPU times: total: 39min 11s
Wall time: 5min 44s
99.97334431413474
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.96      0.82      0.89      2045

    accuracy                           1.00   1590655
   macro avg       0.98      0.91      0.94   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588546      64]
 [    360    1685]]
```

[ ]:
```
# Not much difference
# Lets try another Classification Models
```

[55]:
```python
# LOGISTIC REGRESSION

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

X = data1.
↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
↪axis=1)
y = data1['isFraud']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=42)

lr = LogisticRegression(max_iter=1000, n_jobs=-1, random_state=42)

%time lr.fit(X_train, y_train)

accuracy_lr = lr.score(X_test, y_test) * 100
print(accuracy_lr)

y_pred = lr.predict(X_test)

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

```
CPU times: total: 1.53 s
Wall time: 1min 51s
99.91443776305987
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.74      0.51      0.61      2045

    accuracy                           1.00   1590655
   macro avg       0.87      0.75      0.80   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588251     359]
 [   1002    1043]]
```

[ ]:
```python
# More wrong classification than Random Forest
```

[64]:
```python
# XGBOOST

from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
```

```python
from sklearn.metrics import classification_report, confusion_matrix
import warnings
warnings.filterwarnings("ignore")


X = data1.
 ↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
 ↪axis=1)
y = data1['isFraud']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)

xgb_model = XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=6,␣
 ↪scale_pos_weight=5, use_label_encoder=False, eval_metric='logloss')

%time xgb_model.fit(X_train, y_train)

accuracy_xgb = xgb_model.score(X_test, y_test) * 100
print(accuracy_xgb)

y_pred = xgb_model.predict(X_test)

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

```
CPU times: total: 1min 22s
Wall time: 13.8 s
99.96183961952781
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.87      0.82      0.85      2045

    accuracy                           1.00   1590655
   macro avg       0.94      0.91      0.92   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588368     242]
 [    365    1680]]
```

[39]:

```python
# DECISION TREE

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
```

```
X = data1.
  ↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
  ↪axis=1)
y = data1['isFraud']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
  ↪random_state=42)

dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)

%time dt_model.fit(X_train, y_train)

accuracy_dt = dt_model.score(X_test, y_test) * 100
print(accuracy_dt)

y_pred = dt_model.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
```

```
CPU times: total: 3min 42s
Wall time: 3min 49s
99.97114396270719
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.89      0.89      0.89      2045

    accuracy                           1.00   1590655
   macro avg       0.94      0.94      0.94   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588386     224]
 [    235    1810]]
```

[40]:

```
# DECISION TREE WITH BALANCED WEIGHT

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

X = data1.
  ↪drop(['isFraud','origFreq','isFlaggedFraud','amountRisk','businessHours_Off-hours','busines
  ↪axis=1)
y = data1['isFraud']
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)

dt_model_balanced = DecisionTreeClassifier(class_weight='balanced',␣
 ↪random_state=42)
dt_model_balanced.fit(X_train, y_train)

%time dt_model_balanced.fit(X_train, y_train)

accuracy_dt_balanced = dt_model_balanced.score(X_test, y_test) * 100
print(accuracy_dt_balanced)

y_pred_balanced = dt_model_balanced.predict(X_test)
print(classification_report(y_test, y_pred_balanced))
print(confusion_matrix(y_test, y_pred_balanced))
```

```
CPU times: total: 2min 31s
Wall time: 2min 34s
99.97051529087074
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588610
           1       0.90      0.87      0.88      2045

    accuracy                           1.00   1590655
   macro avg       0.95      0.93      0.94   1590655
weighted avg       1.00      1.00      1.00   1590655

[[1588411     199]
 [    270    1775]]
```

[45]:
```python
# Deep Learning
```

[46]:
```python
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

```python
X = data1.drop(['isFraud', 'origFreq', 'isFlaggedFraud', 'amountRisk', 'businessHours_Off-hours', 'businessHours_Business'], axis=1)
y = data1['isFraud']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X_train_scaled, y_train)

model = Sequential()
model.add(Dense(128, input_dim=X_res.shape[1], activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(1, activation='sigmoid'))

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

early_stop = EarlyStopping(monitor='val_loss', patience=3)

%time history = model.fit(X_res, y_res, epochs=10, batch_size=512, validation_split=0.2, callbacks=[early_stop])

y_pred = model.predict(X_test_scaled)
y_pred = (y_pred > 0.5).astype(int)

print("Classification Report:")
print(classification_report(y_test, y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Epoch 1/10
14894/14894 [==============================] - 139s 9ms/step - loss: 0.0456 -
accuracy: 0.9845 - val_loss: 0.0497 - val_accuracy: 0.9889
Epoch 2/10
14894/14894 [==============================] - 141s 9ms/step - loss: 0.0275 -
accuracy: 0.9915 - val_loss: 0.0265 - val_accuracy: 0.9947
Epoch 3/10
14894/14894 [==============================] - 156s 10ms/step - loss: 0.0269 -
accuracy: 0.9916 - val_loss: 0.0225 - val_accuracy: 0.9934
Epoch 4/10
```

```
14894/14894 [==============================] - 154s 10ms/step - loss: 0.0264 -
accuracy: 0.9918 - val_loss: 0.0297 - val_accuracy: 0.9926
Epoch 5/10
14894/14894 [==============================] - 160s 11ms/step - loss: 0.0261 -
accuracy: 0.9921 - val_loss: 0.0271 - val_accuracy: 0.9936
Epoch 6/10
14894/14894 [==============================] - 156s 10ms/step - loss: 0.0258 -
accuracy: 0.9922 - val_loss: 0.0203 - val_accuracy: 0.9955
Epoch 7/10
14894/14894 [==============================] - 161s 11ms/step - loss: 0.0257 -
accuracy: 0.9924 - val_loss: 0.0239 - val_accuracy: 0.9928
Epoch 8/10
14894/14894 [==============================] - 154s 10ms/step - loss: 0.0252 -
accuracy: 0.9926 - val_loss: 0.0207 - val_accuracy: 0.9945
Epoch 9/10
14894/14894 [==============================] - 158s 11ms/step - loss: 0.0250 -
accuracy: 0.9927 - val_loss: 0.0316 - val_accuracy: 0.9925
CPU times: total: 1h 58min 49s
Wall time: 23min
49708/49708 [==============================] - 162s 3ms/step
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00   1588610
           1       0.20      0.99      0.33      2045

    accuracy                           0.99   1590655
   macro avg       0.60      0.99      0.67   1590655
weighted avg       1.00      0.99      1.00   1590655

Confusion Matrix:
[[1580592    8018]
 [     22    2023]]
```

[ ]:

```
*Comparision*

Model                      | Precision (Fraud) | Recall (Fraud) | F1-score
↪(Fraud) | Accuracy | CPU Time | Wall Time

Random Forest              | 0.97              | 0.82           | 0.89
↪ | 99.97%   | ~15 min  | 2.5 min
Random Forest (more trees)| 0.96              | 0.82           | 0.89
↪ | 99.97%   | ~39 min  | 5.7 min
Decision Tree              | 0.89              | 0.89           | 0.89
↪ | 99.97%   | ~3 min   | ~3 min
XGBoost                    | 0.87              | 0.82           | 0.85
↪ | 99.96%   | 1.5 min  | 13.8 s
```

```
DL (SMOTE)                  | 0.20               | 0.99             | 0.33          ␣
↪  | 99.00%   | 1h 58min | 23 min
```

[ ]:
```
*FINAL Verdict*

1.If you want balance (high precision & recall) → Random Forest

2.If you want to catch all frauds no matter what (high recall) → Deep Learning␣
↪(with SMOTE)

3.If you are running in low-resource settings or want fast results → Decision␣
↪Tree
```

[ ]:
```
'''
*Answers to the Questions*

1. Data cleaning including missing values, outliers, and multi-collinearity.
Answer:The dataset had no missing values, so no imputation was required.
       Outliers were retained because in fraud detection, outliers can indicate␣
↪abnormal activity and are therefore meaningful.
       Regarding multi-collinearity, I dropped features that were highly␣
↪correlated or redundant after performing exploratory data analysis (EDA) and␣
↪feature importance checks, such as isFlaggedFraud and some one-hot encoded␣
↪time features.

2. Describe your fraud detection model in elaboration.
Answer:I selected the Deep Learning model as the best for fraud detection after␣
↪comparing it with Logistic Regression, Random Forest, XGBoost, and Decision␣
↪Tree.
       Why Deep Learning?
       It achieved ~99% recall for fraud cases, which is crucial because␣
↪catching fraud is more important than occasionally flagging genuine␣
↪transactions. The model was trained using SMOTE to balance the classes and␣
↪built with Keras using dense layers and dropout to prevent overfitting.
       Evaluation showed high accuracy and recall, making it ideal for␣
↪minimizing missed frauds, even if precision is lower due to false positives.

3. How did you select variables to be included in the model?
Answer:I started with feature engineering-creating new features like␣
↪netChangeOrig, netChangeDest, amountRisk, etc.
       Features like amount, oldbalanceOrg, newbalanceDest, etc., were retained␣
↪due to their importance in financial transactions.
       I eliminated less informative or redundant features such as␣
↪isFlaggedFraud or business hour encodings.
       Feature importance from tree-based models and correlation analysis were␣
↪used to guide the selection.
```

```
4. Demonstrate the performance of the model by using best set of tools.
Answer:Decision Tree achieved high performance with very few false negatives,␣
↪making it ideal for fraud detection.
       I evaluated all models using:
       Accuracy
       Precision
       Recall
       F1-Score
       Confusion Matrix
       Execution Time (CPU & Wall Time)
       Compared to other models, Decision Tree was faster than Deep Learning␣
↪and showed competitive recall (essential for detecting fraud cases).

5. What are the key factors that predict fraudulent customers?
Answer:The most predictive factors identified were:
       netChangeOrig, netChangeDest
       oldbalanceOrg, oldbalanceDest
       newbalanceDest, amount
       Transaction Frequency features
       Transaction Type (e.g., CASH_OUT or TRANSFER)

6. Do these factors make sense? If yes, how?
Answer: Yes, they make perfect sense because:
        Net balance changes highlight sudden or abnormal fund movements.
        Transaction types (like TRANSFER or CASH_OUT) are more commonly␣
↪exploited in fraud.
        Frequent or unusual transactions can indicate bot activity or scams.
        These patterns are typical signs of fraud and align with real-world␣
↪fraud behavior.

7. What kind of prevention should be adopted while the company updates its␣
↪infrastructure?
Answer:Implement real-time fraud detection systems using APIs and machine␣
↪learning models.
       Adopt Multi-Factor Authentication (MFA) to secure logins and critical␣
↪transactions.
       Set transaction limits or velocity checks to flag unusual behavior␣
↪quickly.
       Integrate audit trails and activity monitoring for accountability.

8. Assuming these actions have been implemented, how would you determine if␣
↪they work?
Answer:Pre/Post analysis of fraud incidence and trends.
       Monitor model performance metrics (especially recall and false negative␣
↪rate).
```

```
     Gather feedback from fraud investigators on alerts generated by the␣
↪system.
     Continuously update the model with recent data and re-evaluate␣
↪effectiveness over time.
```