Task 2: Credit Card Fraud Detection

```
We are tasked to build a model to detect fraudulent credit card transactions. Using a
dataset containing information about credit card transactions, and We are going to
experiment with algorithms like Logistic Regression, Decision Trees,
or Random Forests to classify transactions as fraudulent or
legitimate.
```

In [1]:
```
## Import Necessary libraries

import pandas as pd
from datetime import datetime
import seaborn as sns
import matplotlib.pyplot as plt


from imblearn.under_sampling import RandomUnderSampler
```

Steps

1. Data Collection

2. Preparing the Data

3. Data Preprocessing

4. Model selection

5. Model Testing

Data Collection

We are going the import the csv files which contain the necessary fraud data you can download it from kaggle .
[https://www.kaggle.com/datasets/kartik2112/fraud-detection (https://www.kaggle.com/datasets/kartik2112/fraud-detection)](https://www.kaggle.com/datasets/kartik2112/fraud-detection)

About the Dataset

```
 This is a simulated credit card transaction dataset containing legitimate and fraud transactions fr
om the duration 1st Jan 2019 - 31st Dec 2020. It covers credit cards of 1000 customers doing transac
tions with a pool of 800 merchants.
```

In [2]:
```python
## Read the data

train_df = pd.read_csv("./Credit Card Dataset/fraudTrain.csv")
test_df = pd.read_csv("./Credit Card Dataset/fraudTest.csv")
```

In [3]:
```python
## View the train data
train_df.head(5)
```

Out[3]:

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	street	...	
0	0	2019-01-01 00:00:18	2703186189652095	fraud_Rippin, Kub and Mann	misc_net	4.97	Jennifer	Banks	F	561 Perry Cove	...	3
1	1	2019-01-01 00:00:44	630423337322	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	Stephanie	Gill	F	43039 Riley Greens Suite 393	...	4
2	2	2019-01-01 00:00:51	38859492057661	fraud_Lind-Buckridge	entertainment	220.11	Edward	Sanchez	M	594 White Dale Suite 530	...	4
3	3	2019-01-01 00:01:16	3534093764340240	fraud_Kutch, Hermiston and Farrell	gas_transport	45.00	Jeremy	White	M	9443 Cynthia Court Apt. 038	...	4
4	4	2019-01-01 00:03:06	375534208663984	fraud_Keeling-Crist	misc_pos	41.96	Tyler	Garcia	M	408 Bradley Rest	...	3

5 rows × 23 columns

Preparing the Data

- Remove any missing columns or rows
- Check for duplicates and remove them
- Remmove unnecessary columns and rows

Check basic Info

In [4]:
```
## First do a basic analysis
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   Unnamed: 0             1296675 non-null  int64  
 1   trans_date_trans_time  1296675 non-null  object 
 2   cc_num                 1296675 non-null  int64  
 3   merchant               1296675 non-null  object 
 4   category               1296675 non-null  object 
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object 
 7   last                   1296675 non-null  object 
 8   gender                 1296675 non-null  object 
 9   street                 1296675 non-null  object 
 10  city                   1296675 non-null  object 
 11  state                  1296675 non-null  object 
 12  zip                    1296675 non-null  int64  
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64  
 16  job                    1296675 non-null  object 
 17  dob                    1296675 non-null  object 
 18  trans_num              1296675 non-null  object 
 19  unix_time              1296675 non-null  int64  
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64  
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

In [5]:
```
## Check Basic statical
train_df.describe( include = "all")
```

Out[5]:

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt	first	last	gender	
count	1.296675e+06	1296675	1.296675e+06	1296675	1296675	1.296675e+06	1296675	1296675	1296675	12
unique	NaN	1274791	NaN	693	14	NaN	352	481	2	
top	NaN	2019-04-22 16:02:01	NaN	fraud_Kilback LLC	gas_transport	NaN	Christopher	Smith	F	E Ap
freq	NaN	4	NaN	4403	131659	NaN	26669	28794	709863	
mean	6.483370e+05	NaN	4.171920e+17	NaN	NaN	7.035104e+01	NaN	NaN	NaN	
std	3.743180e+05	NaN	1.308806e+18	NaN	NaN	1.603160e+02	NaN	NaN	NaN	
min	0.000000e+00	NaN	6.041621e+10	NaN	NaN	1.000000e+00	NaN	NaN	NaN	
25%	3.241685e+05	NaN	1.800429e+14	NaN	NaN	9.650000e+00	NaN	NaN	NaN	
50%	6.483370e+05	NaN	3.521417e+15	NaN	NaN	4.752000e+01	NaN	NaN	NaN	
75%	9.725055e+05	NaN	4.642255e+15	NaN	NaN	8.314000e+01	NaN	NaN	NaN	
max	1.296674e+06	NaN	4.992346e+18	NaN	NaN	2.894890e+04	NaN	NaN	NaN	

11 rows × 23 columns

Remove duplicates and missing values

In [6]:
```
## Check for missing values
train_df.isna().sum()
```

Out[6]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

In [7]:
```
## check for test data null values
test_df.isna().sum()
```

Out[7]:
```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

In [8]:
```
## Check for any duplicates

train_df.duplicated().sum()
```

Out[8]:
```
0
```

In [9]:
```
## Check for duplicates in test data
test_df.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
## Check a single rows of data
train_df.iloc[0,:]
```

Out[10]:
```
Unnamed: 0                                              0
trans_date_trans_time                 2019-01-01 00:00:18
cc_num                                   2703186189652095
merchant                       fraud_Rippin, Kub and Mann
category                                         misc_net
amt                                                  4.97
first                                            Jennifer
last                                                Banks
gender                                                  F
street                                     561 Perry Cove
city                                       Moravian Falls
state                                                  NC
zip                                                 28654
lat                                               36.0788
long                                             -81.1781
city_pop                                             3495
job                             Psychologist, counselling
dob                                            1988-03-09
trans_num                0b242abb623afc578575680df30655b9
unix_time                                      1325376018
merch_lat                                       36.011293
merch_long                                     -82.048315
is_fraud                                                0
Name: 0, dtype: object
```

Removing unnecessary features

In [11]:
```
## Check for unique features in data
train_df["trans_num"].nunique()
```

Out[11]:
```
1296675
```

In [12]:
```
## Chheck for values which have unique values in them
for column_name in train_df.columns:
    unique_values = train_df[column_name].nunique()
    print(f'Unique values in column {column_name}: {unique_values}')
```

```
Unique values in column Unnamed: 0: 1296675
Unique values in column trans_date_trans_time: 1274791
Unique values in column cc_num: 983
Unique values in column merchant: 693
Unique values in column category: 14
Unique values in column amt: 52928
Unique values in column first: 352
Unique values in column last: 481
Unique values in column gender: 2
Unique values in column street: 983
Unique values in column city: 894
Unique values in column state: 51
Unique values in column zip: 970
Unique values in column lat: 968
Unique values in column long: 969
Unique values in column city_pop: 879
Unique values in column job: 494
Unique values in column dob: 968
Unique values in column trans_num: 1296675
Unique values in column unix_time: 1274823
Unique values in column merch_lat: 1247805
Unique values in column merch_long: 1275745
Unique values in column is_fraud: 2
```

In [13]:
```
## Drop unneccesary columns like unnamed:0
dropColumn =["Unnamed: 0","job" ,"cc_num","trans_num","zip" ,"unix_time","merch_lat","merch_long","dob","firs
train_df.drop(dropColumn,axis = 1,inplace = True)
test_df.drop(dropColumn,axis = 1,inplace = True)
```

In [14]:
```
## View the data after dropping unnecessary columns
train_df.head(2)
```

Out[14]:

	trans_date_trans_time	merchant	category	amt	gender	state	lat	long	city_pop	is_fraud
0	2019-01-01 00:00:18	fraud_Rippin, Kub and Mann	misc_net	4.97	F	NC	36.0788	-81.1781	3495	0
1	2019-01-01 00:00:44	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	F	WA	48.8878	-118.2105	149	0

In [15]:
```
## Create a fuction convert the trans_time_into day of week
def datetoDay(time):
    timestamp = datetime.strptime(time, "%Y-%m-%d %H:%M:%S")

    # Get the day of the week as a string
    day_of_week = timestamp.strftime("%A")
    return day_of_week
```

In [16]:
```
## Apply the conversion on each sample of test and train
train_df["trans_date_trans_time"] = train_df["trans_date_trans_time"].apply(datetoDay)
test_df["trans_date_trans_time"] = test_df["trans_date_trans_time"].apply(datetoDay)
```

In [17]:
```
train_df.head()
```

Out[17]:

	trans_date_trans_time	merchant	category	amt	gender	state	lat	long	city_pop	is_fraud
0	Tuesday	fraud_Rippin, Kub and Mann	misc_net	4.97	F	NC	36.0788	-81.1781	3495	0
1	Tuesday	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23	F	WA	48.8878	-118.2105	149	0
2	Tuesday	fraud_Lind-Buckridge	entertainment	220.11	M	ID	42.1808	-112.2620	4154	0
3	Tuesday	fraud_Kutch, Hermiston and Farrell	gas_transport	45.00	M	MT	46.2306	-112.1138	1939	0
4	Tuesday	fraud_Keeling-Crist	misc_pos	41.96	M	VA	38.4207	-79.4629	99	0

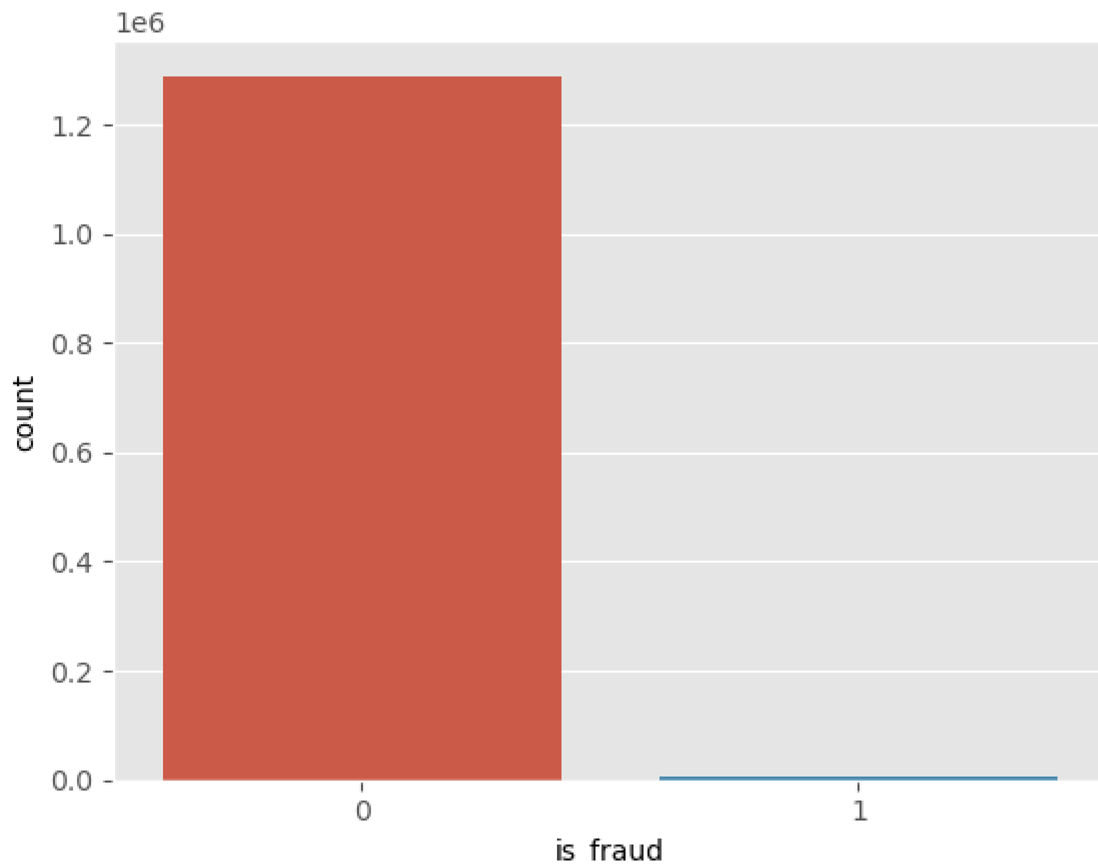
Data Visualization

In [18]:
```
## Check for imbalanced data
train_df["is_fraud"].value_counts()
```

Out[18]:
```
0    1289169
1       7506
Name: is_fraud, dtype: int64
```

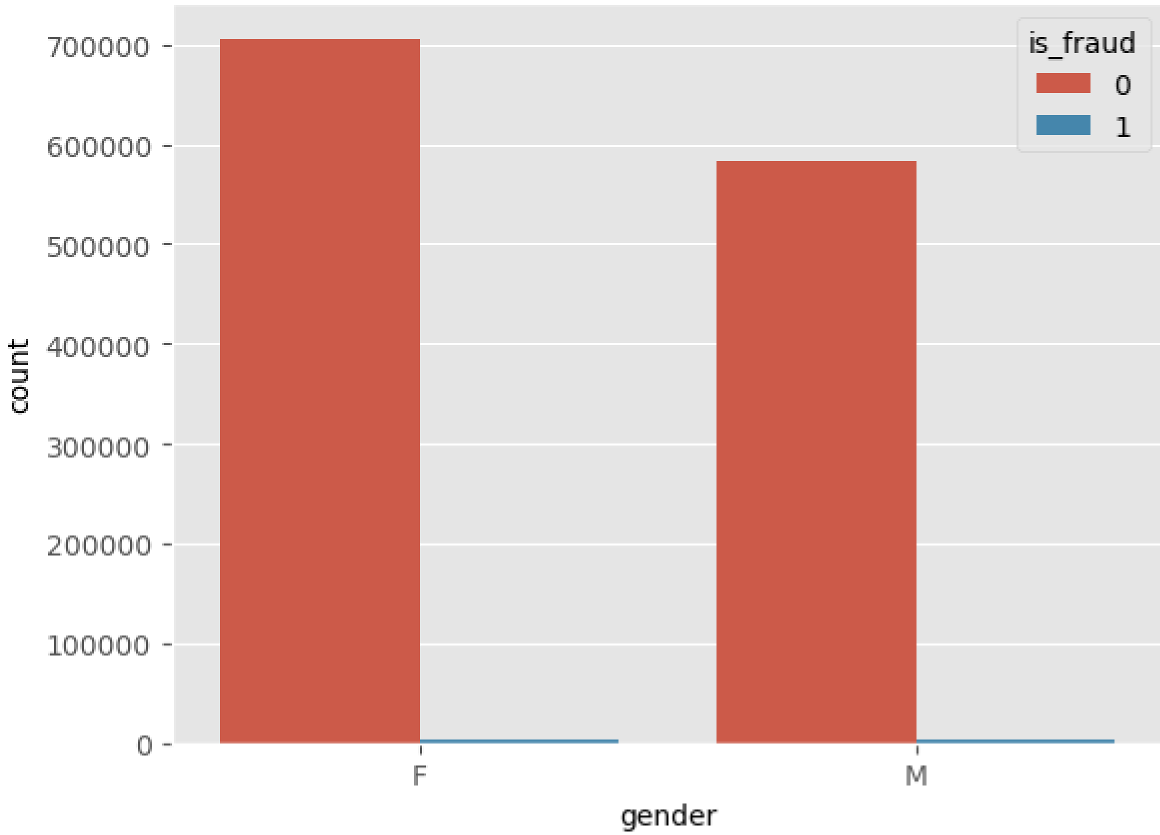
In [19]:
```
## Plot the unbalanced data
plt.style.use("ggplot")
sns.countplot(x= train_df["is_fraud"])
```

Out[19]: <Axes: xlabel='is_fraud', ylabel='count'>



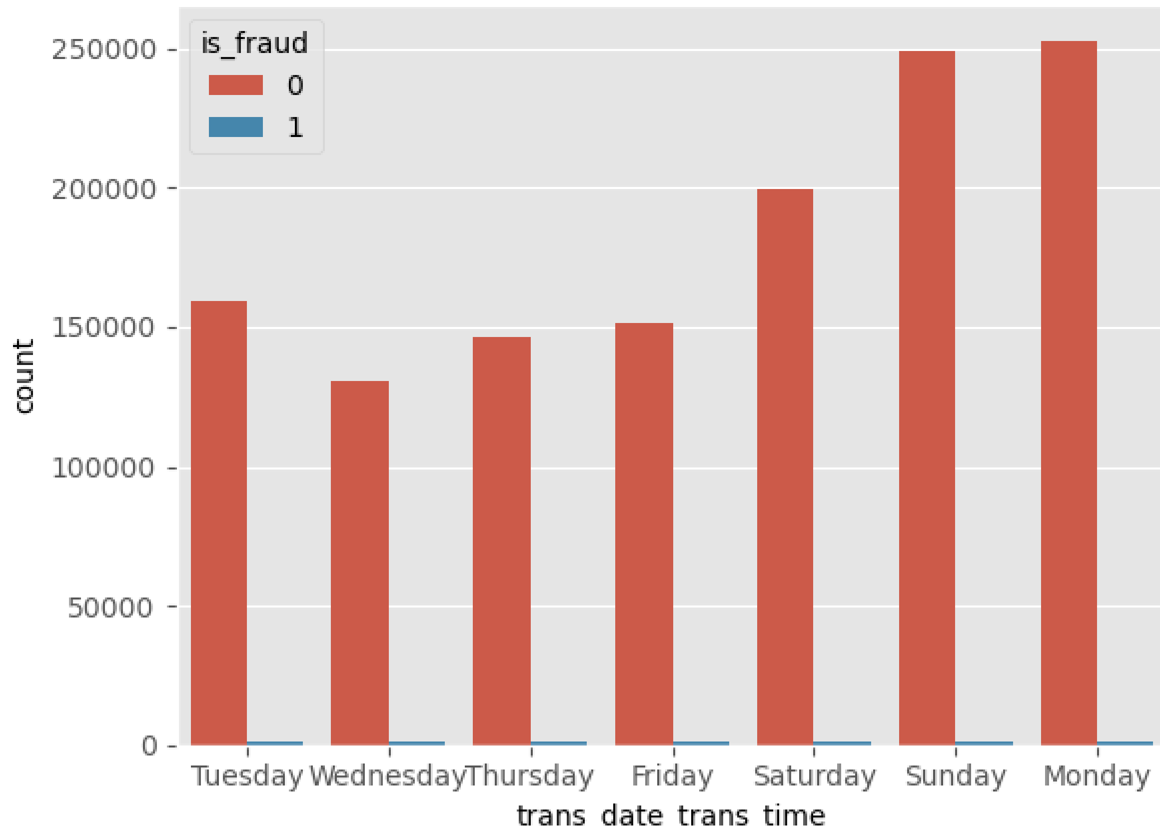
In [20]:
```
## Plot a count plot gender and fraud
sns.countplot(x= train_df["gender"],hue = "is_fraud",data = train_df)
```

Out[20]: <Axes: xlabel='gender', ylabel='count'>



In [21]:
```
## Plot the day and fraud occur more
sns.countplot(x= train_df["trans_date_trans_time"],hue = "is_fraud",data = train_df)
```

Out[21]: <Axes: xlabel='trans_date_trans_time', ylabel='count'>



In [ ]:

Data Preprocessing

Without Handling Imbalanced Data

In [22]:
```
## Import necessary libraries for preprocessing

from sklearn.preprocessing import OneHotEncoder , StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.compose import ColumnTransformer

x_train = train_df.drop("is_fraud" ,axis = 1)
y_train = train_df["is_fraud"]

x_test = test_df.drop("is_fraud" ,axis = 1)
y_test = test_df["is_fraud"]


categ = ["trans_date_trans_time","merchant","category","gender","state"]
numeric = ["amt","lat" ,"long" ,"city_pop"]



encoder = OneHotEncoder()
scaler = StandardScaler()

transf = ColumnTransformer(transformers = [("categorical",encoder ,categ),
                                           ("num",scaler,numeric)],remainder="passthrough")
x_train = transf.fit_transform(x_train)
x_test = transf.transform(x_test)
```

In [23]:
```
## Check the shape of each data

x_train.shape,x_test.shape ,y_train.shape ,y_test.shape
```

Out[23]:
```
((1296675, 771), (555719, 771), (1296675,), (555719,))
```

In [24]:
```
## Create a testing function for model
def model_testing(estimator):
    ## Prediction on data
    y_preds = estimator.predict(x_test)

    ##Print accuracy score
    print("Accuracy Score : ",accuracy_score(y_test,y_preds))

    ## Print classification report
    print("\nConfussion Matrix :\n " ,confusion_matrix(y_test ,y_preds),"\n")

    ## Check confusion matrix
    print("classification_report: \n\n",classification_report(y_test ,y_preds))
```

Model selection

In [25]:
```
## Import all the models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
```

Logistic Regression

- Apply LogisticRegression without balancing the data

In [26]:
```
## Logistic regression without balancing data
model = LogisticRegression()
model.fit(x_train ,y_train)
model_testing(model)
```

```
C:\Users\Barcha\anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/prep
rocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/
stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(

Accuracy Score :  0.995531914510751

Confussion Matrix :
  [[553235    339]
 [  2144      1]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.00      0.00      0.00      2145

    accuracy                           1.00    555719
   macro avg       0.50      0.50      0.50    555719
weighted avg       0.99      1.00      0.99    555719
```

In [ ]:
```

```

DecisionTreeClassifier

In [27]:
```
## Logistic regression without balancing data
dt = DecisionTreeClassifier()
dt.fit(x_train ,y_train)
model_testing(dt)
dt.score(x_test ,y_test)
```

```
Accuracy Score :  0.9964154545732645

Confussion Matrix :
  [[552469   1105]
 [   887   1258]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.53      0.59      0.56      2145

    accuracy                           1.00    555719
   macro avg       0.77      0.79      0.78    555719
weighted avg       1.00      1.00      1.00    555719
```

Out[27]: 0.9964154545732645

In [ ]:

RandomForestClassifier

In [28]:

```
## Logistic regression without balancing data
rf = RandomForestClassifier()
rf.fit(x_train ,y_train)
model_testing(rf)
rf.score(x_test ,y_test)
```

```
Accuracy Score :  0.997430355989268

Confussion Matrix :
  [[553400    174]
 [  1254    891]]

classification_report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.84      0.42      0.56      2145

    accuracy                           1.00    555719
   macro avg       0.92      0.71      0.78    555719
weighted avg       1.00      1.00      1.00    555719
```

Out[28]: 0.997430355989268

In [ ]:

Conclusiom

```
As we can see from above that the accuracy was high but the recall and and f1 score was very low thi
s is because due to larger samples of False Value the model is showing biaseness toward a single cla
ss and count predict the low sample class correctly. To solve this issue we will
- Balanced the samples either(underSampling or OverSampling)
```

Model prediction by Balancing Samples

UnderSampling

In [29]:
```
## Balance the imbalanced data apply undersampling
from imblearn.under_sampling import RandomUnderSampler

sampler = RandomUnderSampler()

x_train = train_df.drop("is_fraud" ,axis = 1)
y_train = train_df["is_fraud"]

x_test = test_df.drop("is_fraud" ,axis = 1)
y_test = test_df["is_fraud"]

x_sampled ,y_sampled =sampler.fit_resample(x_train ,y_train)

categ = ["trans_date_trans_time","merchant","category","gender","state"]
numeric = ["amt","lat" ,"long" ,"city_pop"]



encoder = OneHotEncoder()
scaler = StandardScaler()

transf = ColumnTransformer(transformers = [("categorical",encoder ,categ),
                                            ("num",scaler,numeric)],remainder="passthrough")
x_train = transf.fit_transform(x_sampled)
x_test = transf.transform(x_test)
```

In [30]:
```
## Check the shape of each data

x_train.shape,x_test.shape ,y_sampled.shape ,y_test.shape
```

Out[30]:
```
((15012, 771), (555719, 771), (15012,), (555719,))
```

In [ ]:

```

```

Logistic Regression

- Model Training on Undersampled Data

In [31]:
```
model = LogisticRegression()
model.fit(x_train ,y_sampled)
model_testing(model)
```

```
C:\Users\Barcha\anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/prep
rocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/
stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(

Accuracy Score :  0.8800400922048733

Confussion Matrix :
  [[487453  66121]
 [   543   1602]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      0.88      0.94    553574
           1       0.02      0.75      0.05      2145

    accuracy                           0.88    555719
   macro avg       0.51      0.81      0.49    555719
weighted avg       1.00      0.88      0.93    555719
```

In [ ]:

DecisionTreeClassifier

- Model Training on Undersampled Data

In [32]:
```
## Logistic regression without balancing data
dt = DecisionTreeClassifier()
dt.fit(x_train ,y_sampled)
model_testing(dt)
dt.score(x_test ,y_test)
```

```
Accuracy Score :  0.9529438439211184

Confussion Matrix :
  [[527522  26052]
 [    98   2047]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      0.95      0.98    553574
           1       0.07      0.95      0.14      2145

    accuracy                           0.95    555719
   macro avg       0.54      0.95      0.56    555719
weighted avg       1.00      0.95      0.97    555719
```

Out[32]:
```
0.9529438439211184
```

In [ ]:
```

```

RandomForestClassifier

- Model Training on Undersampled Data

In [33]:
```
## Logistic regression without balancing data
rf = RandomForestClassifier()
rf.fit(x_train ,y_sampled)
model_testing(rf)
rf.score(x_test ,y_test)
```

```
Accuracy Score :  0.9735909695367623

Confussion Matrix :
  [[539141  14433]
 [   243   1902]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      0.97      0.99    553574
           1       0.12      0.89      0.21      2145

    accuracy                           0.97    555719
   macro avg       0.56      0.93      0.60    555719
weighted avg       1.00      0.97      0.98    555719
```

Out[33]: 0.9735909695367623

In [ ]:

OverSampling

In [34]:
```
## Balance the imbalanced data using Oversampling
from imblearn.over_sampling import SMOTE

Over_sampler = SMOTE()

x_train = train_df.drop("is_fraud" ,axis = 1)
y_train = train_df["is_fraud"]

x_test = test_df.drop("is_fraud" ,axis = 1)
y_test = test_df["is_fraud"]

x_sampled_O ,y_sampled_O =Over_sampler.fit_resample(x_train ,y_train)

categ = ["trans_date_trans_time","merchant","category","gender","state"]
numeric = ["amt","lat" ,"long" ,"city_pop"]



encoder = OneHotEncoder()
scaler = StandardScaler()

transf = ColumnTransformer(transformers = [("categorical",encoder ,categ),
                                            ("num",scaler,numeric)],remainder="passthrough")
x_train = transf.fit_transform(x_sampled_O)
x_test = transf.transform(x_test)
```

LogisticRegression

- Model Training on Oversampled Data

In [35]:
```
## Logistic regression without balancing data
model = LogisticRegression()
model.fit(x_train ,y_sampled_O)
model_testing(model)
```

```
C:\Users\Barcha\anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/prep
rocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/
stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(

Accuracy Score :  0.8865451784085122

Confussion Matrix :
  [[491074  62500]
 [   549   1596]]

classification_report:

              precision    recall  f1-score   support

           0       1.00      0.89      0.94    553574
           1       0.02      0.74      0.05      2145

    accuracy                           0.89    555719
   macro avg       0.51      0.82      0.49    555719
weighted avg       1.00      0.89      0.94    555719
```

DecisionTreeClassifier

- Model Training on Oversampled Data

In [36]:
```
## Logistic regression without balancing data
dt = DecisionTreeClassifier()
dt.fit(x_train ,y_sampled_O)
model_testing(dt)
dt.score(x_test ,y_test)
```

```
Accuracy Score :  0.9959313969830076

Confussion Matrix :
  [[552219   1355]
 [   906   1239]]

classification_report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.48      0.58      0.52      2145

    accuracy                           1.00    555719
   macro avg       0.74      0.79      0.76    555719
weighted avg       1.00      1.00      1.00    555719
```

Out[36]:
```
0.9959313969830076
```

RandomForestClassifier

- Model Training on Oversampled Data

In [37]:
```
## Logistic regression without balancing data
rf = RandomForestClassifier()
rf.fit(x_train ,y_sampled_O)
model_testing(rf)
rf.score(x_test ,y_test)
```

```
Accuracy Score :  0.9974321554598637

Confussion Matrix :
  [[553277    297]
 [  1130   1015]]

classification_report:

               precision    recall  f1-score   support

           0       1.00      1.00      1.00    553574
           1       0.77      0.47      0.59      2145

    accuracy                           1.00    555719
   macro avg       0.89      0.74      0.79    555719
weighted avg       1.00      1.00      1.00    555719
```

Out[37]: 0.9974321554598637