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Project Name = Fraud Transactions

Importing Libraries

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # Data processing
import matplotlib.pyplot as plt #Data visualization
import seaborn as sns # Data visualization
from sklearn.preprocessing import LabelEncoder # Label Encoding
from sklearn.preprocessing import MinMaxScaler #Data scaling
from imblearn.over_sampling import SMOTE # Balancing data
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score , precision_score , recall_
from sklearn.metrics import roc_auc_score,roc_curve
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_csv('Fraud.csv')
```

In [3]:
```
df.shape
```

Out[3]: (6362620, 11)

In [4]:
```
df.head()
```

Out[4]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703

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

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

In [6]:
```
# Checking Nulls
df.isna().mean()*100
```

Out[6]:
```
step              0.0
type              0.0
amount            0.0
nameOrig          0.0
oldbalanceOrg     0.0
newbalanceOrig    0.0
nameDest          0.0
oldbalanceDest    0.0
newbalanceDest    0.0
isFraud           0.0
isFlaggedFraud    0.0
dtype: float64
```

In [7]:
```
df.dtypes
```

Out[7]:
```
step                int64
type               object
amount            float64
nameOrig           object
oldbalanceOrg     float64
newbalanceOrig    float64
nameDest           object
oldbalanceDest    float64
newbalanceDest    float64
isFraud             int64
isFlaggedFraud      int64
dtype: object
```

In [8]:
```
pd.set_option('display.float_format', '{:.2f}'.format) # To see actual
df.describe()
```

Out[8]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanc
count	6362620.00	6362620.00	6362620.00	6362620.00	6362620.00	6362(
mean	243.40	179861.90	833883.10	855113.67	1100701.67	1224(
std	142.33	603858.23	2888242.67	2924048.50	3399180.11	36741
min	1.00	0.00	0.00	0.00	0.00	
25%	156.00	13389.57	0.00	0.00	0.00	
50%	239.00	74871.94	14208.00	0.00	132705.66	214(
75%	335.00	208721.48	107315.18	144258.41	943036.71	1111(
max	743.00	92445516.64	59585040.37	49585040.37	356015889.35	356179:

In [9]:
```
df.describe(include= 'object')
```

Out[9]:

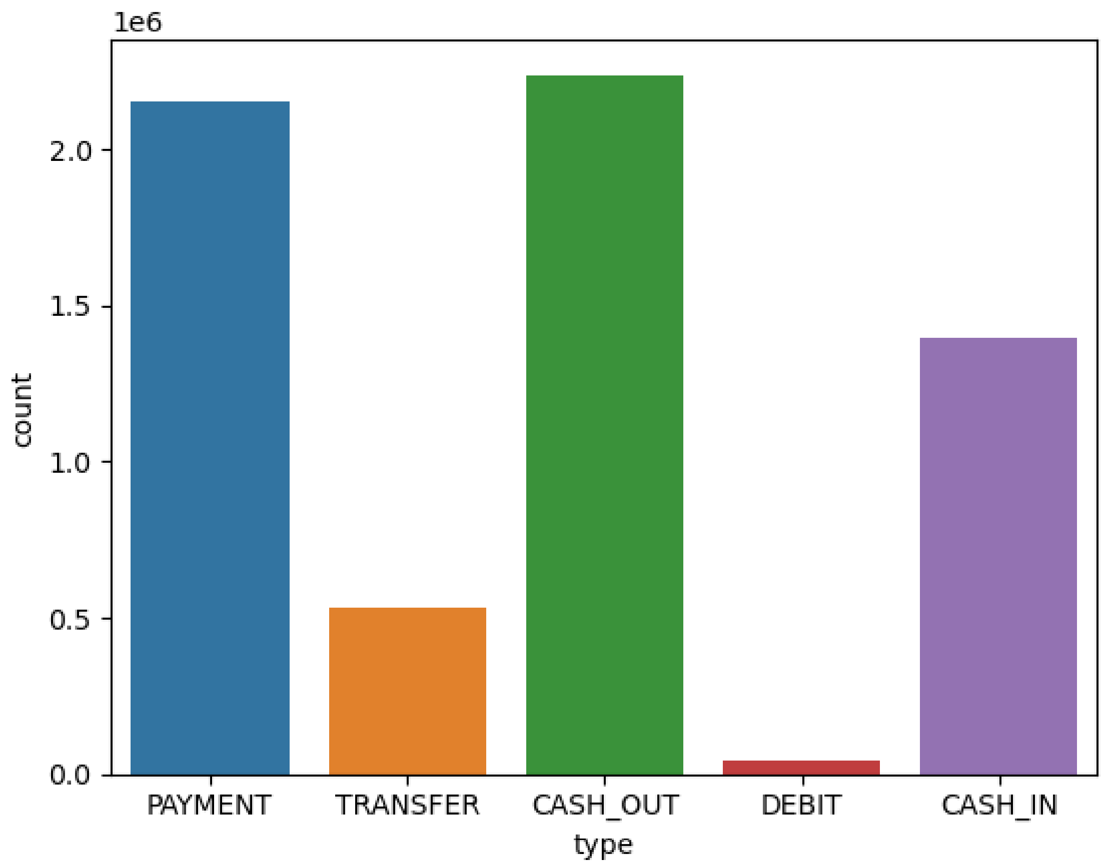
	type	nameOrig	nameDest
count	6362620	6362620	6362620
unique	5	6353307	2722362
top	CASH_OUT	C1902386530	C1286084959
freq	2237500	3	113

In [10]:
```
df.duplicated().sum()
```

Out[10]: 0

In [11]:
```
sns.countplot(df['type'])
```

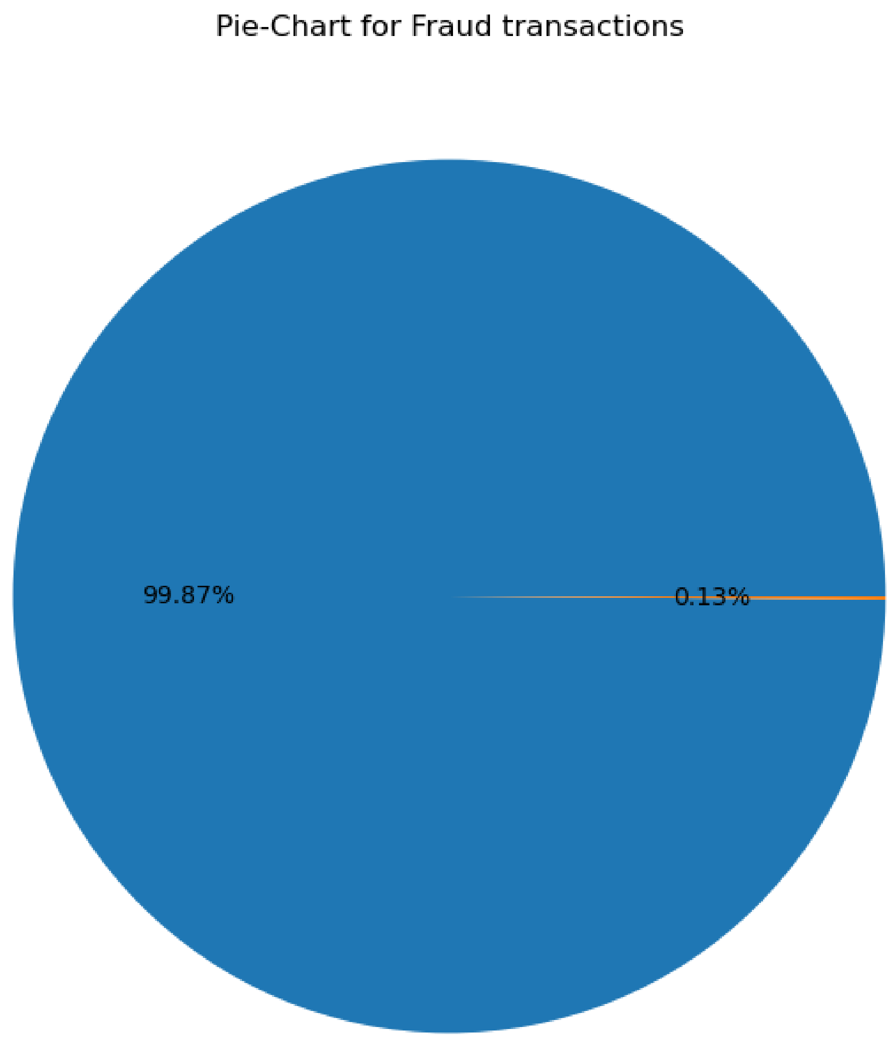
Out[11]: <AxesSubplot:xlabel='type', ylabel='count'>



In [12]:
```
df['isFraud'].value_counts()
```

Out[12]:
```
0    6354407
1       8213
Name: isFraud, dtype: int64
```

In [13]:
```
plt.figure(figsize=(12,8))
plt.title('Pie-Chart for Fraud transactions')
plt.pie(df['isFraud'].value_counts(),  autopct='%.2f%%')
plt.show()
```



In [14]:
```
df.nunique()
```

Out[14]:
```
step                  743
type                    5
amount            5316900
nameOrig          6353307
oldbalanceOrg     1845844
newbalanceOrig    2682586
nameDest          2722362
oldbalanceDest    3614697
newbalanceDest    3555499
isFraud                 2
isFlaggedFraud          2
dtype: int64
```

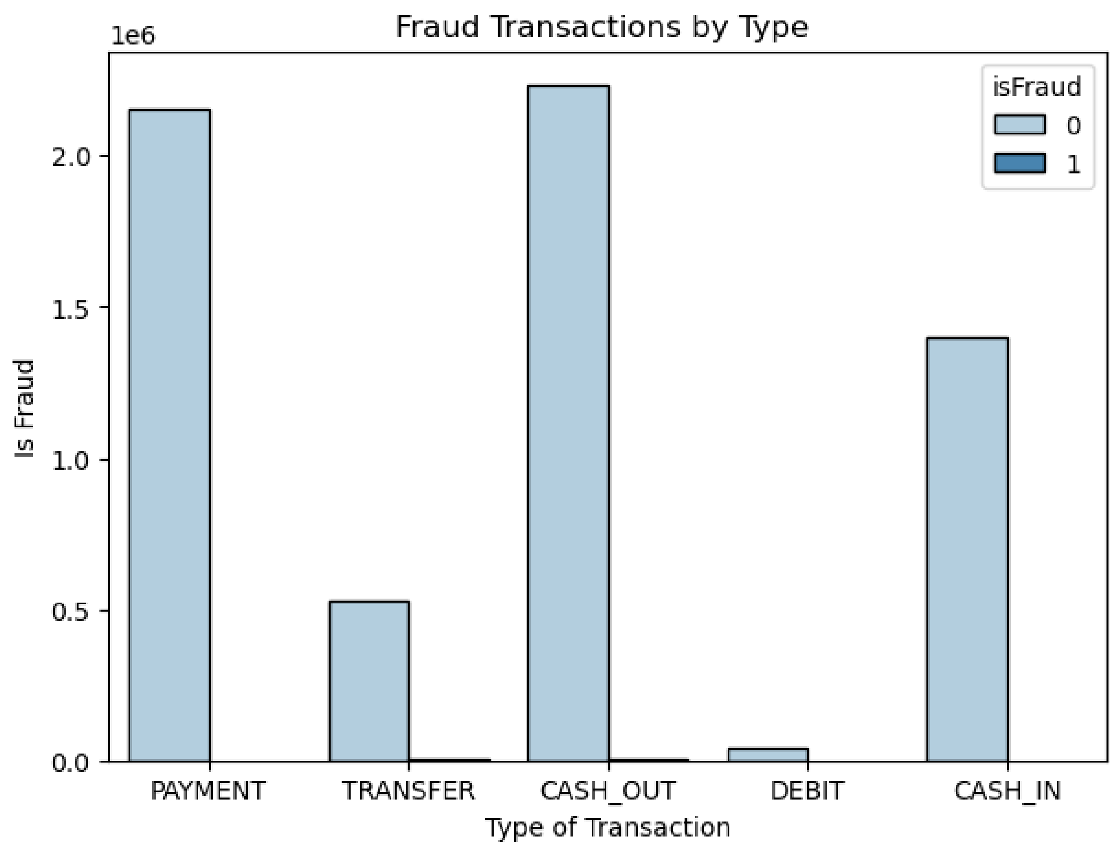
In [15]:
```
((df.loc[df["isFraud"]== 1]).groupby("type").sum())
```

Out[15]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newb
type						
CASH_OUT	1513537	5989202243.83	5984124999.99	298767.61	4465524469.93	1049
TRANSFER	1512246	6067213184.01	7564595045.72	1579821917.66	4397651.53	1

In [16]:
```
plt.figure(figsize=(7,5))
sns.countplot(x='type',hue='isFraud',palette='Blues',data=df,edgecolor
plt.title("Fraud Transactions by Type ")
plt.xlabel("Type of Transaction")
plt.ylabel("Is Fraud")
```

Out[16]: Text(0, 0.5, 'Is Fraud')



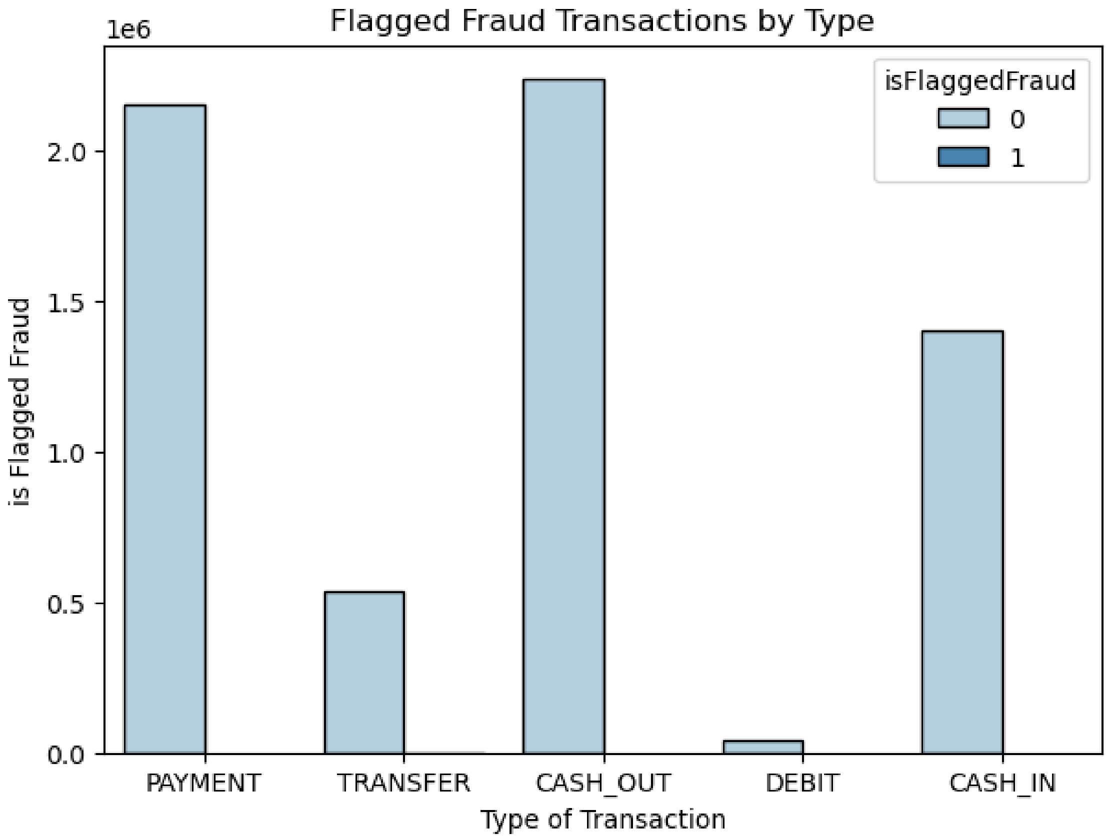
In [17]:
```
((df.loc[df["isFlaggedFraud"]== 1]).groupby("type").sum())
```

Out[17]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalance
type						
TRANSFER	8601	77785563.69	125085904.19	125085904.19	0.00	

In [18]:
```
plt.figure(figsize=(7,5))
sns.countplot(x='type',hue='isFlaggedFraud',palette='Blues',data=df,ec
plt.title("Flagged Fraud Transactions by Type")
plt.xlabel("Type of Transaction")
plt.ylabel("is Flagged Fraud")
```

Out[18]: Text(0, 0.5, 'is Flagged Fraud')

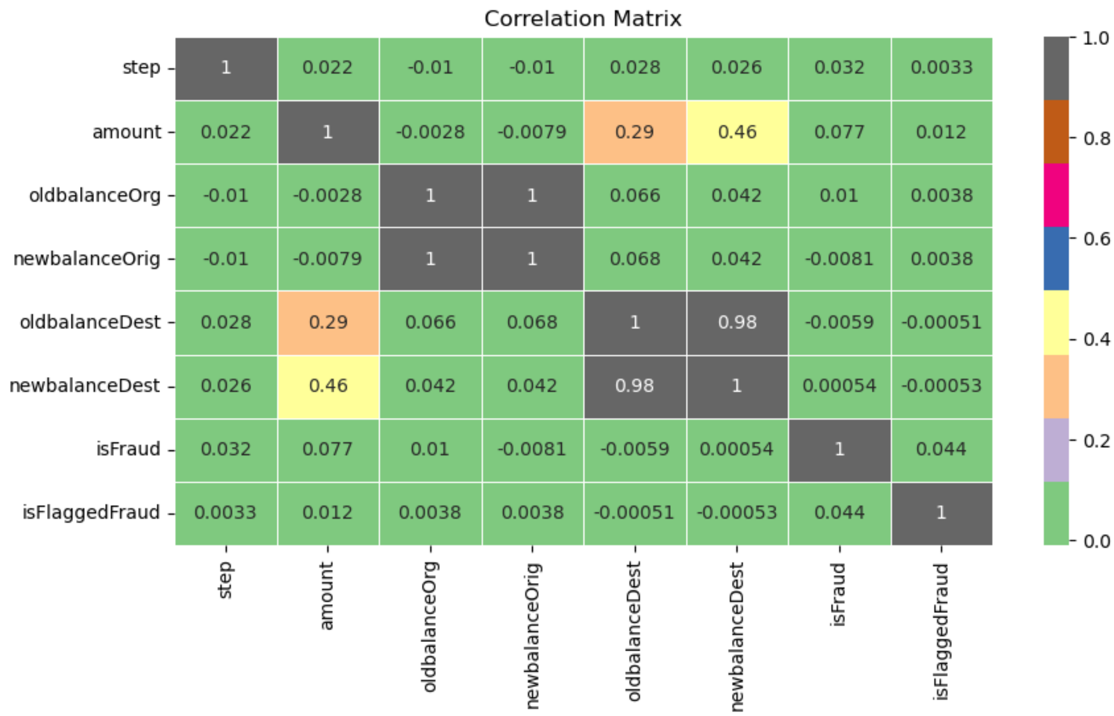


from above we conlcude that

1) Only in CASH_OUT and TRANSFER type "Fraud" is happen
2) Only 16 times "Flagged Fraud" happen which is also in TRANSFER type.

In [19]:

```
#check for correlation
ig ,ax = plt.subplots(figsize=(10,5))
sns.heatmap(data=df.corr(),cmap="Accent",annot=True,linewidths=.5,ax=a
plt.show()
```



So multicollinearity exists between "oldbalanceOrg" and "newbalanceOrg" ; "oldbalanceDest" and "newbalanceDest".

Let us try to build the model without removing features.

Feature engineering

In [20]:
```
print("Shape : ",(df.loc[(df["isFraud"] == 1 ) & (df["isFlaggedFraud"]
df.loc[(df["isFraud"] == 1 ) & (df["isFlaggedFraud"] == 1 )]
```

Shape : (16, 11)

Out[20]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	r
2736446	212	TRANSFER	4953893.08	C728984460	4953893.08	4953893.08	C6
3247297	250	TRANSFER	1343002.08	C1100582606	1343002.08	1343002.08	C11
3760288	279	TRANSFER	536624.41	C1035541766	536624.41	536624.41	C11
5563713	387	TRANSFER	4892193.09	C908544136	4892193.09	4892193.09	C8
5996407	425	TRANSFER	10000000.00	C689608084	19585040.37	19585040.37	C13
5996409	425	TRANSFER	9585040.37	C452586515	19585040.37	19585040.37	C11
6168499	554	TRANSFER	3576297.10	C193696150	3576297.10	3576297.10	C4
6205439	586	TRANSFER	353874.22	C1684585475	353874.22	353874.22	C17
6266413	617	TRANSFER	2542664.27	C786455622	2542664.27	2542664.27	C6
6281482	646	TRANSFER	10000000.00	C19004745	10399045.08	10399045.08	C18
6281484	646	TRANSFER	399045.08	C724693370	10399045.08	10399045.08	C19
6296014	671	TRANSFER	3441041.46	C917414431	3441041.46	3441041.46	C10
6351225	702	TRANSFER	3171085.59	C1892216157	3171085.59	3171085.59	C13
6362460	730	TRANSFER	10000000.00	C2140038573	17316255.05	17316255.05	C13
6362462	730	TRANSFER	7316255.05	C1869569059	17316255.05	17316255.05	C18
6362584	741	TRANSFER	5674547.89	C992223106	5674547.89	5674547.89	C13

Conclusion: When "Flagged Fraud" is happen also "Fraud" is happen, So, Don't need of "Flagged Fraud" feature that's why we drop it

Lebel Encoding

In [21]:
```
df["type"].unique()
```

Out[21]:
```
array(['PAYMENT', 'TRANSFER', 'CASH_OUT', 'DEBIT', 'CASH_IN'],
      dtype=object)
```

In [22]:
```
# checking Object Columns
df.columns[df.dtypes == 'object']
```

Out[22]:
```
Index(['type', 'nameOrig', 'nameDest'], dtype='object')
```

In [23]:
```
# for Label Encoder

le = {}
for i in df.select_dtypes('object').columns:
    le[i] = LabelEncoder()
    df[i] = le[i].fit_transform(df[i])
```

In [24]:
```
df.head(2)
```

Out[24]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDe
0	1	3	9839.64	757869	170136.00	160296.36	1662094	0.(
1	1	3	1864.28	2188998	21249.00	19384.72	1733924	0.(

Balancing Dependent Variable

In [25]:
```
# cheacking dependent variable is balanced or not?
df["isFraud"].value_counts()
```

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

In [26]:
```
X = df.drop(columns=['isFraud'])
y = df['isFraud']
```

In [27]:
```
over_sample = SMOTE()
X,y = over_sample.fit_resample(X,y)
```

In [28]:
```
y.value_counts() #resampled
```

Out[28]:
```
0    6354407
1    6354407
Name: isFraud, dtype: int64
```

Train Test Split

In [29]:
```
#import required libraries and split the data into train anad test

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

In [30]:

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(10167051, 10)
(2541763, 10)
(10167051,)
(2541763,)
```

Scaling values

In [31]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

Model Building

Logistic Regression

In [32]:

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()

logreg.fit(X_train, y_train)

pred_logreg = logreg.predict(X_test)
```

In [33]:

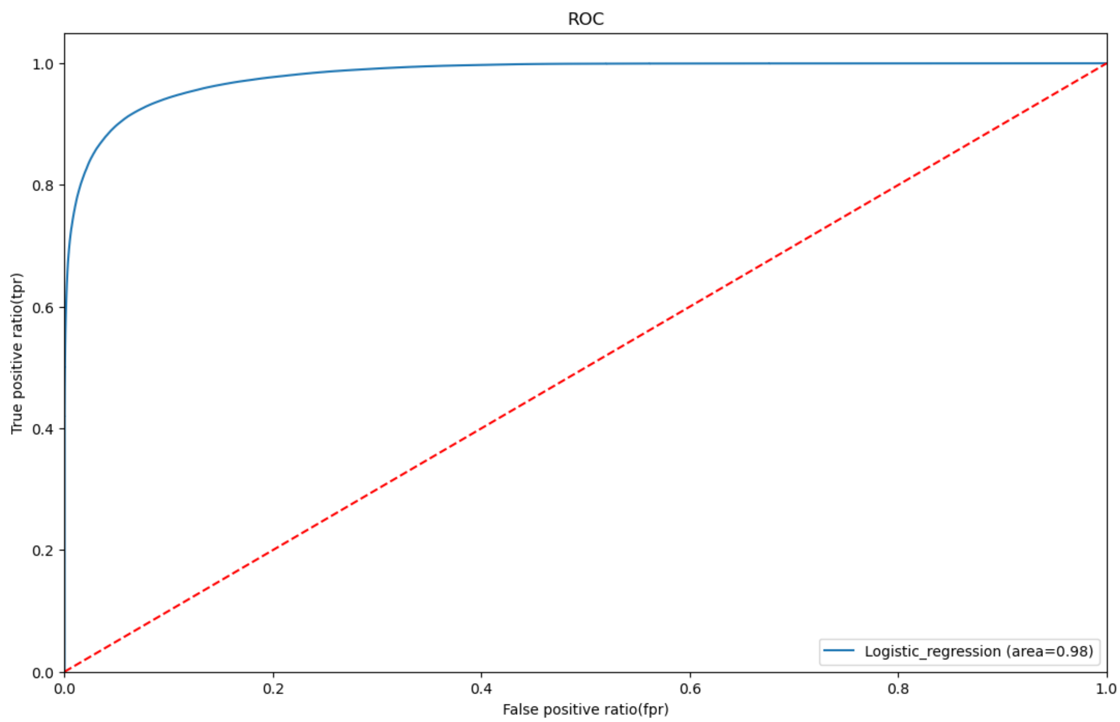
```
conf_logreg = confusion_matrix(y_test , pred_logreg)
print("Confusion Matrix :")
print(conf_logreg)
print(" ")
print("Accuracy    :", accuracy_score( y_test, pred_logreg ) * 100)
print("Precision   :", precision_score( y_test, pred_logreg ) * 100)
print("TPR/ Recall :", recall_score( y_test, pred_logreg ) * 100)
print("FPR         :", conf_logreg[0][1] / ( conf_logreg[0][1] * conf_
print("F1_Ratio    :", f1_score( y_test, pred_logreg ) * 100)
```

```
Confusion Matrix :
[[1199565   73043]
 [ 116268 1152887]]

Accuracy    : 92.55198065279886
Precision   : 94.04182946824044
TPR/ Recall : 90.83894402180978
FPR         : 8.33635526211585e-05
F1_Ratio    : 92.41264325664257
```

In [34]:
```
#plotting the roc curve and getting the value of auroc

logit_roc_auc=roc_auc_score(y_test,logreg.predict_proba(X_test)[:,1])
fpr,tpr,thresholds=roc_curve(y_test,logreg.predict_proba(X_test)[:,1]
plt.figure(figsize=(13,8))
plt.plot(fpr,tpr,label="Logistic_regression (area=%0.2f)"% logit_roc_a
plt.plot([0,1],[0,1],"r--")
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel("False positive ratio(fpr)")
plt.ylabel("True positive ratio(tpr)")
plt.title("ROC")
plt.legend(loc="lower right")
plt.savefig("Log_ROC")
plt.show()
```



Checking our Model is Overfit or Not

In [35]:
```
from sklearn.model_selection import cross_val_score
```

In [36]:
```
cvs = cross_val_score(logreg,X,y,cv=3)
print(cvs)
```

```
[0.94134843 0.95013728 0.90772687]
```

In [37]:
```
cvs.mean()
```

Out[37]:
```
0.9330708586751232
```

Cross validation score is less than accuracy. So this is a case of underfitting.

Trying to improve accuracy by removing multi-collinearity and selecting the best features

Improving accuracy

Select the best 8 features

In [38]:
```
df
```

Out[38]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	old
0	1	3	9839.64	757869	170136.00	160296.36	1662094	
1	1	3	1864.28	2188998	21249.00	19384.72	1733924	
2	1	4	181.00	1002156	181.00	0.00	439685	
3	1	1	181.00	5828262	181.00	0.00	391696	
4	1	3	11668.14	3445981	41554.00	29885.86	828919	
...	...	...	...	...	...	...	...	
6362615	743	1	339682.13	5651847	339682.13	0.00	505863	
6362616	743	4	6311409.28	1737278	6311409.28	0.00	260949	
6362617	743	1	6311409.28	533958	6311409.28	0.00	108224	
6362618	743	4	850002.52	2252932	850002.52	0.00	319713	
6362619	743	1	850002.52	919229	850002.52	0.00	534595	

6362620 rows × 11 columns

Now we can build a new logistic regression model using only these 8 features

In [39]:
```
df.drop(["nameOrig","nameDest"],inplace=True,axis=1)
```

In [40]:
```
df.tail()
```

Out[40]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalan
6362615	743	1	339682.13	339682.13	0.00	0.00	339
6362616	743	4	6311409.28	6311409.28	0.00	0.00	
6362617	743	1	6311409.28	6311409.28	0.00	68488.84	637
6362618	743	4	850002.52	850002.52	0.00	0.00	
6362619	743	1	850002.52	850002.52	0.00	6510099.11	7360

Now we can build a new logistic regression model using only these 8 features

In [41]:
```
X_new = df.iloc[:,:-1]
y_new = df.iloc[:,-1]
```

In [42]:
```
X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_
```

In [43]:
```
#  Scaling values
X_new_train = scaler.fit_transform(X_new_train)

X_new_test = scaler.transform(X_new_test)
```

In [44]:
```
logreg_new = LogisticRegression()

logreg_new.fit(X_new_train, y_new_train)

pred_new_logreg = logreg_new.predict(X_new_test)
```

In [45]:
```
conf_new_logreg = confusion_matrix(y_new_test , pred_new_logreg)
print("Confusion Matrix :")
print(conf_logreg)
print(" ")
print("Accuracy    :", accuracy_score(y_new_test , pred_new_logreg) *
print("Precision   :", precision_score(y_new_test , pred_new_logreg) *
print("TPR/ Recall :", recall_score(y_new_test , pred_new_logreg) * 10
print("FPR         :", conf_new_logreg[0][1] / ( conf_new_logreg[0][1]
print("F1_Ratio    :", f1_score(y_new_test , pred_new_logreg) * 100)
```

```
Confusion Matrix :
[[1199565   73043]
 [ 116268 1152887]]

Accuracy    : 99.99984283204088
Precision   : 0.0
TPR/ Recall : 0.0
FPR         : nan
F1_Ratio    : 0.0
```

So final accuracy turns out to be 99.99%, which is a big improvement from previous case

In [ ]:
```

```

In [ ]:
```

```