In [3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

DATA EXPLORATION

In [4]:

```
df = pd.read_csv("D:\EXCLER solution\Project Files\Fraud.csv")
df
```

Out[4]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	
...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	3
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	63
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	73

6362620 rows × 11 columns

In [5]:

```
#Shape of the data
df.shape
```

Out[5]:

```
(6362620, 11)
```

In [6]:

```
#Information of data
df.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
```

```
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

In [7]:

```python
#Description of data
df.describe()
```

Out[7]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlagge
count	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.3626
mean	2.433972e+02	1.798619e+05	8.338831e+05	8.551137e+05	1.100702e+06	1.224996e+06	1.290820e-03	2.5146
std	1.423320e+02	6.038582e+05	2.888243e+06	2.924049e+06	3.399180e+06	3.674129e+06	3.590480e-02	1.5857
min	1.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.0000
25%	1.560000e+02	1.338957e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.0000
50%	2.390000e+02	7.487194e+04	1.420800e+04	0.000000e+00	1.327057e+05	2.146614e+05	0.000000e+00	0.0000
75%	3.350000e+02	2.087215e+05	1.073152e+05	1.442584e+05	9.430367e+05	1.111909e+06	0.000000e+00	0.0000
max	7.430000e+02	9.244552e+07	5.958504e+07	4.958504e+07	3.560159e+08	3.561793e+08	1.000000e+00	1.0000

EXPLORATORY DATA ANALYSIS (EDA)

In [8]:

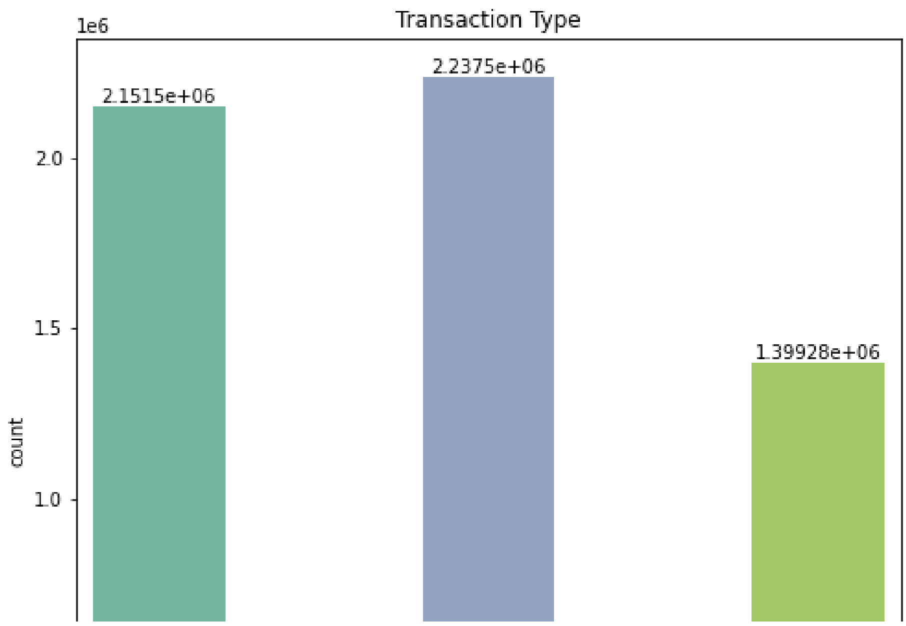
```python
#Checking for Null values
print('Null Values:',df.isnull().values.any())
```

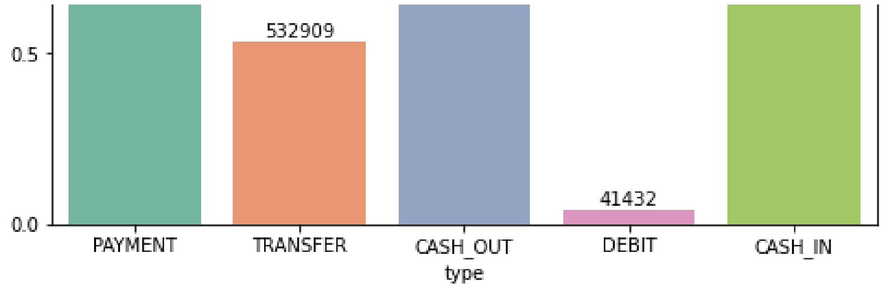
```
Null Values: False
```

Distribution of the Transaction Type column

In [9]:

```python
#Visualization
fig, ax=plt.subplots(1,1, figsize=(8,8))
sns.countplot(x=df.type, palette="Set2",ax=ax).set_title("Transaction Type")
ax.bar_label(ax.containers[0])
plt.show()
```





Fraud Dataset And Valid Dataset

In [10]:

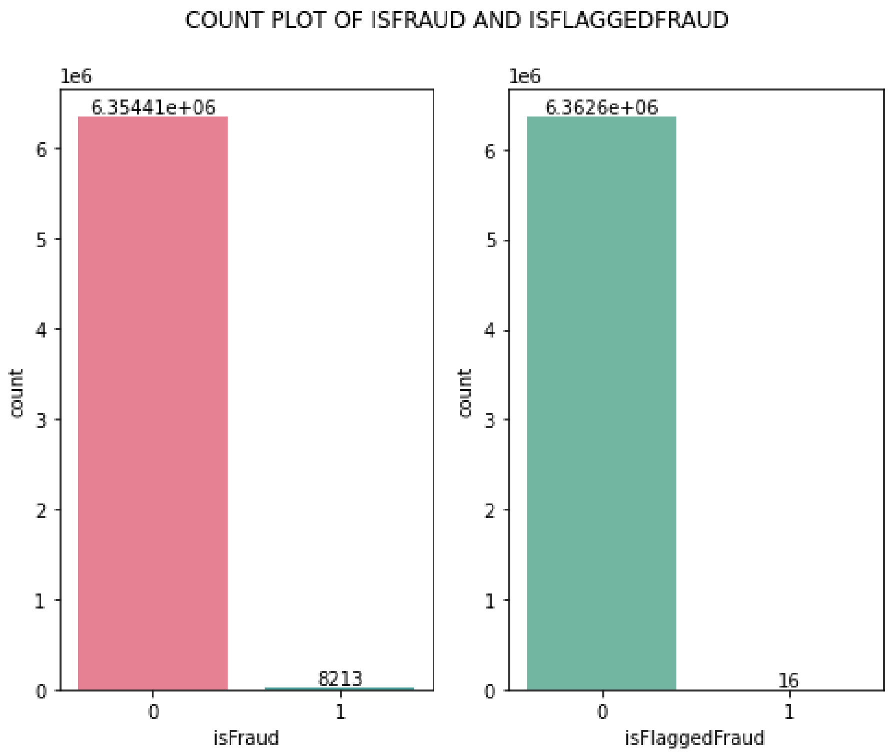
```
#Fraud and non-Fraud Distribution
fraud = df[df['isFraud']==1]
valid = df[df['isFraud']==0]
print("Fraud:",fraud.shape)
print("Valid:",valid.shape)
```

```
Fraud: (8213, 11)
Valid: (6354407, 11)
```

Relation between the Fraud Transaction and the Transactions Flagged by the system

In [11]:

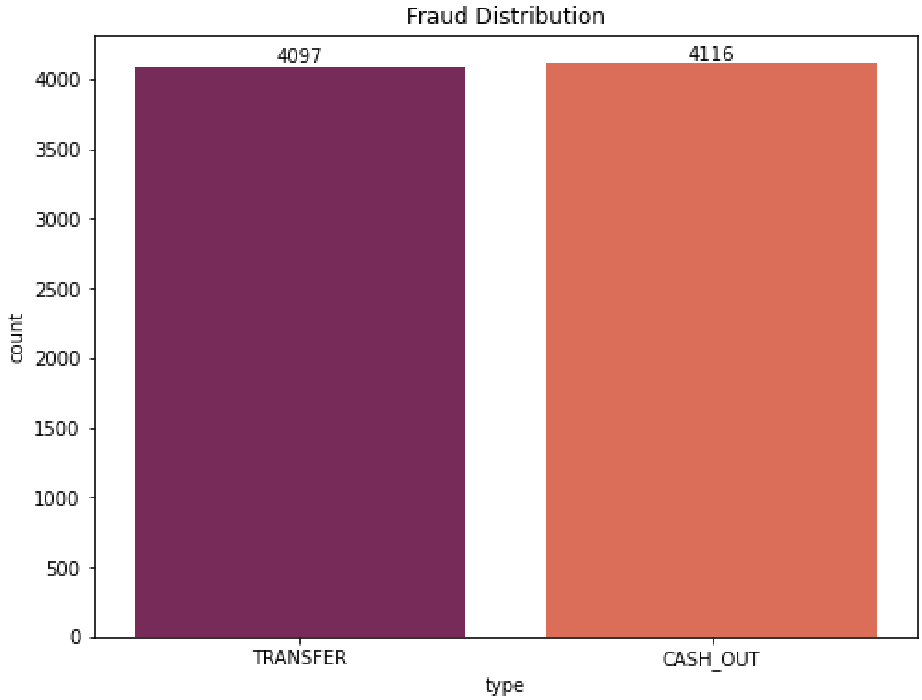
```
# chart for label class
plt.figure(figsize=(8,6))

plt.subplot(121)
ax = sns.countplot(data=df, x='isFraud',palette="husl")
ax.bar_label(ax.containers[0])

plt.subplot(122)
ax = sns.countplot(data=df, x='isFlaggedFraud',palette="Set2")
ax.bar_label(ax.containers[0])

plt.suptitle('COUNT PLOT OF ISFRAUD AND ISFLAGGEDFRAUD')
plt.show()
```



Fraud Transactions and Transaction types

In [12]:

```
plt.figure(figsize=(8,6))
ax=sns.countplot('type', data=fraud,palette="rocket")
for i in range(len(ax.containers)):
    ax.bar_label(ax.containers[i])
plt.title('Fraud Distribution')
plt.show()
```



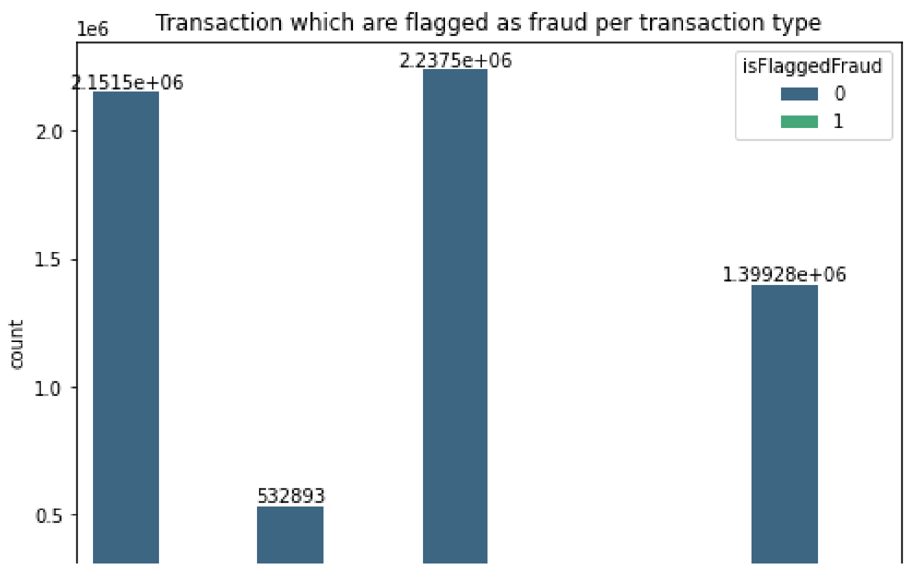
INFERENCES:¶

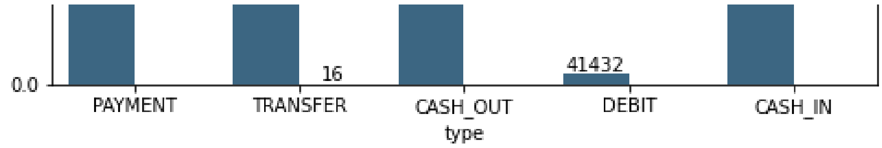
From the above graph we can see that the Fraudulent transfers are from TRANSFER(4097) and CASH_OUT(4116), transaction types.

Flagged As Fraud per transaction

In [13]:

```
# Count of the type feature
plt.figure(figsize=(8,6))
ax = sns.countplot(data=df, x='type', hue='isFlaggedFraud',palette="viridis")
for i in range(len(ax.containers)):
    ax.bar_label(ax.containers[i])
plt.title("Transaction which are flagged as fraud per transaction type")
plt.show()
```





INFERENCES:

From the above graph we can see that the money transfers that are flagged fraud are from TRANSFER Transaction type. So out of 4097 only 16 were Flagged Fraud by the system.

However, only 16 out of 6 million transactions were flagged by the system. It is safe to say that the system uses an unreasonable parameter to detect fraud transactions.

Dealing with Account Ids 'nameOrig' and 'nameDest'

In [14]:

```
print("All Transactions ID:", df['nameOrig'].size)
print("Unique Transactions ID:", df['nameOrig'].unique().size)
print('Transactions from existing accounts: ',df['nameOrig'].size-df['nameOrig'].unique(
).size)
```

```
All Transactions ID: 6362620
Unique Transactions ID: 6353307
Transactions from existing accounts:  9313
```

In [15]:

```
print("All Transactions ID:", df['nameDest'].size)
print("Unique Transactions ID:", df['nameDest'].unique().size)
print("Transactions from existing accounts:",df['nameDest'].size-df['nameOrig'].unique()
.size)
```

```
All Transactions ID: 6362620
Unique Transactions ID: 2722362
Transactions from existing accounts: 9313
```

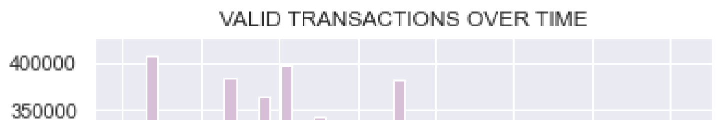
CONCLUSION:

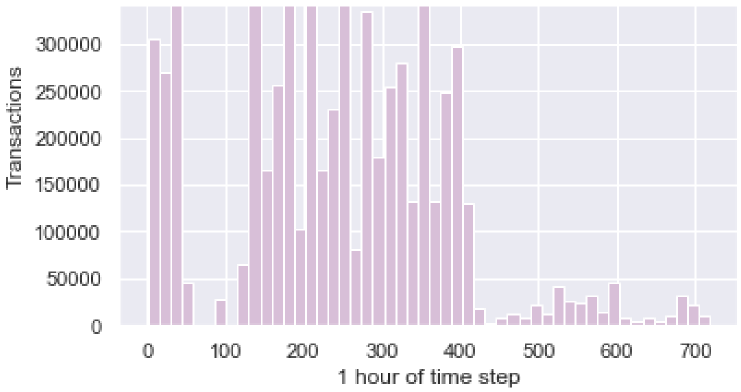
We do not get any beneficial information from the nameOrig or nameDest, so we'll be dropping these columns.

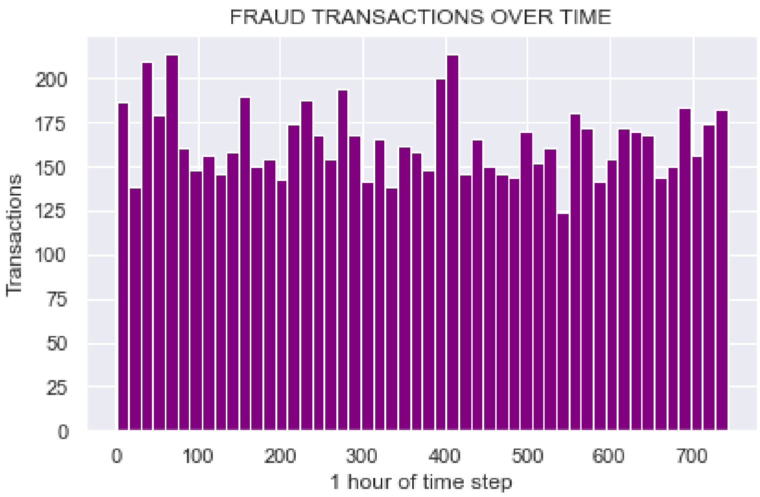
Taking note of the Step Feature

In [16]:

```
#Time Patterns
sns.set_theme(style="darkgrid")
bins = 50
valid.hist(column="step", color="thistle", bins=bins)
plt.xlabel("1 hour of time step")
plt.ylabel("Transactions")
plt.title("VALID TRANSACTIONS OVER TIME")

fraud.hist(column="step", color="purple", bins=bins)
plt.xlabel("1 hour of time step")
plt.ylabel("Transactions")
plt.title("FRAUD TRANSACTIONS OVER TIME")

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







INFERENCE:

1.A lot of VALID TRANSACTIONS occur during 0 to 60 hours and then again 120 to 400 hours.

2.The FRAUD TRANSACTIONS don't change much throughout the time frame.

Feature Engineering and Data Cleaning

As We know Dataset is totally Biased, 8231 are fraud transactions(minority class) where as remainings are non fraud transactions(majority class). However We are trying to make content small so that we could balanced the dataset. Hence we are going to take 12000 data from each type(Payment,Transfer,Cash_out,Debit,Cash_in) which is non fraud and will make one dataframe of fraud data i.e 8231 and we will combine all the dataframe to perform further steps.

In [17]:

```
fraud = df[df['isFraud']==1]
fraud
```

Out[17]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
2	1	TRANSFER	181.00	C1305486145	181.00	0.0	C553264065	0.00	
3	1	CASH_OUT	181.00	C840083671	181.00	0.0	C38997010	21182.00	
251	1	TRANSFER	2806.00	C1420196421	2806.00	0.0	C972765878	0.00	
252	1	CASH_OUT	2806.00	C2101527076	2806.00	0.0	C1007251739	26202.00	
680	1	TRANSFER	20128.00	C137533655	20128.00	0.0	C1848415041	0.00	
...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	3:
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	63:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.0	C873221189	6510099.11	73

8213 rows × 11 columns

In [18]:

```
transfer = df[(df['type']=='TRANSFER') & (df['isFraud']==0)]
transfer1=transfer.head(12000)
transfer1
```

Out[18]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalan
19	1	TRANSFER	215310.30	C1670993182	705.00	0.00	C1100439041	22425.00	
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.00	C932583850	6267.00	271
58	1	TRANSFER	62610.80	C1976401987	79114.00	16503.20	C1937962514	517.00	8
78	1	TRANSFER	42712.39	C283039401	10363.39	0.00	C1330106945	57901.66	24
79	1	TRANSFER	77957.68	C207471778	0.00	0.00	C1761291320	94900.00	22
...	...	...	...	...	...	...	...	...	
142949	11	TRANSFER	689978.77	C1207589610	166088.00	0.00	C1005856130	10870.00	70
142964	11	TRANSFER	216388.35	C942594959	462358.00	245969.65	C778384023	0.00	21
142966	11	TRANSFER	2130918.93	C188286369	745503.96	0.00	C2018751567	0.00	213
142997	11	TRANSFER	2023924.17	C1540907040	545456.09	0.00	C173961721	2178730.76	420
143009	11	TRANSFER	408034.79	C1738964594	12457.00	0.00	C1408588829	568134.84	97

12000 rows × 11 columns

In [19]:

```
payment = df[(df['type']=='PAYMENT') & (df['isFraud']==0)]
payment1=payment.head(12000)
payment1
```

Out[19]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceD
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.0	
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.0	
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.0	
5	1	PAYMENT	7817.71	C90045638	53860.00	46042.29	M573487274	0.0	
6	1	PAYMENT	7107.77	C154988899	183195.00	176087.23	M408069119	0.0	
...	...	...	...	...	...	...	...	...	
24108	8	PAYMENT	13802.70	C1653572480	56710.00	42907.30	M2087721404	0.0	
24110	8	PAYMENT	1942.96	C1427144523	274.00	0.00	M1260221930	0.0	
24112	8	PAYMENT	6402.51	C1299972350	99926.00	93523.49	M465622077	0.0	
24113	8	PAYMENT	11738.52	C1003638922	17829.85	6091.33	M1830688100	0.0	
24114	8	PAYMENT	12550.45	C1078494153	6091.33	0.00	M1572128449	0.0	

12000 rows × 11 columns

In [20]:

In [20]:

```
cash_out = df[(df['type']=='CASH_OUT') & (df['isFraud']==0)]
cash_out1 = cash_out.head(12000)
cash_out1
```

Out[20]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalance
15	1	CASH_OUT	229133.94	C905080434	15325.00	0.0	C476402209	5083.00	515
42	1	CASH_OUT	110414.71	C768216420	26845.41	0.0	C1509514333	288800.00	24
47	1	CASH_OUT	56953.90	C1570470538	1942.02	0.0	C824009085	70253.00	641
48	1	CASH_OUT	5346.89	C512549200	0.00	0.0	C248609774	652637.00	64534
51	1	CASH_OUT	23261.30	C2072313080	20411.53	0.0	C2001112025	25742.00	
...	...	...	...	...	...	...	...	...	
45560	9	CASH_OUT	398135.92	C1956662442	0.00	0.0	C1423983240	549002.09	9471
45561	9	CASH_OUT	173296.72	C1399983549	11961.00	0.0	C685786661	150393.07	3236
45562	9	CASH_OUT	134749.83	C735655415	0.00	0.0	C1102319340	10388343.43	105230
45564	9	CASH_OUT	260556.81	C1533020913	4846.00	0.0	C397672119	0.00	2605
45566	9	CASH_OUT	316468.08	C1368163464	51686.00	0.0	C168639687	0.00	3164

12000 rows × 11 columns

In [21]:

```
debit = df[(df['type']=='DEBIT') & (df['isFraud']==0)]
debit1 = debit.head(12000)
debit1
```

Out[21]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDes
9	1	DEBIT	5337.77	C712410124	41720.0	36382.23	C195600860	41898.00	40348.7
10	1	DEBIT	9644.94	C1900366749	4465.0	0.00	C997608398	10845.00	157982.1
21	1	DEBIT	9302.79	C1566511282	11299.0	1996.21	C1973538135	29832.00	16896.7
22	1	DEBIT	1065.41	C1959239586	1817.0	751.59	C515132998	10330.00	0.0
41	1	DEBIT	5758.59	C1466917878	32604.0	26845.41	C1297685781	209699.00	16997.2
...	...	...	...	...	...	...	...	...	.
1832908	163	DEBIT	34791.71	C1495384278	22309.0	0.00	C1623181854	404097.91	438889.6
1833413	163	DEBIT	5359.39	C1366381782	102439.0	97079.61	C1351586913	32459.15	37818.5
1833577	163	DEBIT	6476.81	C374254767	3835.0	0.00	C1778727790	996802.90	1003279.7
1833583	163	DEBIT	13872.04	C383929568	16070.0	2197.96	C352914906	5254379.71	5268251.7
1834393	163	DEBIT	18043.70	C682436441	13557.0	0.00	C2129359968	2914259.43	2952848.8

12000 rows × 11 columns

In [22]:

```
cash_in = df[(df['type']=='CASH_IN') & (df['isFraud']==0)]
cash_in1 = cash_in.head(12000)
cash_in1
```

Out[22]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceD

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceD
389	1	CASH_IN	143236.26	[illegible]	0.00	143236.26	[illegible]	608932.17	[illegible]
390	1	CASH_IN	228451.89	C1614133563	143236.26	371688.15	C2083562754	719678.38	1186556
391	1	CASH_IN	35902.49	C839771540	371688.15	407590.65	C2001112025	49003.30	0
392	1	CASH_IN	232953.64	C1037163664	407590.65	640544.28	C33524623	1172672.27	1517262
393	1	CASH_IN	65912.95	C180316302	640544.28	706457.23	C1330106945	104198.26	24044
...	...	...	...	...	...	...	...	...	
63673	9	CASH_IN	60925.49	C569900309	8611069.67	8671995.16	C456930332	145527.37	18246
63674	9	CASH_IN	46388.49	C697840884	8671995.16	8718383.65	C352211689	81999.93	35611
63675	9	CASH_IN	122487.44	C258282341	8718383.65	8840871.10	C1910963690	204940.81	0
63676	9	CASH_IN	327979.11	C248222613	8840871.10	9168850.21	C459857341	329646.12	320251
63677	9	CASH_IN	666052.56	C273336332	9168850.21	9834902.77	C1703466391	773325.04	0

12000 rows × 11 columns

In [23]:

```
data = pd.concat([transfer1,payment1,cash_out1,debit1,cash_in1,fraud], axis=0)
data
```

Out[23]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
19	1	TRANSFER	215310.30	C1670993182	705.00	0.0	C1100439041	22425.00	
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.0	C932583850	6267.00	27
58	1	TRANSFER	62610.80	C1976401987	79114.00	16503.2	C1937962514	517.00	
78	1	TRANSFER	42712.39	C283039401	10363.39	0.0	C1330106945	57901.66	:
79	1	TRANSFER	77957.68	C207471778	0.00	0.0	C1761291320	94900.00	:
...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	3:
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	63
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.0	C873221189	6510099.11	73

68213 rows × 11 columns

In [24]:

```
#We do not get any beneficial information from the nameOrig or nameDest. Hence, we'll be dropping these columns.
data1 = data.drop(['nameOrig','nameDest'],axis=1)
data
```

Out[24]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
19	1	TRANSFER	215310.30	C1670993182	705.00	0.0	C1100439041	22425.00	
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.0	C932583850	6267.00	27
58	1	TRANSFER	62610.80	C1976401987	79114.00	16503.2	C1937962514	517.00	
78	1	TRANSFER	42712.39	C283039401	10363.39	0.0	C1330106945	57901.66	:
79	1	TRANSFER	77957.68	C207471778	0.00	0.0	C1761291320	94900.00	:
...	...	...	...	...	...	...	...	...	

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbala
...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	3
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	63
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.0	C873221189	6510099.11	73

68213 rows × 11 columns

Taking note of the balances before and after transactions

As most of the transactions has errors in showing the account balances before and after transaction, we calculate the error

In [25]:

```
zero_balance = list(data.loc[(data1.oldbalanceOrg == 0) & (data1.newbalanceOrig == 0) &
(data1.amount != 0)].type.values)

print('Number of transcation where oldbalanceorig & newbalanceorig is zero but amount of
transaction is not zero :{}'.format(len(zero_balance)))
```

```
Number of transcation where oldbalanceorig & newbalanceorig is zero but amount of transac
tion is not zero :17098
```

In [26]:

```
print('number of recipients who have newbalanceDest and oldbalanceDest is zero :{}'
      .format(len(data1.loc[(data1.newbalanceDest == 0) & (data1.oldbalanceDest == 0) ].
values)))
```

```
number of recipients who have newbalanceDest and oldbalanceDest is zero :16831
```

Taking note of the balances before and after transactions

As most of the transactions has errors in showing the account balances before and after transaction, we calculate the error

In [27]:

```
data1['origin_bal_change'] = data1['oldbalanceOrg'] - data1['newbalanceOrig']
data1['dest_bal_increase'] = data1['newbalanceDest'] - data1['oldbalanceDest']
data1
```

Out[27]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedF
19	1	TRANSFER	215310.30	705.00	0.0	22425.00	0.00	0	
24	1	TRANSFER	311685.89	10835.00	0.0	6267.00	2719172.89	0	
58	1	TRANSFER	62610.80	79114.00	16503.2	517.00	8383.29	0	
78	1	TRANSFER	42712.39	10363.39	0.0	57901.66	24044.18	0	
79	1	TRANSFER	77957.68	0.00	0.0	94900.00	22233.65	0	
...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	339682.13	0.0	0.00	339682.13	1	
6362616	743	TRANSFER	6311409.28	6311409.28	0.0	0.00	0.00	1	
6362617	743	CASH_OUT	6311409.28	6311409.28	0.0	68488.84	6379898.11	1	
6362618	743	TRANSFER	850002.52	850002.52	0.0	0.00	0.00	1	

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedF
6362619	743	CASH_OUT	850002.52	850002.52	0.0	6510099.11	7360101.63	1	

68213 rows × 11 columns

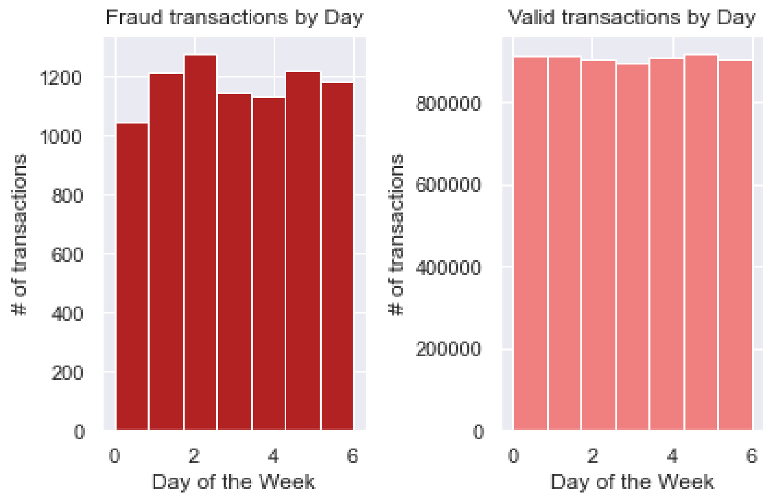
Converting the step feature from hours into days

In [28]:

```
num_days = 7
num_hours = 24
fraud_days = fraud.step % num_days
fraud_hours = fraud.step % num_hours
valid_days = valid.step % num_days
valid_hours = valid.step % num_hours
```

In [29]:

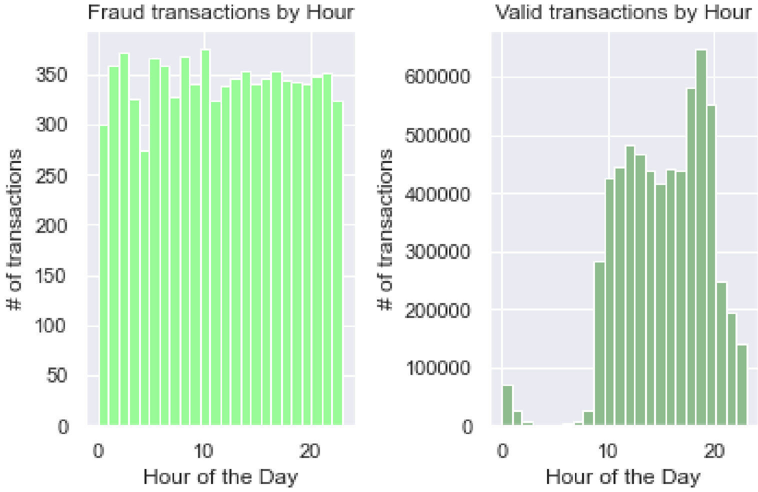
```
# plotting scatterplot of the days of the week,
plt.subplot(1, 2, 1)
fraud_days.hist(bins=num_days,color="firebrick")
plt.title('Fraud transactions by Day')
plt.xlabel('Day of the Week')
plt.ylabel("# of transactions")

plt.subplot(1,2,2)
valid_days.hist(bins=num_days,color="lightcoral")
plt.title('Valid transactions by Day')
plt.xlabel('Day of the Week')
plt.ylabel("# of transactions")

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



In [30]:

```
# plotting scatterplot of the hours of days, identifying the fraudulent transactions (red
) from the valid transactions (green)
plt.subplot(1, 2, 1)
fraud_hours.hist(bins=num_hours, color="palegreen")
plt.title('Fraud transactions by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel("# of transactions")


plt.subplot(1, 2, 2)
valid_hours.hist(bins=num_hours, color="darkseagreen")
plt.title('Valid transactions by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel("# of transactions")

plt.tight_layout()
```

```
plt.show()
```



INFERENCE:

From the graphs above, there is strong evidence to suggest that from hour 0 to hour 9, valid transactions very rarely occur. On the other hand, fraudulent transactions still occur at similar rates to any hour of the day outside of hours 0 to 9.

So I will add a new feature hour_of_day which is just the [(step column) %24]

In [31]:

```
data1['HourOfDay'] = np.nan # initializing feature column
data1.HourOfDay = data1['step'].apply(lambda i: i/24)
data1
```

Out[31]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedF
19	1	TRANSFER	215310.30	705.00	0.0	22425.00	0.00	0	
24	1	TRANSFER	311685.89	10835.00	0.0	6267.00	2719172.89	0	
58	1	TRANSFER	62610.80	79114.00	16503.2	517.00	8383.29	0	
78	1	TRANSFER	42712.39	10363.39	0.0	57901.66	24044.18	0	
79	1	TRANSFER	77957.68	0.00	0.0	94900.00	22233.65	0	
...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	339682.13	0.0	0.00	339682.13	1	
6362616	743	TRANSFER	6311409.28	6311409.28	0.0	0.00	0.00	1	
6362617	743	CASH_OUT	6311409.28	6311409.28	0.0	68488.84	6379898.11	1	
6362618	743	TRANSFER	850002.52	850002.52	0.0	0.00	0.00	1	
6362619	743	CASH_OUT	850002.52	850002.52	0.0	6510099.11	7360101.63	1	

68213 rows × 12 columns

Heat Map

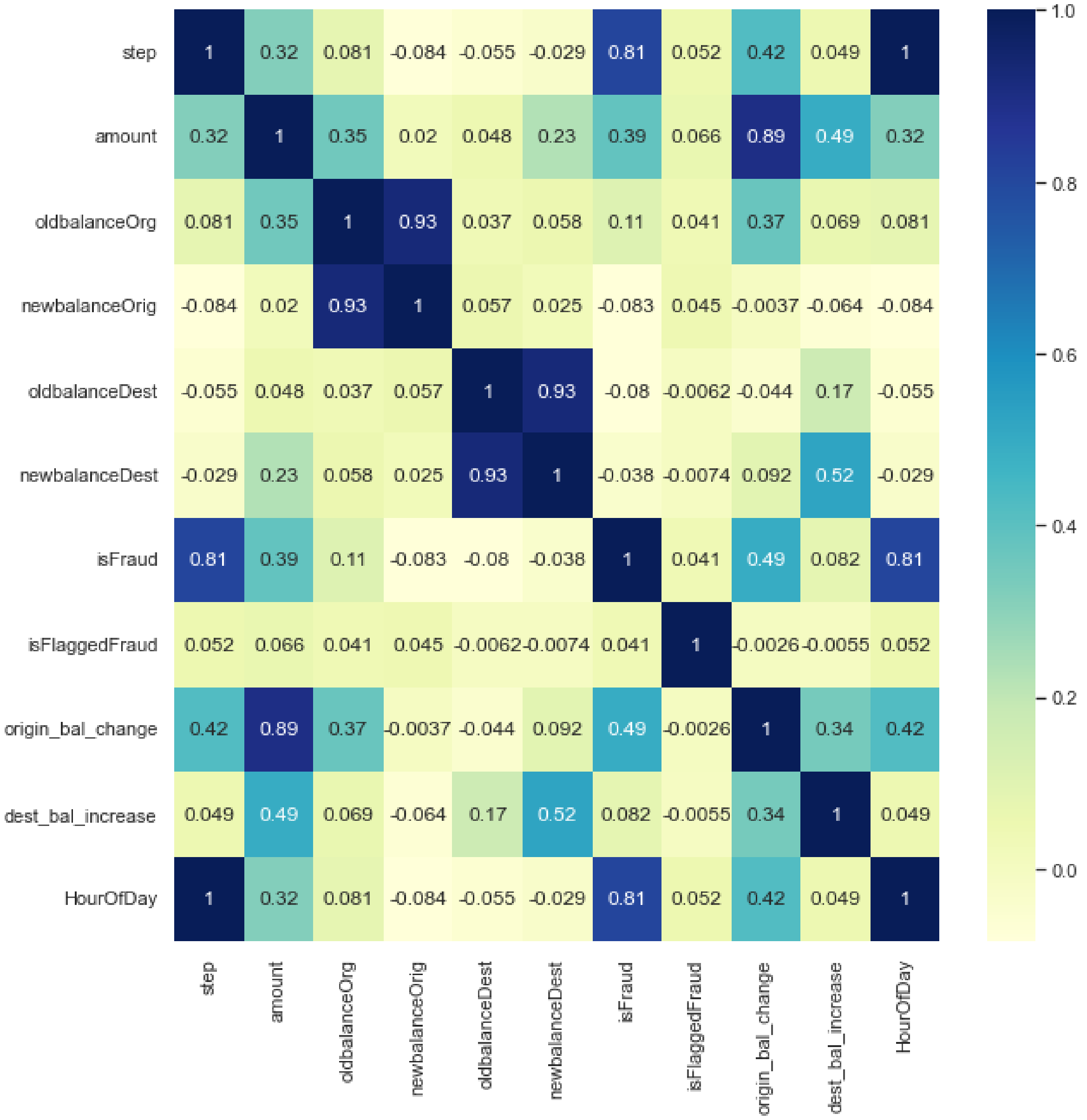
In [32]:

```
import matplotlib.pyplot as plt
import seaborn as sns
cormat = data1.corr()
top_corr_features = cormat.index
plt.figure(figsize=(10,10))
```

```
sns.heatmap(data1[top_corr_features].corr(),annot=True,cmap="YlGnBu")
```

Out[32]:

<AxesSubplot:>



DATA PREPARATION

We apply Label_encoding to convert string datatype into float datatype

In [33]:

```
#Converting string datatypes into float datatypes
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
data1['type'] = label_encoder.fit_transform(data1['type'])
data1
```

Out[33]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
19	1	4	215310.30	705.00	0.0	22425.00	0.00	0	0
24	1	4	311685.89	10835.00	0.0	6267.00	2719172.89	0	0
58	1	4	62610.80	79114.00	16503.2	517.00	8383.29	0	0
78	1	4	42712.39	10363.39	0.0	57901.66	24044.18	0	0
79	1	4	77957.68	0.00	0.0	94900.00	22233.65	0	0

...	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
6362615	743	1	339682.13	339682.13	0.0	0.00	339682.13	1	0
6362616	743	4	6311409.28	6311409.28	0.0	0.00	0.00	1	0
6362617	743	1	6311409.28	6311409.28	0.0	68488.84	6379898.11	1	0
6362618	743	4	850002.52	850002.52	0.0	0.00	0.00	1	0
6362619	743	1	850002.52	850002.52	0.0	6510099.11	7360101.63	1	0

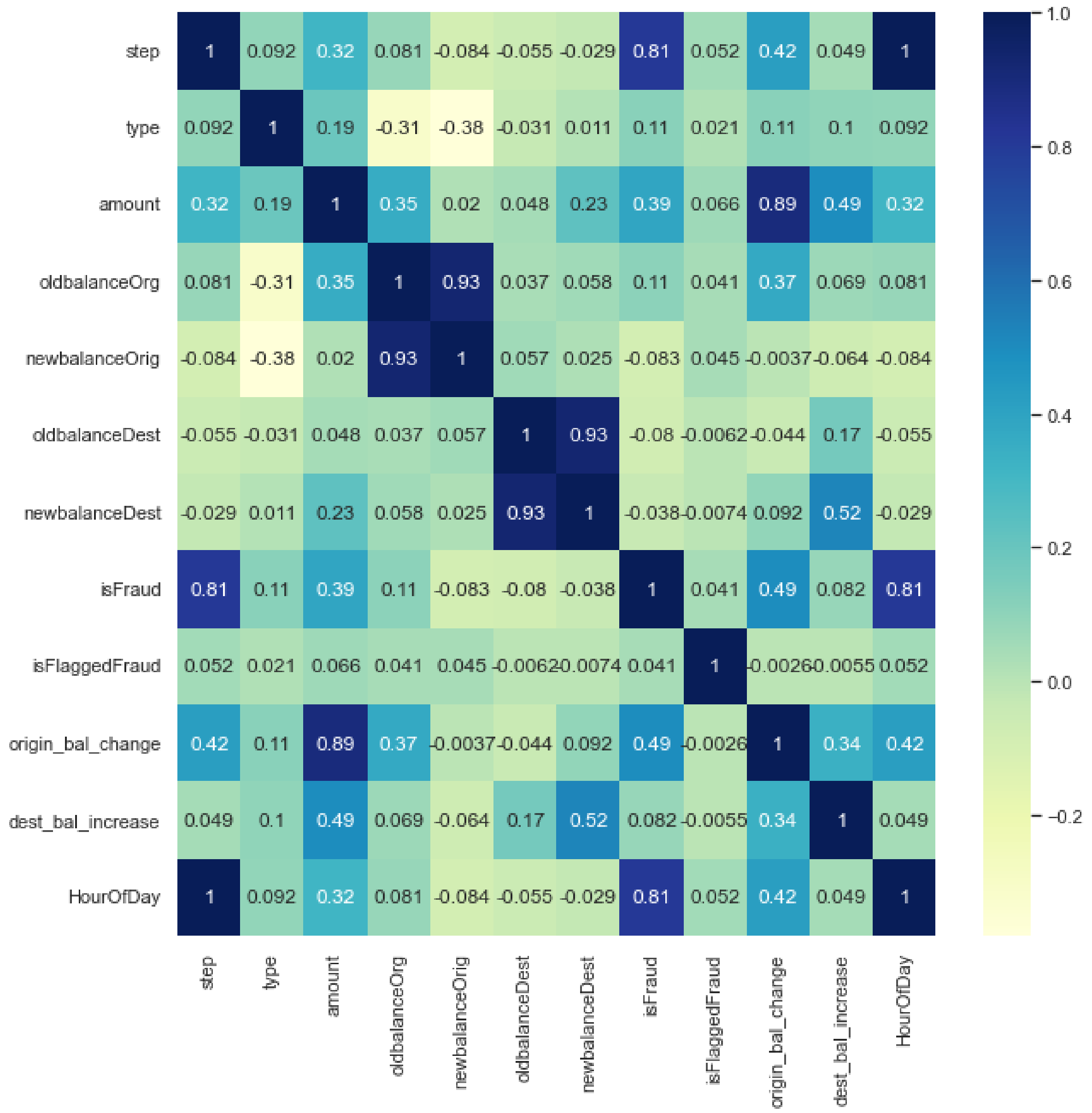
68213 rows × 12 columns

In [34]:

```
import matplotlib.pyplot as plt
import seaborn as sns
corrmat = data1.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(10,10))
sns.heatmap(data1[top_corr_features].corr(),annot=True,cmap="YlGnBu")
```

Out[34]:

```
<AxesSubplot:>
```



In [35]:

```
data1.type.value_counts()
```

Out[35]:

```
1    16116
4    16097
3    12000
2    12000
0    12000
Name: type, dtype: int64
```

In [36]:

```
#Importing Packages
from random import seed, sample
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [37]:

```
X = data1.drop(["isFraud","step"], axis=1)
Y = data1.isFraud
```

In [38]:

```
X
```

Out[38]:

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFlaggedFraud	origin_bal_chan
19	4	215310.30	705.00	0.0	22425.00	0.00	0	705.
24	4	311685.89	10835.00	0.0	6267.00	2719172.89	0	10835.
58	4	62610.80	79114.00	16503.2	517.00	8383.29	0	62610.
78	4	42712.39	10363.39	0.0	57901.66	24044.18	0	10363.
79	4	77957.68	0.00	0.0	94900.00	22233.65	0	0.
...	...	...	...	...	...	...	...	
6362615	1	339682.13	339682.13	0.0	0.00	339682.13	0	339682.
6362616	4	6311409.28	6311409.28	0.0	0.00	0.00	0	6311409.
6362617	1	6311409.28	6311409.28	0.0	68488.84	6379898.11	0	6311409.
6362618	4	850002.52	850002.52	0.0	0.00	0.00	0	850002.
6362619	1	850002.52	850002.52	0.0	6510099.11	7360101.63	0	850002.

68213 rows × 10 columns

In [39]:

```
Y
```

Out[39]:

```
19         0
24         0
58         0
78         0
79         0
          ..
6362615    1
6362616    1
6362617    1
6362618    1
6362619    1
Name: isFraud, Length: 68213, dtype: int64
```

In [40]:

```
x_train, x_test, y_train, y_test = train_test_split(X,Y, test_size=0.2, random_state=42)
```

In [41]:

```
#Normalizing data so that all variables follow the same scale (0 to 1)
scaler = StandardScaler()

#Fit only to the training data
scaler.fit(x_train)

#Now apply the transformations to the data:
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
```

In [42]:

```
print("Shape of x_train:", x_train.shape)
print("Shape of x_test:", x_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

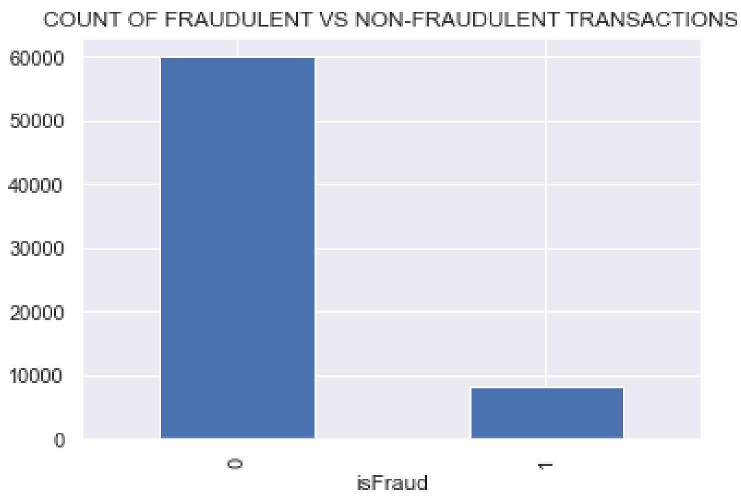
```
Shape of x_train: (54570, 10)
Shape of x_test: (13643, 10)
Shape of y_train: (54570,)
Shape of y_test: (13643,)
```

In [43]:

```
pd.Series(Y).value_counts().plot(kind='bar',title='COUNT OF FRAUDULENT VS NON-FRAUDULENT TRANSACTIONS', xlabel='isFraud')
```

Out[43]:

```
<AxesSubplot:title={'center':'COUNT OF FRAUDULENT VS NON-FRAUDULENT TRANSACTIONS'}, xlabel='isFraud'>
```



MODEL SELECTION

Model1: LOGISTIC REGRESSION

In [44]:

```
#Importing Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import average_precision_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, roc_curve, auc, precision_score
classifier=LogisticRegression()
classifier.fit(x_train,y_train)
```

Out[44]:

```
LogisticRegression()
```

In [45]:

```
#Predicting on Train data
predt_log = classifier.predict(x_train)
#Accuracy on Train data
print("Train data Accuracy is:", np.mean(predt_log==y_train))
```

```
Train data Accuracy is: 0.9840388491845337
```

In [46]:

```
#Predicting on test data
preds1 = classifier.predict(x_test)
#Accuracy on Test data
print("Test data Accuracy is:", np.mean(preds1==y_test))
```

```
Test data Accuracy is: 0.9843143003738181
```

In [47]:

```
# Evaluating model
CM_log = confusion_matrix(y_test,preds1)
CM_log
```

Out[47]:

```
array([[11966,    22],
       [  192,  1463]], dtype=int64)
```

In [48]:

```
CR_log=classification_report(preds1,y_test)
print(CR_log)
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99     12158
           1       0.88      0.99      0.93      1485

    accuracy                           0.98     13643
   macro avg       0.94      0.98      0.96     13643
weighted avg       0.99      0.98      0.98     13643
```

Model 2: Decision Tree

In [49]:

```
#Importing packages
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
#Train Model
DT = DecisionTreeClassifier()
model1 = DecisionTreeClassifier(criterion = 'entropy', max_depth=10)
model1.fit(x_train,y_train)
```

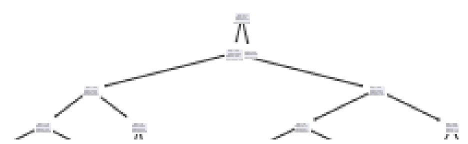
Out[49]:

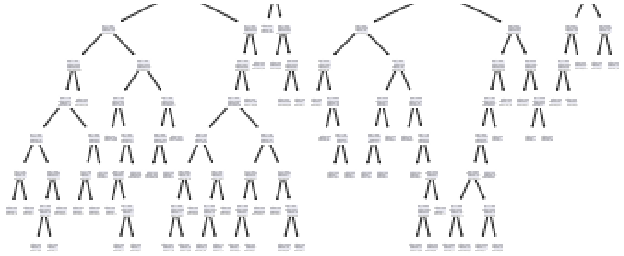
```
DecisionTreeClassifier(criterion='entropy', max_depth=10)
```

In [50]:

```
#PLot the Decision Tree
tree.plot_tree(model1);
print("No. Of Leaves:",model1.get_n_leaves())
```

```
No. Of Leaves: 63
```





In [51]:

```
#Predicting on test data
preds2= model1.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(preds2==y_test))
```

```
Test data Accuracy is: 0.9983874514402991
```

In [52]:

```
# Evaluating model
CM_2 = confusion_matrix(y_test,preds2)
CM_2
```

Out[52]:

```
array([[11981,     7],
       [   15,  1640]], dtype=int64)
```

In [53]:

```
CR_2=classification_report(preds2,y_test)
print(CR_2)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     11996
           1       0.99      1.00      0.99      1647

    accuracy                           1.00     13643
   macro avg       1.00      1.00      1.00     13643
weighted avg       1.00      1.00      1.00     13643
```

Model 3: Random Forest

In [54]:

```
# Random Forest Classification

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
```

In [55]:

```
# Train model
parametersRF = {'n_estimators':15,'class_weight': "balanced",'n_jobs':-1,'random_state':
42}
RF = RandomForestClassifier(**parametersRF)
model_3 = RF.fit(x_train, y_train)

# Predict on testing set
preds_3 = RF.predict(x_test)


fprRF, recallRF, thresholdsRF = roc_curve(y_test, preds_3)
AUC_rf = auc(fprRF, recallRF)

resultsRF = {"Area Under Curve":AUC_rf}
```

```
# showing results from Random Forest

for measure in resultsRF:
    print(measure,": \n",resultsRF[measure])
```

```
Area Under Curve :
 0.9933117659452
```

In [56]:

```
# Evaluating model
CM_3 = confusion_matrix(y_test,preds_3)
CM_3
```

Out[56]:

```
array([[11987,     1],
       [   22,  1633]], dtype=int64)
```

In [57]:

```
CR_3=classification_report(y_test,preds_3)
print(CR_3)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     11988
           1       1.00      0.99      0.99      1655

    accuracy                           1.00     13643
   macro avg       1.00      0.99      1.00     13643
weighted avg       1.00      1.00      1.00     13643
```

Model 4: XGBoost Classifier

In [58]:

```
from xgboost import XGBClassifier
# Training model
model4 = XGBClassifier()
model4.fit(x_train, y_train)
```

Out[58]:

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, ...)
```

In [59]:

```
#Predicting on train data
preds4= model4.predict(x_test)
#Accuracy on train data
print('Test data Accuracy is:',np.mean(preds4==y_test))
```

```
Test data Accuracy is: 0.9988272374111266
```

In [60]:

```
# Evaluating model
CM_4 = confusion_matrix(y_test,preds4)
CM_4
```

Out[60]:

```
array([[11986,     2],
       [   14,  1641]], dtype=int64)
```

In [61]:

```
CR_4=classification_report(preds4,y_test)
print(CR_4)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     12000
           1       0.99      1.00      1.00      1643

    accuracy                           1.00     13643
   macro avg       1.00      1.00      1.00     13643
weighted avg       1.00      1.00      1.00     13643
```

Model 5: Light GBM Classifier

In [62]:

```
import lightgbm as lgb
model5 = lgb.LGBMClassifier()
model5.fit(x_train,y_train)
```

Out[62]:

```
LGBMClassifier()
```

In [63]:

```
#Predicting on Test data
preds5 = model5.predict(x_test)
#Accuracy on Test data
print('Test data Accuracy is:',np.mean(preds5==y_test))
```

```
Test data Accuracy is: 0.9989005350729312
```

In [64]:

```
# Evaluating model
CM_5 = confusion_matrix(y_test,preds5)
CM_5
```

Out[64]:

```
array([[11987,     1],
       [   14,  1641]], dtype=int64)
```

In [65]:

```
CR_5=classification_report(preds5,y_test)
print(CR_5)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     12001
           1       0.99      1.00      1.00      1642

    accuracy                           1.00     13643
   macro avg       1.00      1.00      1.00     13643
weighted avg       1.00      1.00      1.00     13643
```

Model 6: K-Fold Cross Validation

In [66]:

```
from sklearn.model_selection import KFold, StratifiedKFold, cross_val_score
logreg=LogisticRegression()
skf=StratifiedKFold(n_splits=5)
score=cross_val_score(logreg,X,Y,cv=skf)
print("Cross Validation Scores are {}".format(score))
print("Average Cross Validation score :{}".format(score.mean()))
```

```
Cross Validation Scores are [0.95316279 0.78626402 0.93835667 0.93996481 0.98966427]
Average Cross Validation score :0.9214825130702433
```

Model 7: Gaussian Navie Bayes

In [67]:

```
#Importing Libraries
from sklearn.naive_bayes import GaussianNB as GB
classifier_gb = GB()
classifier_gb.fit(x_train,y_train)
```

Out[67]:

```
GaussianNB()
```

In [68]:

```
#Predicting on test data
preds6 = classifier_gb.predict(x_test)
#Accuracy on Test data
print("Test data Accuracy is:", np.mean(preds6==y_test))
```

```
Test data Accuracy is: 0.967602433482372
```

In [69]:

```
# Evaluating model
CM_6 = confusion_matrix(y_test,preds6)
CM_6
```

Out[69]:

```
array([[11875,   113],
       [  329,  1326]], dtype=int64)
```

In [70]:

```
CR_6=classification_report(preds6,y_test)
print(CR_6)
```

```
              precision    recall  f1-score   support

           0       0.99      0.97      0.98     12204
           1       0.80      0.92      0.86      1439

    accuracy                           0.97     13643
   macro avg       0.90      0.95      0.92     13643
weighted avg       0.97      0.97      0.97     13643
```

Model 8: K-Fold Cross Validation

In [71]:

```
from sklearn.model_selection import KFold, StratifiedKFold, cross_val_score
logreg=LogisticRegression()
skf=StratifiedKFold(n_splits=5)
score_k=cross_val_score(logreg,x_test,y_test,cv=skf)
print("Cross Validation Scores are {}".format(score_k))
print("Average Cross Validation score :{}".format(score_k.mean()))
```

```
Cross Validation Scores are [0.98021253 0.98387688 0.98351044 0.98460411 0.98497067]
```

```
Average Cross Validation score :0.983434926696963
```

Model 9: AdaBoost Classification

In [72]:

```
from sklearn.ensemble import AdaBoostClassifier
clf = AdaBoostClassifier(random_state=96)
preds8=clf.fit(x_test,y_test)
print("Test data Accuracy:",preds8.score(x_test,y_test))
score=cross_val_score(clf,x_test,y_test)
print("Cross Validation Scores are {}".format(score))
```

```
Test data Accuracy: 0.9978010701458624
Cross Validation Scores are [0.9989007  0.99633565 0.99633565 0.99743402 0.99780059]
```

Model 9: Baggigng Classification

In [73]:

```
from sklearn.ensemble import BaggingClassifier
kfold = KFold(n_splits=10)
cart = DecisionTreeClassifier()
num_trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees)
results_bag = cross_val_score(model, x_test, y_test, cv=kfold)
print(results_bag.mean())
```

```
0.9973611334901659
```

Comparing the models: UnBalanced data

In [74]:

```
print("Accuracy of Logistic Regression:",np.mean(preds1==y_test))
print("Accuracy of Decision Tree:",np.mean(preds2==y_test))
print("Accuracy of Random Forest:",AUC_rf)
print("Accuracy of XGBoost Classifier:",np.mean(preds4==y_test))
print("Accuracy of Light GBM Classifier:",np.mean(preds5==y_test))
print("Accuracy of Gaussian Navie Bayes:",np.mean(preds6==y_test))
print("Accuracy of K-Fold Cross Validation:",format(score_k.mean()))
print("Accuracy of AdaBoost Classification:",preds8.score(x_test,y_test))
print("Accuracy of Baggigng Classification:",results_bag.mean())
```

```
Accuracy of Logistic Regression: 0.9843143003738181
Accuracy of Decision Tree: 0.9983874514402991
Accuracy of Random Forest: 0.9933117659452
Accuracy of XGBoost Classifier: 0.9988272374111266
Accuracy of Light GBM Classifier: 0.9989005350729312
Accuracy of Gaussian Navie Bayes: 0.967602433482372
Accuracy of K-Fold Cross Validation: 0.983434926696963
Accuracy of AdaBoost Classification: 0.9978010701458624
Accuracy of Baggigng Classification: 0.9973611334901659
```

Handling Imbalanced Data

In [75]:

```
from collections import Counter
from sklearn.datasets import make_classification
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=42)
x_resampled, y_resampled = ros.fit_resample(X,Y)
print("Resampled shape of X: ", x_resampled.shape)
print("Resampled shape of Y: ", y_resampled.shape)
value_counts = Counter(y_resampled)
print(value_counts)
```

```
train_x,test_x, train_y,test_y = train_test_split(x_resampled,y_resampled, test_size=0.3
, random_state=42)
```

```
Resampled shape of X:  (120000, 10)
Resampled shape of Y:  (120000,)
Counter({0: 60000, 1: 60000})
```

In [76]:

```
print("Shape of resampled x_train:", train_x.shape)
print("Shape of resampled x_test:", test_x.shape)
print("Shape of resampled y_train:", train_y.shape)
print("Shape of resampled y_test:", test_y.shape)
```

```
Shape of resampled x_train: (84000, 10)
Shape of resampled x_test: (36000, 10)
Shape of resampled y_train: (84000,)
Shape of resampled y_test: (36000,)
```

In [77]:

```
#Value Counts of ISFRAUD columns after resampling
print("resample y train counts:\n",train_y.value_counts())
print("resample y test counts:\n",test_y.value_counts())
```

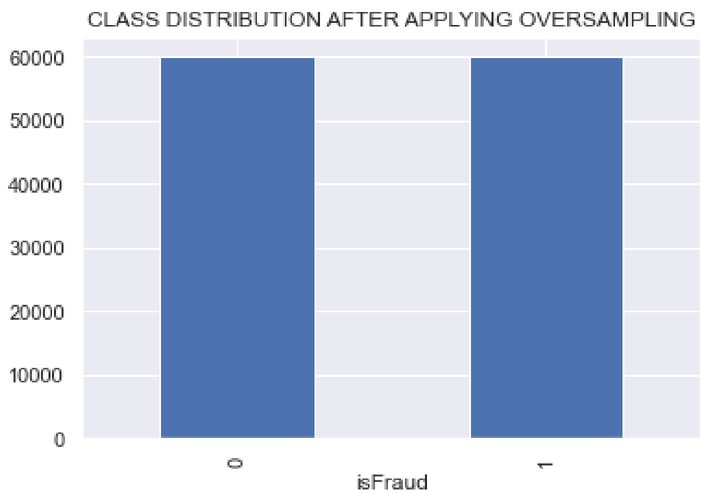
```
resample y train counts:
 1    42160
0    41840
Name: isFraud, dtype: int64
resample y test counts:
 0    18160
1    17840
Name: isFraud, dtype: int64
```

In [78]:

```
pd.Series(y_resampled).value_counts().plot(kind='bar',title='CLASS DISTRIBUTION AFTER AP
PLYING OVERSAMPLING', xlabel='isFraud')
```

Out[78]:

```
<AxesSubplot:title={'center':'CLASS DISTRIBUTION AFTER APPLYING OVERSAMPLING'}, xlabel='i
sFraud'>
```



Model : Logistic Regression

In [79]:

```
#Importing Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

In [80]:

```
classifier=LogisticRegression()
classifier.fit(train_x,train_y)
```

Out[80]:

```
LogisticRegression()
```

In [81]:

```
#Predicting on Train data
predt_log = classifier.predict(train_x)
#Accuracy on Train data
print("Train data Accuracy is:", np.mean(predt_log==train_y))
```

```
Train data Accuracy is: 0.9156785714285715
```

In [82]:

```
#Predicting on test data
preds_log = classifier.predict(test_x)
#Accuracy on Test data
print("Test data Accuracy is:", np.mean(preds_log==test_y))
```

```
Test data Accuracy is: 0.9161666666666667
```

In [83]:

```
# Evaluating model
CM_log = confusion_matrix(test_y,preds_log)
CM_log
```

Out[83]:

```
array([[15603,  2557],
       [  461, 17379]], dtype=int64)
```

In [84]:

```
CR_log=classification_report(preds_log,test_y)
print(CR_log)
```

```
              precision    recall  f1-score   support

           0       0.86      0.97      0.91     16064
           1       0.97      0.87      0.92     19936

    accuracy                           0.92     36000
   macro avg       0.92      0.92      0.92     36000
weighted avg       0.92      0.92      0.92     36000
```

Model : Decision Tree

In [85]:

```
#Train Model
DT = DecisionTreeClassifier()
model_dt = DecisionTreeClassifier(criterion = 'entropy', max_depth = 10)
model_dt.fit(train_x,train_y)
```

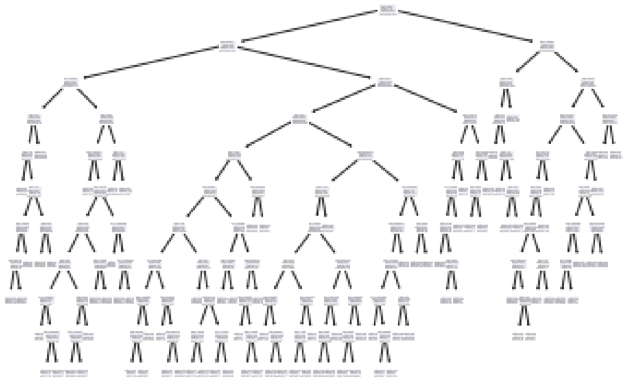
Out[85]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=10)
```

In [86]:

```
#Plot the Decision Tree
tree.plot_tree(model_dt);
print("No. Of Leaves:",model_dt.get_n_leaves())
```

```
No. Of Leaves: 89
```



In [87]:

```
#Predicting on test data
preds_dt = model_dt.predict(test_x)
#Accuracy on Test data
print("Test data Accuracy is:", np.mean(preds_dt==test_y))
```

```
Test data Accuracy is: 0.9983055555555556
```

In [88]:

```
# Evaluating model
CM_dt = confusion_matrix(test_y,preds_dt)
CM_dt
```

Out[88]:

```
array([[18130,    30],
       [   31, 17809]], dtype=int64)
```

In [89]:

```
CR_dt=classification_report(preds_dt,test_y)
print(CR_dt)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18161
           1       1.00      1.00      1.00     17839

    accuracy                           1.00     36000
   macro avg       1.00      1.00      1.00     36000
weighted avg       1.00      1.00      1.00     36000
```

Model : Random Forest

In [90]:

```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
```

In [91]:

```
# Train model
parametersRF = {'n_estimators':15,'class_weight': "balanced",'n_jobs':-1,'random_state':
42}
RF = RandomForestClassifier(**parametersRF)
model_rf= RF.fit(train_x, train_y)

# Predict on testing set
preds_rf = RF.predict(test_x)
```

```
fprRF, recallRF, thresholdsRF = roc_curve(test_y, preds_rf)
AUC_RF = auc(fprRF, recallRF)

resultsRF = {"Area Under Curve":AUC_RF}

# showing results from Random Forest

for measure in resultsRF:
    print(measure,": \n",resultsRF[measure])
```

```
Area Under Curve :
 0.9998623348017621
```

In [92]:

```
# Evaluating model
CM_rf = confusion_matrix(test_y,preds_rf)
CM_rf
```

Out[92]:

```
array([[18155,     5],
       [    0, 17840]], dtype=int64)
```

In [93]:

```
CR_rf=classification_report(preds_rf,test_y)
print(CR_rf)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18155
           1       1.00      1.00      1.00     17845

    accuracy                           1.00     36000
   macro avg       1.00      1.00      1.00     36000
weighted avg       1.00      1.00      1.00     36000
```

Model : XGBoost Classifier

In [94]:

```
# Training model
model3 = XGBClassifier()
model3.fit(train_x, train_y)
```

Out[94]:

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, ...)
```

In [95]:

```
#Predicting on test data
preds_xg= model3.predict(test_x)
#Accuracy on train data
print('Test data Accuracy is:',np.mean(preds_xg==test_y))
```

```
Test data Accuracy is: 0.9998611111111111
```

In [96]:

```
# Evaluating model
CM_xg = confusion_matrix(test_y,preds_xg)
CM_xg
```

Out[96]:

```
array([[18155,     5],
       [    0, 17840]], dtype=int64)
```

In [97]:

```
CR_xg=classification_report(preds_xg,test_y)
print(CR_xg)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18155
           1       1.00      1.00      1.00     17845

    accuracy                           1.00     36000
   macro avg       1.00      1.00      1.00     36000
weighted avg       1.00      1.00      1.00     36000
```

Model : Light GBM Classifier

In [98]:

```
import lightgbm as lgb
model4 = lgb.LGBMClassifier()
model4.fit(train_x,train_y)
```

Out[98]:

```
LGBMClassifier()
```

In [99]:

```
#Predicting on Train data
predt_lg = model4.predict(train_x)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(predt_lg==train_y))
```

```
Train data Accuracy is: 1.0
```

In [100]:

```
#Predicting on Test data
preds_lg = model4.predict(test_x)
#Accuracy on Test data
print('Test data Accuracy is:',np.mean(preds_lg==test_y))
```

```
Test data Accuracy is: 0.9998055555555555
```

In [101]:

```
# Evaluating model
CM_lg = confusion_matrix(test_y,preds_lg)
CM_lg
```

Out[101]:

```
array([[18153,     7],
       [    0, 17840]], dtype=int64)
```

In [102]:

```
CR_lg=classification_report(preds_lg,test_y)
print(CR_lg)
```

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

```
           0       1.00      1.00      1.00     18153
           1       1.00      1.00      1.00     17847

    accuracy                           1.00     36000
   macro avg       1.00      1.00      1.00     36000
weighted avg       1.00      1.00      1.00     36000
```

Model: Gaussian Navie Bayes

In [103]:

```
#Importing Libraries
from sklearn.naive_bayes import GaussianNB as GB
classifier_gb = GB()
classifier_gb.fit(train_x,train_y)
```

Out[103]:

```
GaussianNB()
```

In [104]:

```
#Predicting on test data
preds_gb = classifier_gb.predict(test_x)
#Accuracy on Test data
print("Test data Accuracy is:", np.mean(preds_gb==test_y))
```

```
Test data Accuracy is: 0.7285833333333334
```

In [105]:

```
# Evaluating model
CM_gb = confusion_matrix(test_y,preds_gb)
CM_gb
```

Out[105]:

```
array([[17269,   891],
       [ 8880,  8960]], dtype=int64)
```

In [106]:

```
CR_gb=classification_report(preds_gb,test_y)
print(CR_gb)
```

```
              precision    recall  f1-score   support

           0       0.95      0.66      0.78     26149
           1       0.50      0.91      0.65      9851

    accuracy                           0.73     36000
   macro avg       0.73      0.78      0.71     36000
weighted avg       0.83      0.73      0.74     36000
```

Model 6: K-Fold Cross Validation

In [107]:

```
from sklearn.model_selection import KFold, StratifiedKFold, cross_val_score
logreg=LogisticRegression()
skf=StratifiedKFold(n_splits=5)
score1=cross_val_score(logreg,test_x,test_y,cv=skf)
print("Cross Validation Scores are {}".format(score1))
print("Average Cross Validation score :{}".format(score1.mean()))
```

```
Cross Validation Scores are [0.90819444 0.90541667 0.91069444 0.90277778 0.89652778]
Average Cross Validation score :0.9047222222222222
```

Model7: AdaBoost Classification

In [108]:

```
from sklearn.ensemble import AdaBoostClassifier
clf = AdaBoostClassifier(random_state=96)
pred_ada=clf.fit(test_x,test_y)
print("Test data Accuracy:",pred_ada.score(test_x,test_y))
score=cross_val_score(clf,test_x,test_y)
print("Cross Validation Scores are {}".format(score))
```

```
Test data Accuracy: 0.9961666666666666
Cross Validation Scores are [0.99569444 0.99638889 0.99638889 0.99611111 0.99541667]
```

Model8: Baggigng Classification

In [109]:

```
from sklearn.ensemble import BaggingClassifier
kfold = KFold(n_splits=10)
cart = DecisionTreeClassifier()
num_trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees)
results = cross_val_score(model, test_x, test_y, cv=kfold)
print(results.mean())
```

```
0.9988333333333334
```

Comparing the models: Balanced data

In [110]:

```
print("Accuracy of Logistic Regression:",np.mean(preds_log==test_y))
print("Accuracy of Decision Tree:",np.mean(preds_dt==test_y))
print("Accuracy of Random Forest:",AUC_RF)
print("Accuracy of XGBoost Classifier:",np.mean(preds_xg==test_y))
print("Accuracy of Light GBM Classifier:",np.mean(preds_lg==test_y))
print("Accuracy of Gaussian Navie Bayes:",np.mean(preds_gb==test_y))
print("Accuracy of K-Fold Cross Validation:",format(score1.mean()))
print("Accuracy of AdaBoost Classification:",pred_ada.score(test_x,test_y))
print("Accuracy of Baggigng Classification:",results.mean())
```

```
Accuracy of Logistic Regression: 0.9161666666666667
Accuracy of Decision Tree: 0.9983055555555556
Accuracy of Random Forest: 0.9998623348017621
Accuracy of XGBoost Classifier: 0.9998611111111111
Accuracy of Light GBM Classifier: 0.9998055555555555
Accuracy of Gaussian Navie Bayes: 0.7285833333333334
Accuracy of K-Fold Cross Validation: 0.9047222222222222
Accuracy of AdaBoost Classification: 0.9961666666666666
Accuracy of Baggigng Classification: 0.9988333333333334
```

From above Accuracy Comparision, We got good accuracy in all Algorithms except Logistic Regression, Gaussian Navie Bayes, K-Fold Cross Validation.

As RANDOM FOREST accuracy is very close to 100% however we finalised random forest as our Final Model.

Accuracy of Random Forest: 0.9998623348017621

True negatives: 18155

False positives: 5

False negatives: 0

True Positives: 17840

Final Model with Random Forest Classifier

In [111]:

```
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_recall_curve


RandomForest_Deploy = RandomForestClassifier(class_weight = 'balanced',
                                    max_depth = 7,
                                    max_features = 4,
                                    min_samples_split = 2,
                                    n_estimators = 50,
                                    random_state = 42).fit(train_x,train_y)

y_pred = RandomForest_Deploy.predict(test_x)
y_train_pred = RandomForest_Deploy.predict(train_x)

RandomForest_Deploy_f1 = f1_score(test_y, y_pred)
RandomForest_Deploy_acc = accuracy_score(test_y, y_pred)
RandomForest_Deploy_recall = recall_score(test_y, y_pred)
RandomForest_Deploy_auc = roc_auc_score(test_y, y_pred)
RandomForest_Deploy_pre = precision_score(test_y, y_pred)
precision, recall, _ = precision_recall_curve(test_y, y_pred)
RandomForest_Deploy_recall_auc = auc(recall, precision)

print("RandomForest_Deploy")
print ("------------------")
eval("RandomForest_Deploy, train_x, test_x")
```

```
RandomForest_Deploy
------------------
```

Out[111]:

```
(RandomForestClassifier(class_weight='balanced', max_depth=7, max_features=4,
                        n_estimators=50, random_state=42),
         type      amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
 67451      4  5016884.33     5016884.33            0.00            0.00
 81497      4   113829.89      113829.89            0.00            0.00
 84310      1  8537861.24     8537861.24            0.00            0.00
 100077     1   282500.69      282500.69            0.00        27806.82
 73476      4  3042111.54     3042111.54            0.00            0.00
 ...      ...         ...            ...             ...             ...
 110268     1  2479940.21     2479940.21            0.00            0.00
 119879     1   458361.83      458361.83            0.00            0.00
 103694     1  5489302.04     5489302.04            0.00      1356390.81
 860        4   595846.21      118425.71            0.00        46257.07
 15795      3     6737.87        6867.00          129.13            0.00

         newbalanceDest  isFlaggedFraud  origin_bal_change  dest_bal_increase  \
 67451             0.00               0         5016884.33               0.00
 81497             0.00               0          113829.89               0.00
 84310       8537861.24               0         8537861.24         8537861.24
 100077       310307.51               0          282500.69          282500.69
 73476             0.00               0         3042111.54               0.00
 ...                ...             ...                ...                ...
 110268      2479940.21               0         2479940.21         2479940.21
 119879       458361.83               0          458361.83          458361.83
 103694      6845692.85               0         5489302.04         5489302.04
 860          642103.28               0          118425.71          595846.21
 15795             0.00               0            6737.87               0.00

         HourOfDay
 67451   28.166667
 81497    3.250000
 84310   29.208333
```

```
100077   24.166667
73476    11.208333
...            ...
110268    5.500000
119879   24.666667
103694    2.000000
860       0.291667
15795     0.250000

[84000 rows x 10 columns],
        type      amount  oldbalanceOrg  newbalanceOrig  oldbalanceDest  \
71787      4    57466.42       57466.42            0.00            0.00
67218      1      119.65         119.65            0.00      1183575.58
54066      0   202720.09     9242213.72      9444933.80       275349.50
7168       4  1372129.53           0.00            0.00      3302288.80
29618      1    37128.79       20354.00            0.00       905741.37
...      ...         ...            ...             ...             ...
40470      2     5520.59        2593.00            0.00       910091.00
56954      0   500684.23     8042389.26      8543073.48       867760.07
48654      0   233432.28       56098.00       289530.28         1891.79
65345      4   181104.66      181104.66            0.00            0.00
104868     4   466359.63      466359.63            0.00            0.00

        newbalanceDest  isFlaggedFraud  origin_bal_change  dest_bal_increase  \
71787             0.00               0           57466.42               0.00
67218       1183695.22               0             119.65             119.64
54066        146802.81               0         -202720.08         -128546.69
7168        4674418.34               0               0.00         1372129.54
29618       1079972.85               0           20354.00          174231.48
...                ...             ...                ...                ...
40470        915611.59               0            2593.00            5520.59
56954       1651036.95               0         -500684.22          783276.88
48654             0.00               0         -233432.28           -1891.79
65345             0.00               0          181104.66               0.00
104868            0.00               0          466359.63               0.00

        HourOfDay
71787   12.375000
67218   27.208333
54066    0.333333
7168     0.416667
29618    0.333333
...           ...
40470    1.041667
56954    0.375000
48654    0.083333
65345   20.000000
104868   4.875000

[36000 rows x 10 columns])
```

In [112]:

```
train_x.head()
```

Out[112]:

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFlaggedFraud	origin_bal_chang
67451	4	5016884.33	5016884.33	0.0	0.00	0.00	0	5016884.3
81497	4	113829.89	113829.89	0.0	0.00	0.00	0	113829.8
84310	1	8537861.24	8537861.24	0.0	0.00	8537861.24	0	8537861.2
100077	1	282500.69	282500.69	0.0	27806.82	310307.51	0	282500.6
73476	4	3042111.54	3042111.54	0.0	0.00	0.00	0	3042111.5

In [113]:

```
test_x.head()
```

Out[113]:

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFlaggedFraud	origin_bal_change
71787	4	57466.42	57466.42	0.0	0.00	0.00	0	57466.42
67218	1	119.65	119.65	0.0	1183575.58	1183695.22	0	119.65
54066	0	202720.09	9242213.72	9444933.8	275349.50	146802.81	0	-202720.08
7168	4	1372129.53	0.00	0.0	3302288.80	4674418.34	0	0.00
29618	1	37128.79	20354.00	0.0	905741.37	1079972.85	0	20354.00

In [114]:

```
import pickle
# open a file, where you ant to store the data
# dump information to that file
random_forest_classifier = pickle.dump(RandomForest_Deploy, open('random_forest_model', '
wb'))
```

In [115]:

```
from pickle import dump
from pickle import load
```

In [116]:

```
# save the model to disk
random_forest_classifier= 'random_forest_model.sav'
dump(RandomForest_Deploy, open('random_forest_model', 'wb'))
```

In [117]:

```
# load the model from disk
loaded_model = load(open('random_forest_model', 'rb'))

result = loaded_model.score(test_x ,test_y)
print(result)
```

```
0.9959722222222223
```

In [118]:

```
test_y.head(50)
```

Out[118]:

```
71787     1
67218     1
54066     0
7168      0
29618     0
101425    1
20441     0
2662      0
20371     0
108151    1
15315     0
23538     0
113198    1
201       0
52090     0
15394     0
88288     1
46590     0
14005     0
13752     0
119830    1
82401     1
```

```
1749      0
114630    1
11203     0
59654     0
35527     0
101797    1
11980     0
61754     1
93022     1
13664     0
113757    1
59279     0
61523     1
31154     0
75639     1
47217     0
16528     0
117741    1
78535     1
114609    1
103219    1
2619      0
57662     0
19071     0
72648     1
17792     0
27053     0
110311    1
Name: isFraud, dtype: int64
```

In [119]:

```
test_y.value_counts()
```

Out[119]:

```
0    18160
1    17840
Name: isFraud, dtype: int64
```

In [120]:

```
train_y.value_counts()
```

Out[120]:

```
1    42160
0    41840
Name: isFraud, dtype: int64
```

In [121]:

```
jupyter-nbconvert --to pdfviahtml FRAUDULENT TRANSACTION PREDICTION(P-129).ipynb
```

```
  File "C:\Users\HP\AppData\Local\Temp/ipykernel_15536/508693944.py", line 1
    jupyter-nbconvert --to pdfviahtml FRAUDULENT TRANSACTION PREDICTION(P-129).ipynb
                           ^
SyntaxError: invalid syntax
```