Customer Segmentation

Libraries Importing

In [19]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

from sklearn.cluster import KMeans,DBSCAN,AgglomerativeClustering
from sklearn.metrics import classification_report,confusion_matrix,plot_confusion_matrix,accuracy_score
from sklearn.model_selection import train_test_split,GridSearchCV,RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.linear_model import LogisticRegression

from sklearn.preprocessing import MinMaxScaler,StandardScaler,OneHotEncoder,OrdinalEncoder,LabelEncoder
from sklearn.impute import KNNImputer
from statsmodels.stats.outliers_influence import variance_inflation_factor
import warnings
warnings.filterwarnings('ignore')
```

Problem Statement

A case requires to develop a customer segmentation to give recommendations like saving plans, loans, wealth management, etc. on target customers groups.

Data Gathering

In [2]:

```
df=pd.read_csv('Customer Data.csv')
df.head()
```

Out[2]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FRE
0	C10001	40.900749	0.818182	95.40	0.00	95.4	0.000000	
1	C10002	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	
2	C10003	2495.148862	1.000000	773.17	773.17	0.0	0.000000	
3	C10004	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	
4	C10005	817.714335	1.000000	16.00	16.00	0.0	0.000000	

EDA :- Exploratory Data Analysis

In [3]:

```
df.shape #Here we can observe that we have the 8950 records and the 18 columns
```

Out[3]:

```
(8950, 18)
```

In [4]:

```
df.columns
```

Out[4]:

```
Index(['CUST_ID', 'BALANCE', 'BALANCE_FREQUENCY', 'PURCHASES',
       'ONEOFF_PURCHASES', 'INSTALLMENTS_PURCHASES', 'CASH_ADVANCE',
       'PURCHASES_FREQUENCY', 'ONEOFF_PURCHASES_FREQUENCY',
       'PURCHASES_INSTALLMENTS_FREQUENCY', 'CASH_ADVANCE_FREQUENCY',
       'CASH_ADVANCE_TRX', 'PURCHASES_TRX', 'CREDIT_LIMIT', 'PAYMENTS',
       'MINIMUM_PAYMENTS', 'PRC_FULL_PAYMENT', 'TENURE'],
      dtype='object')
```

In [7]:

```
#checking for null values
df.isna().sum()
```

Out[7]:

```
CUST_ID                             0
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        1
PAYMENTS                            0
MINIMUM_PAYMENTS                  313
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
```

In [8]:

```
#Checking percentage of null values
df.isna().mean()*100
```

Out[8]:

```
CUST_ID                           0.000000
BALANCE                           0.000000
BALANCE_FREQUENCY                 0.000000
PURCHASES                         0.000000
ONEOFF_PURCHASES                  0.000000
INSTALLMENTS_PURCHASES            0.000000
CASH_ADVANCE                      0.000000
PURCHASES_FREQUENCY               0.000000
ONEOFF_PURCHASES_FREQUENCY        0.000000
PURCHASES_INSTALLMENTS_FREQUENCY  0.000000
CASH_ADVANCE_FREQUENCY            0.000000
CASH_ADVANCE_TRX                  0.000000
PURCHASES_TRX                     0.000000
CREDIT_LIMIT                      0.011173
PAYMENTS                          0.000000
MINIMUM_PAYMENTS                  3.497207
PRC_FULL_PAYMENT                  0.000000
TENURE                            0.000000
dtype: float64
```

Feature Engineering

```
<!-- Here we can observe the Customer ID didnt play any important role in the given dataset, It is not important at all so we drop it. -
->
```

In [10]:

```
df.drop('CUST_ID',axis=1,inplace=True)
```

Null Value Imputation

In [12]:

```
knn_imp=KNNImputer()
array=knn_imp.fit_transform(df)
df=pd.DataFrame(array,columns=df.columns)
df.isna().sum()
```

Out[12]:

```
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        0
PAYMENTS                            0
MINIMUM_PAYMENTS                    0
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
```

In [20]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 17 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   BALANCE                           8950 non-null   float64
 1   BALANCE_FREQUENCY                 8950 non-null   float64
 2   PURCHASES                         8950 non-null   float64
 3   ONEOFF_PURCHASES                  8950 non-null   float64
 4   INSTALLMENTS_PURCHASES            8950 non-null   float64
 5   CASH_ADVANCE                      8950 non-null   float64
 6   PURCHASES_FREQUENCY               8950 non-null   float64
 7   ONEOFF_PURCHASES_FREQUENCY        8950 non-null   float64
 8   PURCHASES_INSTALLMENTS_FREQUENCY  8950 non-null   float64
 9   CASH_ADVANCE_FREQUENCY            8950 non-null   float64
 10  CASH_ADVANCE_TRX                  8950 non-null   float64
 11  PURCHASES_TRX                     8950 non-null   float64
 12  CREDIT_LIMIT                      8950 non-null   float64
 13  PAYMENTS                          8950 non-null   float64
 14  MINIMUM_PAYMENTS                  8950 non-null   float64
 15  PRC_FULL_PAYMENT                  8950 non-null   float64
 16  TENURE                            8950 non-null   float64
dtypes: float64(17)
memory usage: 1.2 MB
```

In [21]:

```
df.describe()
```

Out[21]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUEI
count	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	8950.00(
mean	1564.474828	0.877271	1003.204834	592.437371	411.067645	978.871112	0.49(
std	2081.531879	0.236904	2136.634782	1659.887917	904.338115	2097.163877	0.401
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00(
25%	128.281915	0.888889	39.635000	0.000000	0.000000	0.000000	0.083
50%	873.385231	1.000000	361.280000	38.000000	89.000000	0.000000	0.50(
75%	2054.140036	1.000000	1110.130000	577.405000	468.637500	1113.821139	0.916
max	19043.138560	1.000000	49039.570000	40761.250000	22500.000000	47137.211760	1.00(

In [13]:

```
df.corr()
```

Out[13]:

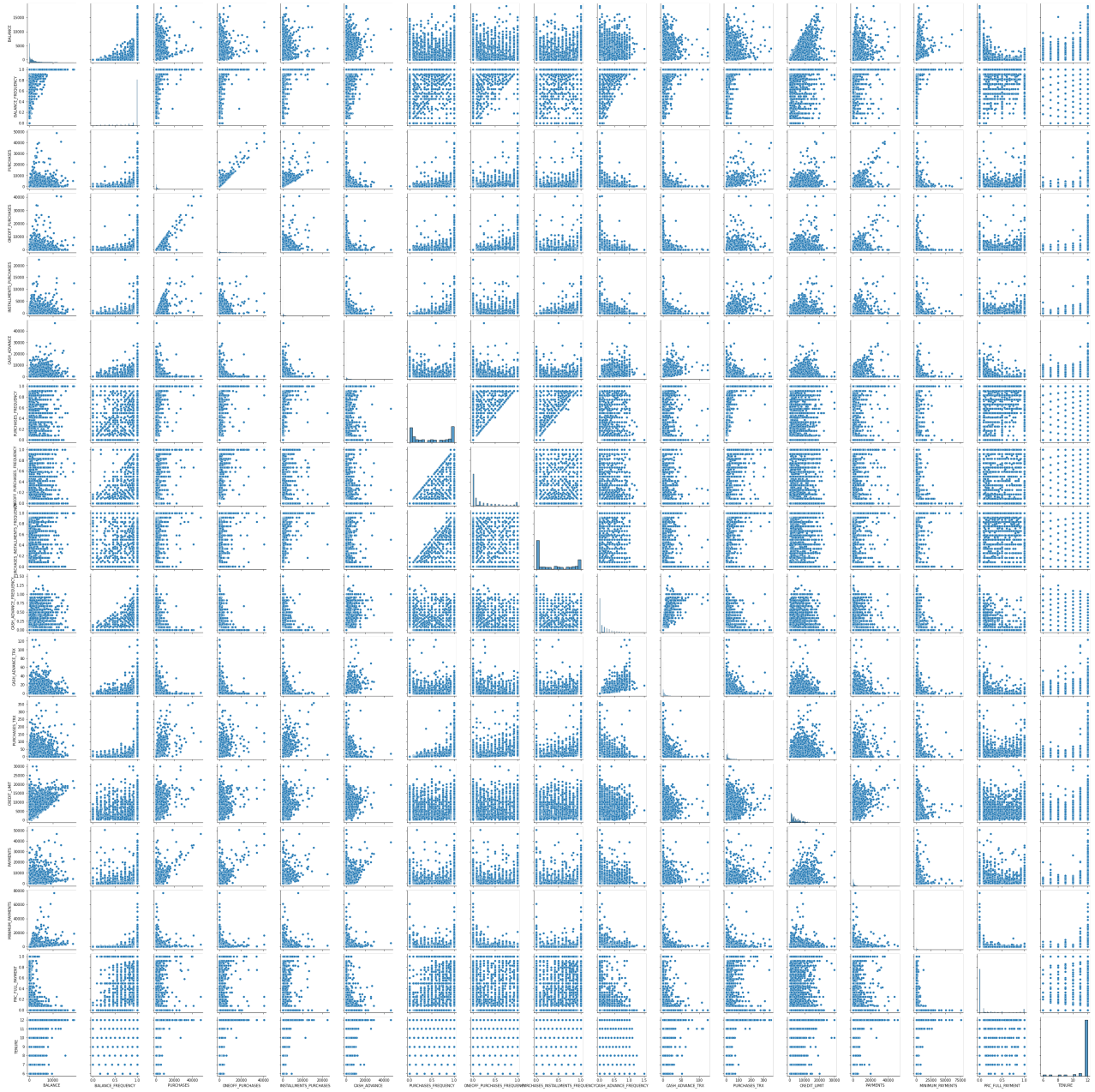
	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_
BALANCE	1.000000	0.322412	0.181261	0.164350	0.126469	
BALANCE_FREQUENCY	0.322412	1.000000	0.133674	0.104323	0.124292	
PURCHASES	0.181261	0.133674	1.000000	0.916845	0.679896	
ONEOFF_PURCHASES	0.164350	0.104323	0.916845	1.000000	0.330622	
INSTALLMENTS_PURCHASES	0.126469	0.124292	0.679896	0.330622	1.000000	
CASH_ADVANCE	0.496692	0.099388	-0.051474	-0.031326	-0.064244	
PURCHASES_FREQUENCY	-0.077944	0.229715	0.393017	0.264937	0.442418	
ONEOFF_PURCHASES_FREQUENCY	0.073166	0.202415	0.498430	0.524891	0.214042	
PURCHASES_INSTALLMENTS_FREQUENCY	-0.063186	0.176079	0.315567	0.127729	0.511351	
CASH_ADVANCE_FREQUENCY	0.449218	0.191873	-0.120143	-0.082628	-0.132318	
CASH_ADVANCE_TRX	0.385152	0.141555	-0.067175	-0.046212	-0.073999	
PURCHASES_TRX	0.154338	0.189626	0.689561	0.545523	0.628108	
CREDIT_LIMIT	0.531309	0.096015	0.356985	0.319740	0.256523	
PAYMENTS	0.322802	0.065008	0.603264	0.567292	0.384084	
MINIMUM_PAYMENTS	0.400530	0.137774	0.095094	0.050073	0.132714	
PRC_FULL_PAYMENT	-0.318959	-0.095082	0.180379	0.132763	0.182569	
TENURE	0.072692	0.119776	0.086288	0.064150	0.086143	

In [15]:

```
sns.pairplot(df)
```

Out[15]:

```
<seaborn.axisgrid.PairGrid at 0x1b69b211300>
```

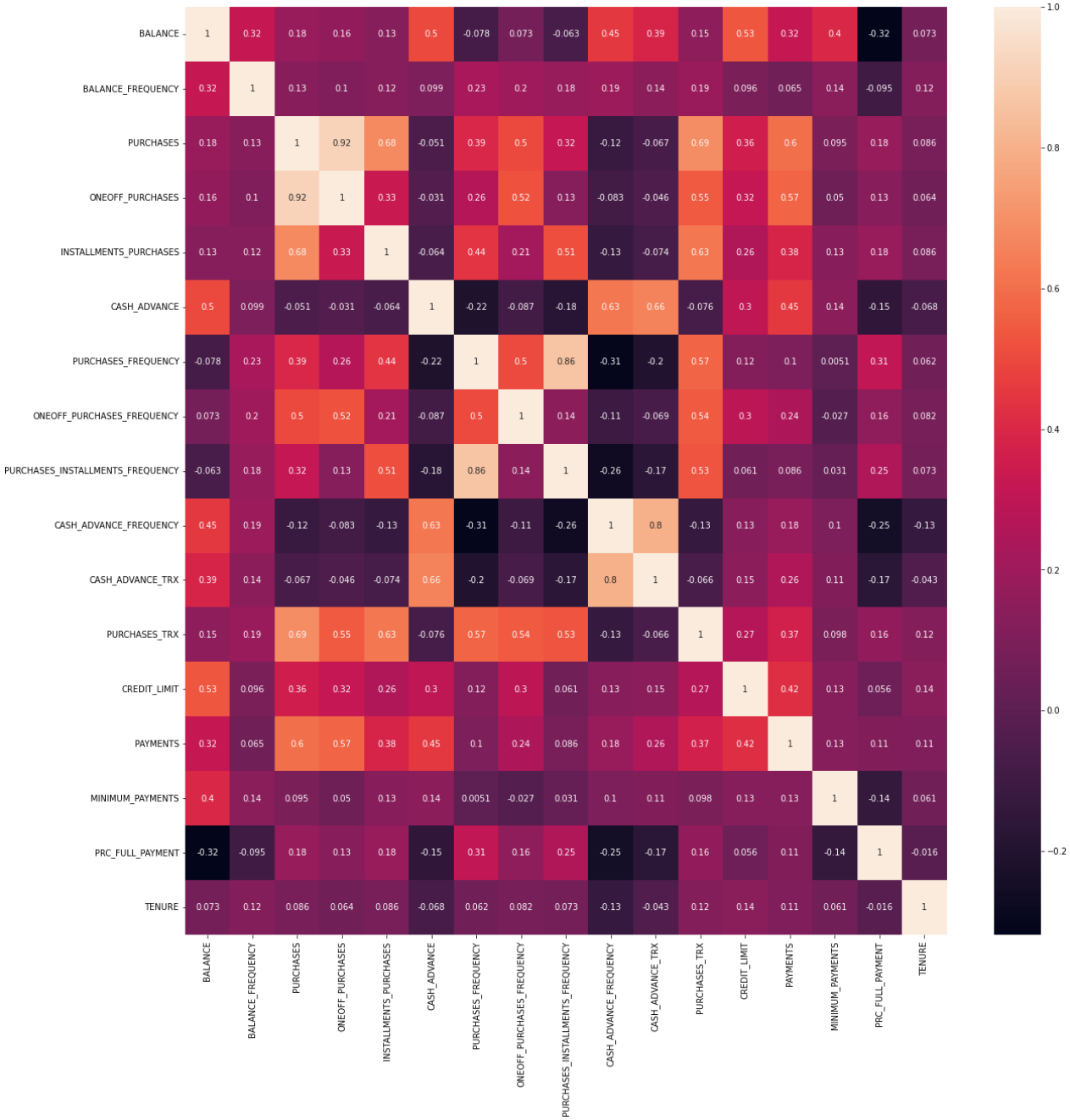


In [18]:

```
plt.figure(figsize=(20,20))
sns.heatmap(df.corr(),annot=True)
```

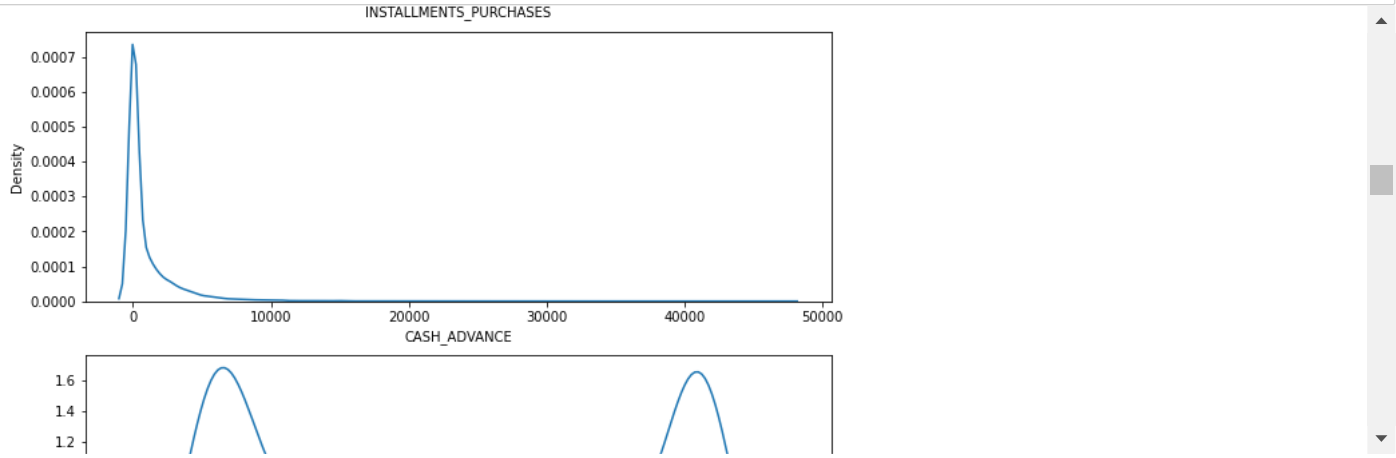
Out[18]:

<AxesSubplot:>



In [34]:

```
plt.figure(figsize=(10,75))
k=1
for i in df.columns:
    plt.subplot(len(df.columns),1,k)
    print(i,"===",df[i].skew())
    sns.kdeplot(df[i])
    k+=1
```

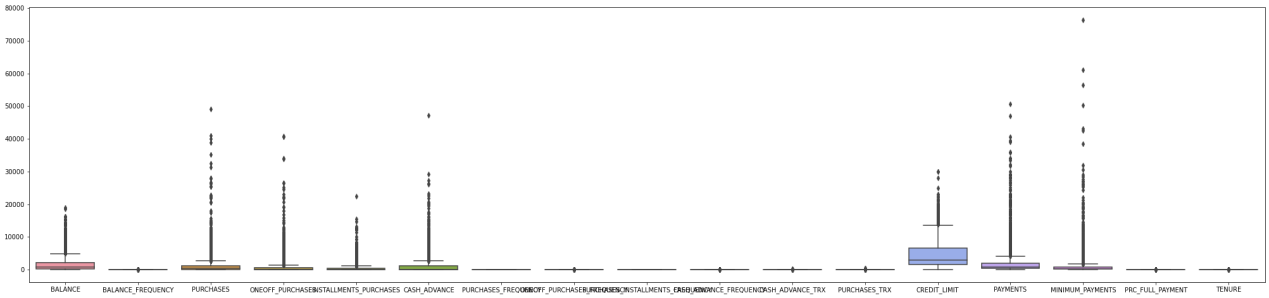


In [37]:

```
plt.figure(figsize=(35,8))
sns.boxplot(df)
```

Out[37]:

<AxesSubplot:>

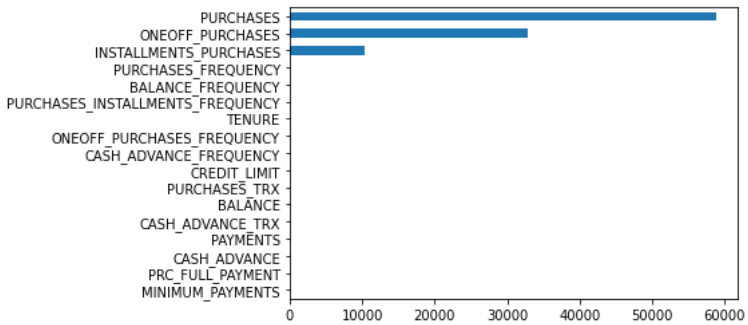


In [38]:

```
vif=[]
for i in range(len(df.columns)):
    v=variance_inflation_factor(df.to_numpy(),i)
    vif.append(v)
s1=pd.Series(vif,index=df.columns)
s1.sort_values().plot(kind='barh')
```

Out[38]:

<AxesSubplot:>



In [39]:

```
kmean=KMeans()
kmean.fit(df)
```

Out[39]:

```
KMeans
KMeans()
```

In [44]:

```
y_pred=kmean.fit_predict(df)
y_pred
```

Out[44]:

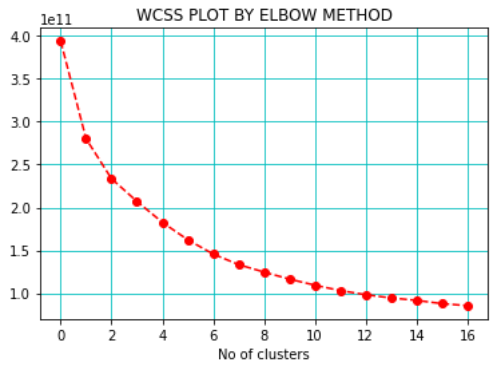
```
array([1, 5, 6, ..., 1, 1, 1])
```

In [50]:

```
wcss_list=[]
for i in range(1,18):
    kmean_model=KMeans(n_clusters=i)
    kmean_model.fit(df)
    wcss_list.append(np.round(kmean_model.inertia_,2))
```

In [54]:

```
plt.plot(wcss_list,'ro--')
plt.title("WCSS PLOT BY ELBOW METHOD")
plt.xlabel("No of clusters")
plt.grid(color='c')
```



In [55]:

```
kmean_model=KMeans(n_clusters=4)
kmean_model.fit(df)
```

Out[55]:

```
KMeans
KMeans(n_clusters=4)
```

In [61]:

```
df['TARGET']=kmean_model.fit_predict(df)
```

In [62]:

```
df.head()
```

Out[62]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY
0	40.900749	0.818182	95.40	0.00	95.4	0.000000	0.166667
1	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	0.000000
2	2495.148862	1.000000	773.17	773.17	0.0	0.000000	1.000000
3	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	0.083333
4	817.714335	1.000000	16.00	16.00	0.0	0.000000	0.083333

In [64]:

```
df['TARGET'].value_counts()
```

Out[64]:

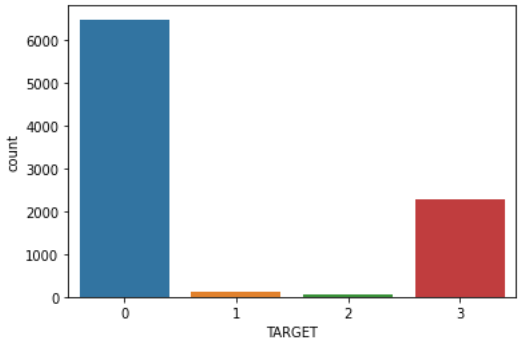
```
0    6476
3    2285
1     129
2      60
Name: TARGET, dtype: int64
```

In [156]:

```
sns.countplot(x=df['TARGET'])
```

Out[156]:

```
<AxesSubplot:xlabel='TARGET', ylabel='count'>
```



Train Test Split

In [86]:

```
x=df.drop('TARGET',axis=1)
y=df['TARGET']
```

In [87]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0,stratify=y)
```

In [ ]:

```
# Data is not normally distributed so we select the MinMaxScalar.
```

In [88]:

```
norm_scal=MinMaxScaler()
train_array=norm_scal.fit_transform(x_train)
x_train_scale=pd.DataFrame(train_array,columns=x.columns)
test_array=norm_scal.transform(x_test)
x_test_scale=pd.DataFrame(test_array,columns=x.columns)
```

In [89]:

```
acc_list={'Train':[],'Test':[]}
models=[]
```

Logistic Regression

In [90]:

```
lr_model=LogisticRegression()
lr_model.fit(x_train,y_train)
```

Out[90]:

```
LogisticRegression
LogisticRegression()
```

In [91]:

```
display("Model Evaluation On Training Data")
y_pred_train=lr_model.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.8798882681564246
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.93      0.92      0.92      5181
           1       0.29      0.41      0.34       103
           2       0.45      0.69      0.54        48
           3       0.81      0.79      0.80      1828

    accuracy                           0.88      7160
   macro avg       0.62      0.70      0.65      7160
weighted avg       0.88      0.88      0.88      7160

********************************************************************************
Confusion Matrix:-
 [[4778   80   38  285]
 [  13   42    1   47]
 [  15    0   33    0]
 [ 354   25    2 1447]]
```

In [92]:

```
display("Model Evaluation On Testing Data")
y_pred_test=lr_model.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.8743016759776536
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.92      0.92      0.92      1295
           1       0.33      0.54      0.41        26
           2       0.40      0.67      0.50        12
           3       0.81      0.78      0.80       457

    accuracy                           0.87      1790
   macro avg       0.61      0.73      0.66      1790
weighted avg       0.88      0.87      0.88      1790

********************************************************************************
Confusion Matrix:-
 [[1185   24   12   74]
 [   1   14    0   11]
 [   4    0    8    0]
 [  94    5    0  358]]
```

In [93]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Logistic Regression")
```

In [95]:

```
lr_model_scale=LogisticRegression()
lr_model_scale.fit(x_train_scale,y_train)
```

Out[95]:

```
LogisticRegression()
```

In [97]:

```
display("Model Evaluation On Training Data")
y_pred_train=lr_model_scale.predict(x_train_scale)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9634078212290503
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.97      0.99      0.98      5181
           1       0.98      0.49      0.65       103
           2       1.00      0.21      0.34        48
           3       0.95      0.92      0.94      1828

    accuracy                           0.96      7160
   macro avg       0.97      0.65      0.73      7160
weighted avg       0.96      0.96      0.96      7160

********************************************************************************
Confusion Matrix:-
 [[5153    0    0   28]
 [   2   50    0   51]
 [  27    0   10   11]
 [ 142    1    0 1685]]
```

In [98]:

```
display("Model Evaluation On Testing Data")
y_pred_test=lr_model_scale.predict(x_test_scale)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9636871508379888
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.97      0.99      0.98      1295
           1       1.00      0.62      0.76        26
           2       1.00      0.25      0.40        12
           3       0.95      0.92      0.93       457

    accuracy                           0.96      1790
   macro avg       0.98      0.70      0.77      1790
weighted avg       0.96      0.96      0.96      1790

********************************************************************************
Confusion Matrix:-
 [[1284    0    0   11]
 [   0   16    0   10]
 [   6    0    3    3]
 [  35    0    0  422]]
```

In [99]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Logistic Regression With Scaling")
```

KNN :- K Nearest Neighbors

In [100]:

```
knn_model=KNeighborsClassifier()
knn_model.fit(x_train,y_train)
```

Out[100]:

KNeighborsClassifier

KNeighborsClassifier()

In [101]:

```
display("Model Evaluation On Training Data")
y_pred_train=knn_model.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9910614525139665
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      1.00      1.00      5181
           1       0.99      0.88      0.93       103
           2       1.00      0.94      0.97        48
           3       0.99      0.98      0.98      1828

    accuracy                           0.99      7160
   macro avg       0.99      0.95      0.97      7160
weighted avg       0.99      0.99      0.99      7160

********************************************************************************
Confusion Matrix:-
 [[5167    0    0   14]
 [   0   91    0   12]
 [   1    1   45    1]
 [  35    0    0 1793]]
```

In [102]:

```
display("Model Evaluation On Testing Data")
y_pred_test=knn_model.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9815642458100559
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.99      0.99      1295
           1       1.00      1.00      1.00        26
           2       0.92      0.92      0.92        12
           3       0.96      0.96      0.96       457

    accuracy                           0.98      1790
   macro avg       0.97      0.97      0.97      1790
weighted avg       0.98      0.98      0.98      1790

********************************************************************************
Confusion Matrix:-
 [[1279    0    0   16]
 [   0   26    0    0]
 [   0    0   11    1]
 [  15    0    1  441]]
```

In [103]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("KNN")
```

In [108]:

```
knn_model_scale=KNeighborsClassifier()
knn_model_scale.fit(x_train_scale,y_train)
```

Out[108]:

KNeighborsClassifier

KNeighborsClassifier()

In [109]:

```
display("Model Evaluation On Training Data")
y_pred_train=knn_model_scale.predict(x_train_scale)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9491620111731843
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.95      0.99      0.97      5181
           1       0.97      0.59      0.73       103
           2       0.95      0.75      0.84        48
           3       0.95      0.86      0.90      1828

    accuracy                           0.95      7160
   macro avg       0.95      0.80      0.86      7160
weighted avg       0.95      0.95      0.95      7160

********************************************************************************
Confusion Matrix:-
 [[5132    0    2   47]
 [   4   61    0   38]
 [   9    0   36    3]
 [ 259    2    0 1567]]
```

In [110]:

```
display("Model Evaluation On Testing Data")
y_pred_test=knn_model_scale.predict(x_test_scale)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9206703910614525
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.92      0.98      0.95      1295
           1       1.00      0.42      0.59        26
           2       1.00      0.75      0.86        12
           3       0.91      0.78      0.84       457

    accuracy                           0.92      1790
   macro avg       0.96      0.73      0.81      1790
weighted avg       0.92      0.92      0.92      1790

********************************************************************************
Confusion Matrix:-
 [[1272    0    0   23]
 [   2   11    0   13]
 [   2    0    9    1]
 [ 101    0    0  356]]
```

In [111]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("KNN With Scaling")
```

Decision Tree

In [112]:

```
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
```

Out[112]:

DecisionTreeClassifier

DecisionTreeClassifier()

In [113]:

```
display("Model Evaluation On Training Data")
y_pred_train=dt_model.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)e5.
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 1.0
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      5181
           1       1.00      1.00      1.00       103
           2       1.00      1.00      1.00        48
           3       1.00      1.00      1.00      1828

    accuracy                           1.00      7160
   macro avg       1.00      1.00      1.00      7160
weighted avg       1.00      1.00      1.00      7160

********************************************************************************
Confusion Matrix:-
 [[5181    0    0    0]
 [   0  103    0    0]
 [   0    0   48    0]
 [   0    0    0 1828]]
```

In [114]:

```
display("Model Evaluation On Testing Data")
y_pred_test=dt_model.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9754189944134078
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.98      0.99      1295
           1       0.91      0.77      0.83        26
           2       0.86      1.00      0.92        12
           3       0.94      0.96      0.95       457

    accuracy                           0.98      1790
   macro avg       0.92      0.93      0.92      1790
weighted avg       0.98      0.98      0.98      1790

********************************************************************************
Confusion Matrix:-
 [[1273    1    0   21]
 [   0   20    1    5]
 [   0    0   12    0]
 [  14    1    1  441]]
```

In [117]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Decision Tree")
```

In [122]:

```
dt_Scale=DecisionTreeClassifier()
param_grid={"criterion":['gini','entropy'],
    "max_depth":np.arange(1,19),
    "min_samples_split":np.arange(1,15),
    "min_samples_leaf":np.arange(1,15)}
rscv=RandomizedSearchCV(dt_Scale,param_grid,cv=5)
rscv.fit(x_train,y_train)
best_hyp=rscv.best_estimator_
best_hyp
```

Out[122]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=17, min_samples_leaf=5,
                       min_samples_split=4)
```

In [123]:

```
dt_hyp=best_hyp
dt_hyp.fit(x_train,y_train)
```

Out[123]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=17, min_samples_leaf=5,
                       min_samples_split=4)
```

In [125]:

```
display("Model Evaluation On Training Data")
y_pred_train=dt_hyp.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9925977653631285
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      5181
           1       0.95      0.94      0.95       103
           2       1.00      0.98      0.99        48
           3       0.98      0.99      0.99      1828

    accuracy                           0.99      7160
   macro avg       0.98      0.98      0.98      7160
weighted avg       0.99      0.99      0.99      7160

********************************************************************************
Confusion Matrix:-
 [[5159    1    0   21]
 [   0   97    0    6]
 [   0    0   47    1]
 [  20    4    0 1804]]
```

In [126]:

```
display("Model Evaluation On Testing Data")
y_pred_test=dt_hyp.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9776536312849162
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.98      0.99      1295
           1       0.84      0.81      0.82        26
           2       1.00      1.00      1.00        12
           3       0.94      0.97      0.96       457

    accuracy                           0.98      1790
   macro avg       0.94      0.94      0.94      1790
weighted avg       0.98      0.98      0.98      1790

********************************************************************************
Confusion Matrix:-
 [[1273    1    0   21]
 [   0   21    0    5]
 [   0    0   12    0]
 [  10    3    0  444]]
```

In [127]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Decision Tree With Hyperparameter Tuning")
```

Random Forest

In [128]:

```
rf_model=RandomForestClassifier()
rf_model.fit(x_train,y_train)
```

Out[128]:

RandomForestClassifier

RandomForestClassifier()

In [129]:

```
display("Model Evaluation On Training Data")
y_pred_train=rf_model.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 1.0
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      5181
           1       1.00      1.00      1.00       103
           2       1.00      1.00      1.00        48
           3       1.00      1.00      1.00      1828

    accuracy                           1.00      7160
   macro avg       1.00      1.00      1.00      7160
weighted avg       1.00      1.00      1.00      7160

********************************************************************************
Confusion Matrix:-
 [[5181    0    0    0]
 [   0  103    0    0]
 [   0    0   48    0]
 [   0    0    0 1828]]
```

In [130]:

```
display("Model Evaluation On Testing Data")
y_pred_test=rf_model.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9837988826815642
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.99      0.99      1295
           1       1.00      0.85      0.92        26
           2       1.00      1.00      1.00        12
           3       0.96      0.98      0.97       457

    accuracy                           0.98      1790
   macro avg       0.99      0.95      0.97      1790
weighted avg       0.98      0.98      0.98      1790

********************************************************************************
Confusion Matrix:-
 [[1281    0    0   14]
 [   0   22    0    4]
 [   0    0   12    0]
 [  11    0    0  446]]
```

In [131]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Random Forest")
```

In [132]:

```
rf_model=RandomForestClassifier()
param_grid={
     "n_estimators":np.arange(50,150),
    "criterion":['gini','entropy'],
    "max_depth":np.arange(1,18),
    "min_samples_split":np.arange(1,18),
    "min_samples_leaf":np.arange(1,19)}
rscv=RandomizedSearchCV(rf_model,param_grid,cv=5)
rscv.fit(x_train,y_train)
best_hyp=rscv.best_estimator_
best_hyp
```

Out[132]:

```
RandomForestClassifier(max_depth=16, min_samples_leaf=3, min_samples_split=16,
                       n_estimators=66)
```

In [133]:

```
rf_hyp=best_hyp
rf_hyp.fit(x_train,y_train)
```

Out[133]:

```
RandomForestClassifier(max_depth=16, min_samples_leaf=3, min_samples_split=16,
                       n_estimators=66)
```

In [134]:

```
display("Model Evaluation On Training Data")
y_pred_train=rf_hyp.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9973463687150838
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      5181
           1       0.99      0.92      0.95       103
           2       1.00      0.98      0.99        48
           3       0.99      1.00      1.00      1828

    accuracy                           1.00      7160
   macro avg       1.00      0.97      0.98      7160
weighted avg       1.00      1.00      1.00      7160

********************************************************************************
Confusion Matrix:-
 [[5177    0    0    4]
 [   1   95    0    7]
 [   0    1   47    0]
 [   6    0    0 1822]]
```

In [135]:

```
display("Model Evaluation On Testing Data")
y_pred_test=rf_hyp.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9843575418994414
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.99      0.99      1295
           1       1.00      0.85      0.92        26
           2       1.00      0.92      0.96        12
           3       0.96      0.98      0.97       457

    accuracy                           0.98      1790
   macro avg       0.99      0.93      0.96      1790
weighted avg       0.98      0.98      0.98      1790

********************************************************************************
Confusion Matrix:-
 [[1282    0    0   13]
 [   0   22    0    4]
 [   0    0   11    1]
 [  10    0    0  447]]
```

In [136]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("Random Forest with Hyperparameter Tuning")
```

AdaBoost

In [137]:

```
ada_clf=AdaBoostClassifier()
ada_clf.fit(x_train,y_train)
```

Out[137]:

AdaBoostClassifier

AdaBoostClassifier()

In [138]:

```
display("Model Evaluation On Training Data")
y_pred_train=ada_clf.predict(x_train)
acc_train=accuracy_score(y_train,y_pred_train)
print("Accuracy Score :-",acc_train)
print("*"*80)
clf=classification_report(y_train,y_pred_train)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_train,y_pred_train)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Training Data'

Accuracy Score :- 0.9216480446927374
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.97      0.93      0.95      5181
           1       0.68      0.86      0.76       103
           2       1.00      1.00      1.00        48
           3       0.81      0.91      0.86      1828

    accuracy                           0.92      7160
   macro avg       0.87      0.93      0.89      7160
weighted avg       0.93      0.92      0.92      7160

********************************************************************************
Confusion Matrix:-
 [[4798    2    0  381]
 [   0   89    0   14]
 [   0    0   48    0]
 [ 124   40    0 1664]]
```

In [139]:

```
display("Model Evaluation On Testing Data")
y_pred_test=ada_clf.predict(x_test)
acc_test=accuracy_score(y_test,y_pred_test)
print("Accuracy Score :-",acc_test)
print("*"*80)
clf=classification_report(y_test,y_pred_test)
print("Classification Report:-\n",clf)
print("*"*80)
cnf=confusion_matrix(y_test,y_pred_test)
print("Confusion Matrix:- \n",cnf)
```

```
'Model Evaluation On Testing Data'

Accuracy Score :- 0.9229050279329609
********************************************************************************
Classification Report:-
               precision    recall  f1-score   support

           0       0.99      0.91      0.95      1295
           1       0.75      0.92      0.83        26
           2       1.00      1.00      1.00        12
           3       0.79      0.95      0.86       457

    accuracy                           0.92      1790
   macro avg       0.88      0.95      0.91      1790
weighted avg       0.93      0.92      0.93      1790

********************************************************************************
Confusion Matrix:-
 [[1183    1    0  111]
 [   0   24    0    2]
 [   0    0   12    0]
 [  17    7    0  433]]
```

In [140]:

```
acc_list['Train'].append(acc_train)
acc_list['Test'].append(acc_test)
models.append("AdaBoost Clf")
```

In [148]:

```
acc_df=pd.DataFrame(acc_list,index=models)
acc_df.sort_values("Test",ascending=False)
```

Out[148]:

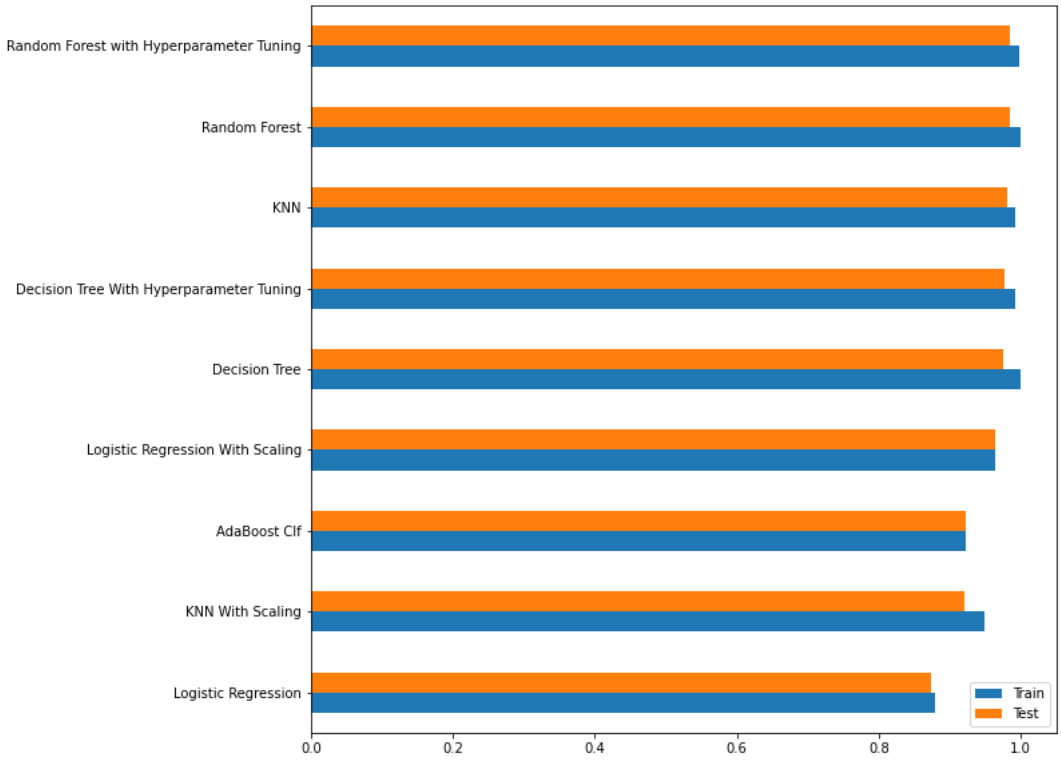
	Train	Test
Random Forest with Hyperparameter Tuning	0.997346	0.984358
Random Forest	1.000000	0.983799
KNN	0.991061	0.981564
Decision Tree With Hyperparameter Tuning	0.992598	0.977654
Decision Tree	1.000000	0.975419
Logistic Regression With Scaling	0.963408	0.963687
AdaBoost Clf	0.921648	0.922905
KNN With Scaling	0.949162	0.920670
Logistic Regression	0.879888	0.874302

In [149]:

```
acc_df.sort_values('Test').plot(kind='barh',figsize=(10,10))
```

Out[149]:

```
<AxesSubplot:>
```



So We Select The Random Forest

In [150]:

```
import pickle
with open('customer_seg_model.pkl','wb')as f:
    pickle.dump(rf_hyp,f)
```

In [153]:

```
columns={"Columns":list(x.columns)}
```

In [154]:

```
import json
with open('customer_seg_data.json','w')as f:
    json.dump(columns,f)
```