NAME: HRISHIKESH SHIVPUTRA KAMBLE

PROJECT:-

SOLVING CLASSIFICATION PREDICTION FOR "SMART HOME DEVICE USAGE" DATASET USING "LOGISTIC REGRESSION","SVC","GAUSSIAN NB","BERNOULLI NB","COMPLEMENT NB","MULTINOMIAL NB","K NEAREST NEIGHBOUR","DECISION TREE CLASSIFIER","ADABOOST","BAGGING","ANN".

APPROACH:

1.LOAD THE REQUIRED LIBRARIES SUCH AS PANDAS,MATPLOTLIB,SEABORN ALONG WITH GIVEN DATASET.

2.PERFORM EDA ON THE GIVEN DATASET.

3.CONVERT ALL THE REQUIRED COLUMNS INTO NUMERIAL COLUMNS USING GET DUMMIES FUNCTION FROM PANDAS LIBRARY.

4.CONVERTING ALL REQUIRED FEATURES IN NUMERIAL , CHECK FOR CORRELATION BETWEEN FEATURES AND TARGET AND CONSIDER THE ONLY FEATURES WITH HIGHER CORRELATION.

5.IMPORT "LOGISTIC REGRESSION","SVC","GAUSSIAN NB","BERNOULLI NB","COMPLEMENT NB","MULTINOMIAL NB","K NEAREST NEIGHBOUR","DECISION TREE CLASSIFIER","ADABOOST","BAGGING","ANN", AND SPLIT THE GIVEN DATASET INTO TRAINING AND TESTING DATA USING TRAIN_TEST_SPLIT FUNCTION.THEN CALCULATE ACCURACY SCORE USING SKLEARN LIBRARY BY IMPORTING METRICS.

6.ONCE WE GET ACCURACY SCORE OF ALL MODELS FOR BOTH TRAING AND TESTING DATA, CREATE A DATAFRAME AND LOAD ALL THE ACCURACY OF ALL MODEL.

7.VISUALIZATION: ONCE THE DATASET IS CREATED PLOT THE ACCURACIES OF ALL THE MODELS USING BARPLOT USING MATPLOTLIB.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
pd.set_option("display.Max_columns",100)
```

```
C:\Users\Hrishikesh\anaconda3\Lib\site-packages\pandas\core\arrays\masked.py:60: UserWarning: Pandas requires version
'1.3.6' or newer of 'bottleneck' (version '1.3.5' currently installed).
  from pandas.core import (
```

In [2]:
```
data=pd.read_csv(r"C:\Users\Hrishikesh\Desktop\DATA SCIENCE\smart_home_device_usage_data.csv")
data
```

Out[2]:

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
0	1	Smart Speaker	15.307188	1.961607	1	4	36	1
1	2	Camera	19.973343	8.610689	1	0	29	1
2	3	Security System	18.911535	2.651777	1	0	20	1
3	4	Camera	7.011127	2.341653	0	3	15	0
4	5	Camera	22.610684	4.859069	1	3	36	1
...	...	...	...	...	...	...	...	...
5398	5399	Thermostat	4.556314	5.871764	1	0	28	0
5399	5400	Lights	0.561856	1.555992	1	4	24	0
5400	5401	Smart Speaker	11.096236	7.677779	0	0	42	0
5401	5402	Security System	8.782169	7.467929	0	2	28	1
5402	5403	Thermostat	13.540381	9.043076	0	0	30	0

5403 rows × 8 columns

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5403 entries, 0 to 5402
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   UserID                5403 non-null   int64  
 1   DeviceType            5403 non-null   object 
 2   UsageHoursPerDay      5403 non-null   float64
 3   EnergyConsumption     5403 non-null   float64
 4   UserPreferences       5403 non-null   int64  
 5   MalfunctionIncidents  5403 non-null   int64  
 6   DeviceAgeMonths       5403 non-null   int64  
 7   SmartHomeEfficiency   5403 non-null   int64  
dtypes: float64(2), int64(5), object(1)
memory usage: 337.8+ KB
```

In [4]:
```
data.shape
```

Out[4]:
```
(5403, 8)
```

In [5]:
```
data.head()
```

Out[5]:

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
0	1	Smart Speaker	15.307188	1.961607	1	4	36	1
1	2	Camera	19.973343	8.610689	1	0	29	1
2	3	Security System	18.911535	2.651777	1	0	20	1
3	4	Camera	7.011127	2.341653	0	3	15	0
4	5	Camera	22.610684	4.859069	1	3	36	1

In [6]:
```
data.isna().sum()
```

Out[6]:
```
UserID                  0
DeviceType              0
UsageHoursPerDay        0
EnergyConsumption       0
UserPreferences         0
MalfunctionIncidents    0
DeviceAgeMonths         0
SmartHomeEfficiency     0
dtype: int64
```

In [7]:
```
data["DeviceType"].unique()
```

Out[7]:
```
array(['Smart Speaker', 'Camera', 'Security System', 'Thermostat',
       'Lights'], dtype=object)
```

In [8]:
```
b=data["DeviceType"].value_counts().reset_index()
b
```

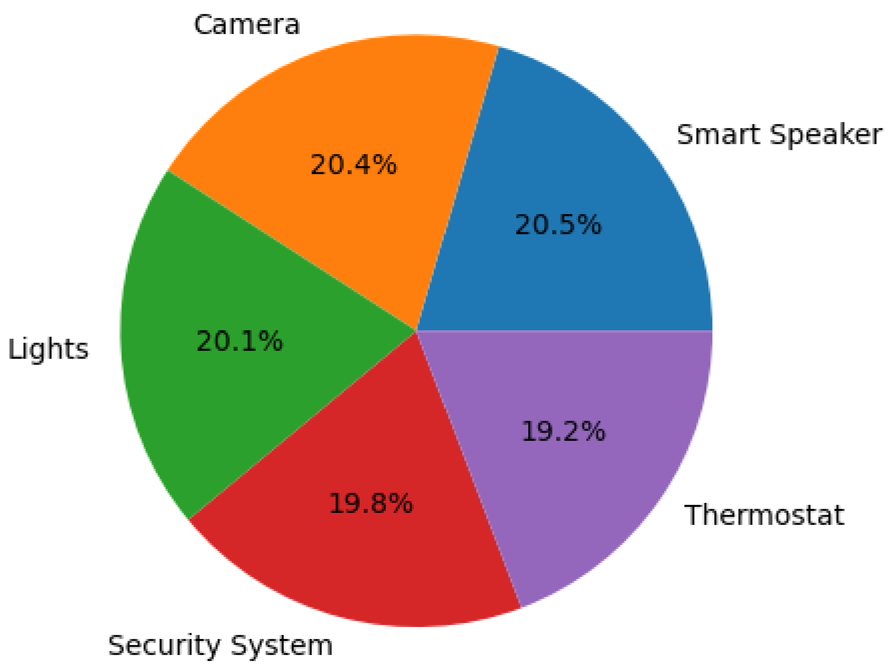
Out[8]:

	DeviceType	count
0	Smart Speaker	1108
1	Camera	1101
2	Lights	1087
3	Security System	1068
4	Thermostat	1039

In [9]:
```
data.columns
```

Out[9]:
```
Index(['UserID', 'DeviceType', 'UsageHoursPerDay', 'EnergyConsumption',
       'UserPreferences', 'MalfunctionIncidents', 'DeviceAgeMonths',
       'SmartHomeEfficiency'],
      dtype='object')
```

In [10]:
```
plt.pie(b["count"],labels=b["DeviceType"],autopct="%1.1f%%")
plt.show()
```



THE ABOVE PIECHART SHOWS THE DISTRIBUTION OF DEVICE TYPES.

In [11]:
```
data=data[['DeviceType', 'UsageHoursPerDay', 'EnergyConsumption',
       'UserPreferences', 'MalfunctionIncidents', 'DeviceAgeMonths',
       'SmartHomeEfficiency']]
data
```

Out[11]:

	DeviceType	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
0	Smart Speaker	15.307188	1.961607	1	4	36	1
1	Camera	19.973343	8.610689	1	0	29	1
2	Security System	18.911535	2.651777	1	0	20	1
3	Camera	7.011127	2.341653	0	3	15	0
4	Camera	22.610684	4.859069	1	3	36	1
...	...	...	...	...	...	...	...
5398	Thermostat	4.556314	5.871764	1	0	28	0
5399	Lights	0.561856	1.555992	1	4	24	0
5400	Smart Speaker	11.096236	7.677779	0	0	42	0
5401	Security System	8.782169	7.467929	0	2	28	1
5402	Thermostat	13.540381	9.043076	0	0	30	0

5403 rows × 7 columns

In [12]:
```
n=pd.get_dummies(data["DeviceType"],drop_first=True).replace({True:1,False:0})
n
```

Out[12]:

	Lights	Security System	Smart Speaker	Thermostat
0	0	0	1	0
1	0	0	0	0
2	0	1	0	0
3	0	0	0	0
4	0	0	0	0
...	...	...	...	...
5398	0	0	0	1
5399	1	0	0	0
5400	0	0	1	0
5401	0	1	0	0
5402	0	0	0	1

5403 rows × 4 columns

In [13]:
```
data=pd.concat([data,n],axis=1).drop(columns="DeviceType")
```

In [14]:
```
data=data[['UsageHoursPerDay', 'EnergyConsumption', 'UserPreferences',
       'MalfunctionIncidents', 'DeviceAgeMonths',
       'Lights', 'Security System', 'Smart Speaker', 'Thermostat', 'SmartHomeEfficiency']]
```

In [15]:
```
data
```

Out[15]:

	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	Lights	Security System	Smart Speaker	Thermostat	S
0	15.307188	1.961607	1	4	36	0	0	1	0	
1	19.973343	8.610689	1	0	29	0	0	0	0	
2	18.911535	2.651777	1	0	20	0	1	0	0	
3	7.011127	2.341653	0	3	15	0	0	0	0	
4	22.610684	4.859069	1	3	36	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	
5398	4.556314	5.871764	1	0	28	0	0	0	1	
5399	0.561856	1.555992	1	4	24	1	0	0	0	
5400	11.096236	7.677779	0	0	42	0	0	1	0	
5401	8.782169	7.467929	0	2	28	0	1	0	0	
5402	13.540381	9.043076	0	0	30	0	0	0	1	

5403 rows × 10 columns

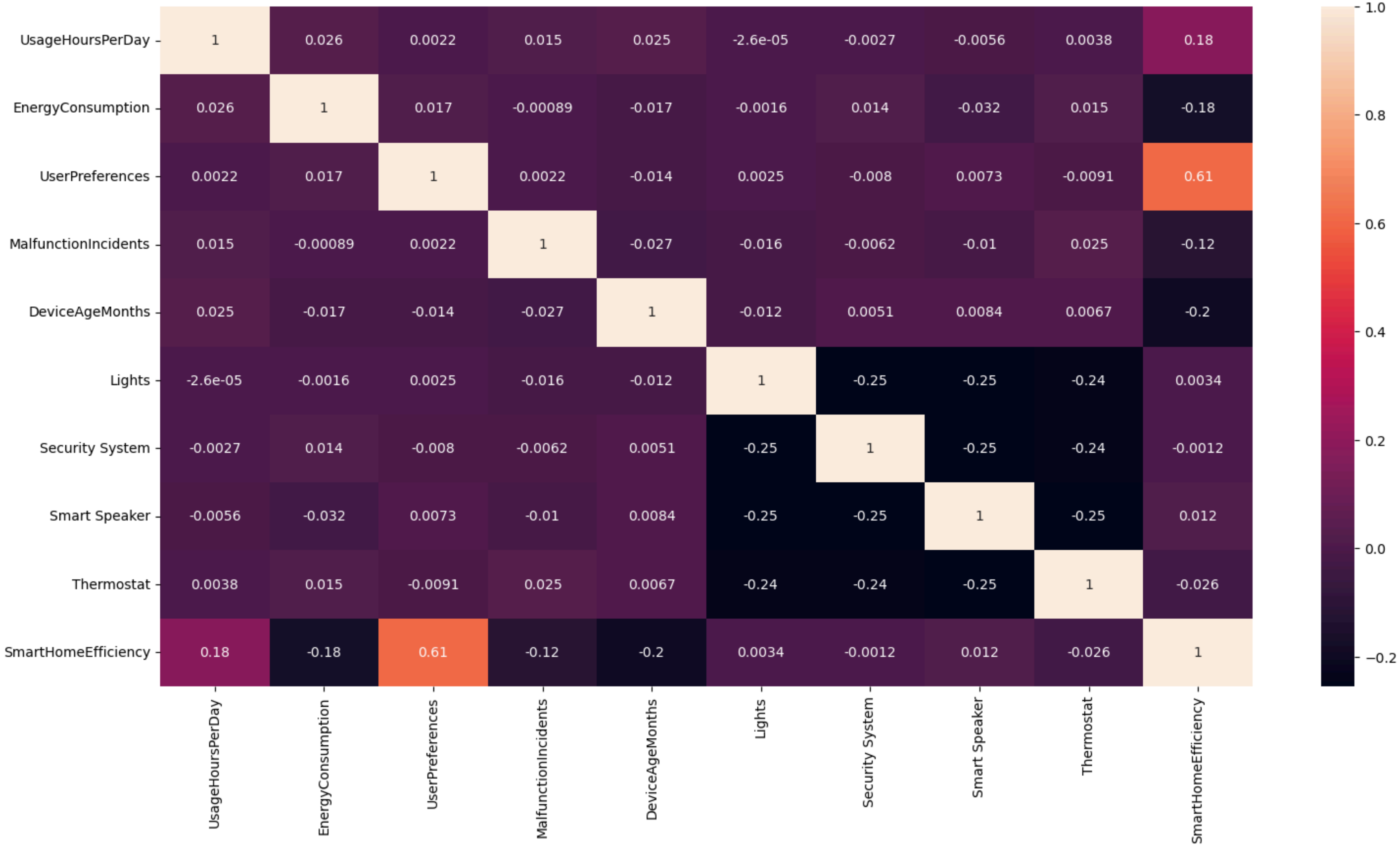
In [16]:
```
data.corr()
```

Out[16]:

	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	Lights	Security System	S Sp
UsageHoursPerDay	1.000000	0.026253	0.002161	0.015126	0.025132	-0.000026	-0.002724	-0.0
EnergyConsumption	0.026253	1.000000	0.016709	-0.000894	-0.016691	-0.001642	0.014465	-0.0
UserPreferences	0.002161	0.016709	1.000000	0.002154	-0.013781	0.002517	-0.007951	0.0
MalfunctionIncidents	0.015126	-0.000894	0.002154	1.000000	-0.027023	-0.015969	-0.006193	-0.0
DeviceAgeMonths	0.025132	-0.016691	-0.013781	-0.027023	1.000000	-0.011805	0.005075	0.0
Lights	-0.000026	-0.001642	0.002517	-0.015969	-0.011805	1.000000	-0.249095	-0.2
Security System	-0.002724	0.014465	-0.007951	-0.006193	0.005075	-0.249095	1.000000	-0.2
Smart Speaker	-0.005574	-0.032159	0.007316	-0.010185	0.008420	-0.254896	-0.252104	1.0
Thermostat	0.003834	0.015264	-0.009124	0.025397	0.006678	-0.244872	-0.242190	-0.2
SmartHomeEfficiency	0.183065	-0.178467	0.608713	-0.120836	-0.197077	0.003420	-0.001203	0.0

In [17]:
```
plt.figure(figsize=(18,9))
sns.heatmap(data.corr(),annot=True)
```

Out[17]: <Axes: >



	UsageHoursPerDay	EnergyConsumption	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	Lights	Security System	Smart Speaker	Thermostat	SmartHomeEfficiency
UsageHoursPerDay	1	0.026	0.0022	0.015	0.025	-2.6e-05	-0.0027	-0.0056	0.0038	0.18
EnergyConsumption	0.026	1	0.017	-0.00089	-0.017	-0.0016	0.014	-0.032	0.015	-0.18
UserPreferences	0.0022	0.017	1	0.0022	-0.014	0.0025	-0.008	0.0073	-0.0091	0.61
MalfunctionIncidents	0.015	-0.00089	0.0022	1	-0.027	-0.016	-0.0062	-0.01	0.025	-0.12
DeviceAgeMonths	0.025	-0.017	-0.014	-0.027	1	-0.012	0.0051	0.0084	0.0067	-0.2
Lights	-2.6e-05	-0.0016	0.0025	-0.016	-0.012	1	-0.25	-0.25	-0.24	0.0034
Security System	-0.0027	0.014	-0.008	-0.0062	0.0051	-0.25	1	-0.25	-0.24	-0.0012
Smart Speaker	-0.0056	-0.032	0.0073	-0.01	0.0084	-0.25	-0.25	1	-0.25	0.012
Thermostat	0.0038	0.015	-0.0091	0.025	0.0067	-0.24	-0.24	-0.25	1	-0.026
SmartHomeEfficiency	0.18	-0.18	0.61	-0.12	-0.2	0.0034	-0.0012	0.012	-0.026	1

MACHINE LEARNING:-

In [18]:
```
features=data[['UsageHoursPerDay', 'EnergyConsumption', 'UserPreferences',
       'MalfunctionIncidents', 'DeviceAgeMonths',
       'Lights', 'Security System', 'Smart Speaker', 'Thermostat']]
target=data['SmartHomeEfficiency']
```

In [19]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(features,target)
```

LOGISTIC REGRESSION:-

In [20]:
```
from sklearn.linear_model import LogisticRegression
L=LogisticRegression()
L.fit(x_train,y_train)
```

Out[20]:
```
▾ LogisticRegression
LogisticRegression()
```

In [21]:
```
L1=L.score(x_train,y_train)*100
L1
```

Out[21]:
```
87.24086870681145
```

In [22]:
```
L2=L.score(x_test,y_test)*100
L2
```

Out[22]:
```
87.71280532938565
```

In [ ]:

SUPPORT VECTOR CLASSIFIER:-

In [23]:
```
from sklearn.svm import SVC
S=SVC()
S.fit(x_train,y_train)
```

Out[23]:
```
▾ SVC
SVC()
```

In [24]:
```
S1=S.score(x_train,y_train)*100
S1
```

Out[24]: 83.21816386969397

In [25]:
```
S2=S.score(x_test,y_test)*100
S2
```

Out[25]: 82.08734270910438

In [ ]:

KNN:-

In [26]:
```
from sklearn.neighbors import KNeighborsClassifier
K=KNeighborsClassifier()
K.fit(x_train,y_train)
```

Out[26]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [27]:
```
K1=K.score(x_train,y_train)*100
K1
```
Out[27]: 83.24284304047383

In [28]:
```
K2=K.score(x_test,y_test)*100
K2
```
Out[28]: 71.50259067357513

In [ ]:

NAVIES BAYES:-

In [29]:
```
from sklearn.naive_bayes import ComplementNB,BernoulliNB,MultinomialNB,GaussianNB
```

In [30]:
```
C=ComplementNB()
B=BernoulliNB()
G=GaussianNB()
M=MultinomialNB()
```

ComplementNB:-

In [31]:
```
C.fit(x_train,y_train)
```
Out[31]:
```
▾ ComplementNB
ComplementNB()
```

In [32]:
```
C1=C.score(x_train,y_train)*100
C1
```
Out[32]: 68.06515301085884

In [33]:
```
C2=C.score(x_test,y_test)*100
C2
```

Out[33]: 67.9496669133975

BernoulliNB:-

In [34]:
```
B.fit(x_train,y_train)
```

Out[34]:
```
▾ BernoulliNB
BernoulliNB()
```

In [35]:
```
B1=B.score(x_train,y_train)*100
B1
```

Out[35]: 79.14610069101678

In [36]:
```
B2=B.score(x_test,y_test)*100
B2
```

Out[36]: 79.34863064396744

In [ ]:

GaussianNB:-

In [37]:
```
G.fit(x_train,y_train)
```

Out[37]:
```
▾ GaussianNB
GaussianNB()
```

In [38]:
```
G1=G.score(x_train,y_train)*100
G1
```

Out[38]: 83.21816386969397

In [39]:
```
G2=G.score(x_test,y_test)*100
G2
```

Out[39]: 83.4937083641747

In [ ]:

MultinomialNB:-

In [40]:
```
M.fit(x_train,y_train)
```

Out[40]:
```
▾ MultinomialNB
MultinomialNB()
```

In [41]:
```
M1=M.score(x_train,y_train)*100
M1
```

Out[41]: 69.69397828232971

In [42]:
```
M2=M.score(x_test,y_test)*100
M2
```

Out[42]: 69.94818652849742

In [ ]:

DECISION TREE:-

In [43]:
```
from sklearn.tree import DecisionTreeClassifier
D=DecisionTreeClassifier()
D.fit(x_train,y_train)
```

Out[43]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [44]:
```
D1=D.score(x_train,y_train)*100
D1
```

Out[44]: 100.0

In [45]:
```
D2=D.score(x_test,y_test)*100
D2
```

Out[45]: 91.85788304959289

In [ ]:

ENSEMBLE:-

ADABOAST:-

In [46]:
```
from sklearn.ensemble import AdaBoostClassifier,BaggingClassifier,StackingClassifier,RandomForestClassifier
A=AdaBoostClassifier()
A.fit(x_train,y_train)
```

Out[46]:
```
▾ AdaBoostClassifier
AdaBoostClassifier()
```

In [47]:
```
A1=A.score(x_train,y_train)*100
A1
```

Out[47]: 94.54590325765054

In [48]:
```
A2=A.score(x_test,y_test)*100
A2
```

Out[48]: 94.52257586972614

BAGGING:-

In [49]:
```
b=BaggingClassifier()
b.fit(x_train,y_train)
```

Out[49]:
```
▾ BaggingClassifier
BaggingClassifier()
```

In [50]:
```
b1=b.score(x_train,y_train)*100
b1
```

Out[50]: 98.81539980256665

In [51]:
```
b2=b.score(x_test,y_test)*100
b2
```

Out[51]: 94.74463360473723

In [ ]:

DEEP LEARNING:-

In [52]:
```
import tensorflow
from tensorflow import keras
```

In [53]:
```
model=keras.Sequential([
    keras.layers.Dense(8,input_shape=(9,),activation="relu"),
    keras.layers.Dense(10,activation="relu"),
    keras.layers.Dense(12,activation="relu"),
    keras.layers.Dense(1,activation="sigmoid")
])
model.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
```

In [54]:
```
model.fit(x_train,y_train,epochs=50)
```

```
Epoch 1/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 1s 871us/step - accuracy: 0.5907 - loss: 0.7091
Epoch 2/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.6562 - loss: 0.6104
Epoch 3/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 743us/step - accuracy: 0.6625 - loss: 0.6048
Epoch 4/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.7099 - loss: 0.5644
Epoch 5/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.7318 - loss: 0.5387
Epoch 6/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.7974 - loss: 0.4962
Epoch 7/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8324 - loss: 0.4389
Epoch 8/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy: 0.8582 - loss: 0.3954
Epoch 9/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.8689 - loss: 0.3499
Epoch 10/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 888us/step - accuracy: 0.8731 - loss: 0.3461
Epoch 11/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 891us/step - accuracy: 0.8647 - loss: 0.3510
Epoch 12/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.8647 - loss: 0.3538
Epoch 13/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 743us/step - accuracy: 0.8551 - loss: 0.3648
Epoch 14/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 753us/step - accuracy: 0.8806 - loss: 0.3126
Epoch 15/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 753us/step - accuracy: 0.8732 - loss: 0.3260
Epoch 16/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 720us/step - accuracy: 0.8648 - loss: 0.3524
Epoch 17/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.8717 - loss: 0.3367
Epoch 18/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.8655 - loss: 0.3401
Epoch 19/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 954us/step - accuracy: 0.8754 - loss: 0.3380
Epoch 20/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 754us/step - accuracy: 0.8695 - loss: 0.3464
Epoch 21/50
```

```
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8706 - loss: 0.3364
Epoch 22/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8793 - loss: 0.3326
Epoch 23/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 748us/step - accuracy: 0.8640 - loss: 0.3424
Epoch 24/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8824 - loss: 0.3109
Epoch 25/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 742us/step - accuracy: 0.8697 - loss: 0.3198
Epoch 26/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy: 0.8812 - loss: 0.3253
Epoch 27/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 929us/step - accuracy: 0.8675 - loss: 0.3476
Epoch 28/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 754us/step - accuracy: 0.8745 - loss: 0.3413
Epoch 29/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 787us/step - accuracy: 0.8768 - loss: 0.3348
Epoch 30/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8814 - loss: 0.3388
Epoch 31/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 752us/step - accuracy: 0.8779 - loss: 0.3162
Epoch 32/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8776 - loss: 0.3308
Epoch 33/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.8851 - loss: 0.3147
Epoch 34/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.8802 - loss: 0.3320
Epoch 35/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 919us/step - accuracy: 0.8735 - loss: 0.3427
Epoch 36/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8866 - loss: 0.3065
Epoch 37/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8808 - loss: 0.3255
Epoch 38/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8834 - loss: 0.3151
Epoch 39/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/step - accuracy: 0.8747 - loss: 0.3149
Epoch 40/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8792 - loss: 0.3214
Epoch 41/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 789us/step - accuracy: 0.8769 - loss: 0.3435
Epoch 42/50
```

```
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 916us/step - accuracy: 0.8839 - loss: 0.3074
Epoch 43/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.8861 - loss: 0.2952
Epoch 44/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8828 - loss: 0.3259
Epoch 45/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8773 - loss: 0.3228
Epoch 46/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.8776 - loss: 0.3201
Epoch 47/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.8743 - loss: 0.3317
Epoch 48/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 919us/step - accuracy: 0.8881 - loss: 0.3041
Epoch 49/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.8780 - loss: 0.3134
Epoch 50/50
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 729us/step - accuracy: 0.8875 - loss: 0.3107
```

Out[54]:

```
<keras.src.callbacks.history.History at 0x1c028da1f90>
```

In [55]:

```
T=model.predict(x_test)
T
```

```
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

Out[55]:

```
array([[0.8194479 ],
       [0.16767004],
       [0.50828475],
       ...,
       [0.03387482],
       [0.8636771 ],
       [0.51185   ]], dtype=float32)
```

In [56]:

```
pred=[]
```

In [57]:
```
for i in T:
    if i>.5:
        pred.append(1)
    else:
        pred.append(0)
```

In [58]:
```
pred
```

Out[58]:
```
[1,
 0,
 1,
 1,
 0,
 0,
 0,
 1,
 0,
 1,
 0,
 0,
 0,
 1,
 1,
 0,
 0,
 0,
 0,
```

In [59]:
```
from sklearn.metrics import confusion_matrix,accuracy_score, classification_report

accuracy_score(y_test,pred)*100
```

Out[59]:
```
89.04515173945225
```

In [60]:
```
confusion_matrix(y_test,pred)
```

Out[60]:
```
array([[784,  58],
       [ 90, 419]], dtype=int64)
```

In [61]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.93      0.91       842
           1       0.88      0.82      0.85       509

    accuracy                           0.89      1351
   macro avg       0.89      0.88      0.88      1351
weighted avg       0.89      0.89      0.89      1351
```

In [62]:
```
train=model.evaluate(x_train,y_train)[1]*100
train
```

```
127/127 ━━━━━━━━━━━━━━━━━━━━ 0s 604us/step - accuracy: 0.8932 - loss: 0.3058
```

Out[62]: 88.69693875312805

In [63]:
```
test=model.evaluate(x_test,y_test)[1]*100
test
```

```
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 831us/step - accuracy: 0.8906 - loss: 0.3166
```

Out[63]: 89.04514908790588

In [ ]:

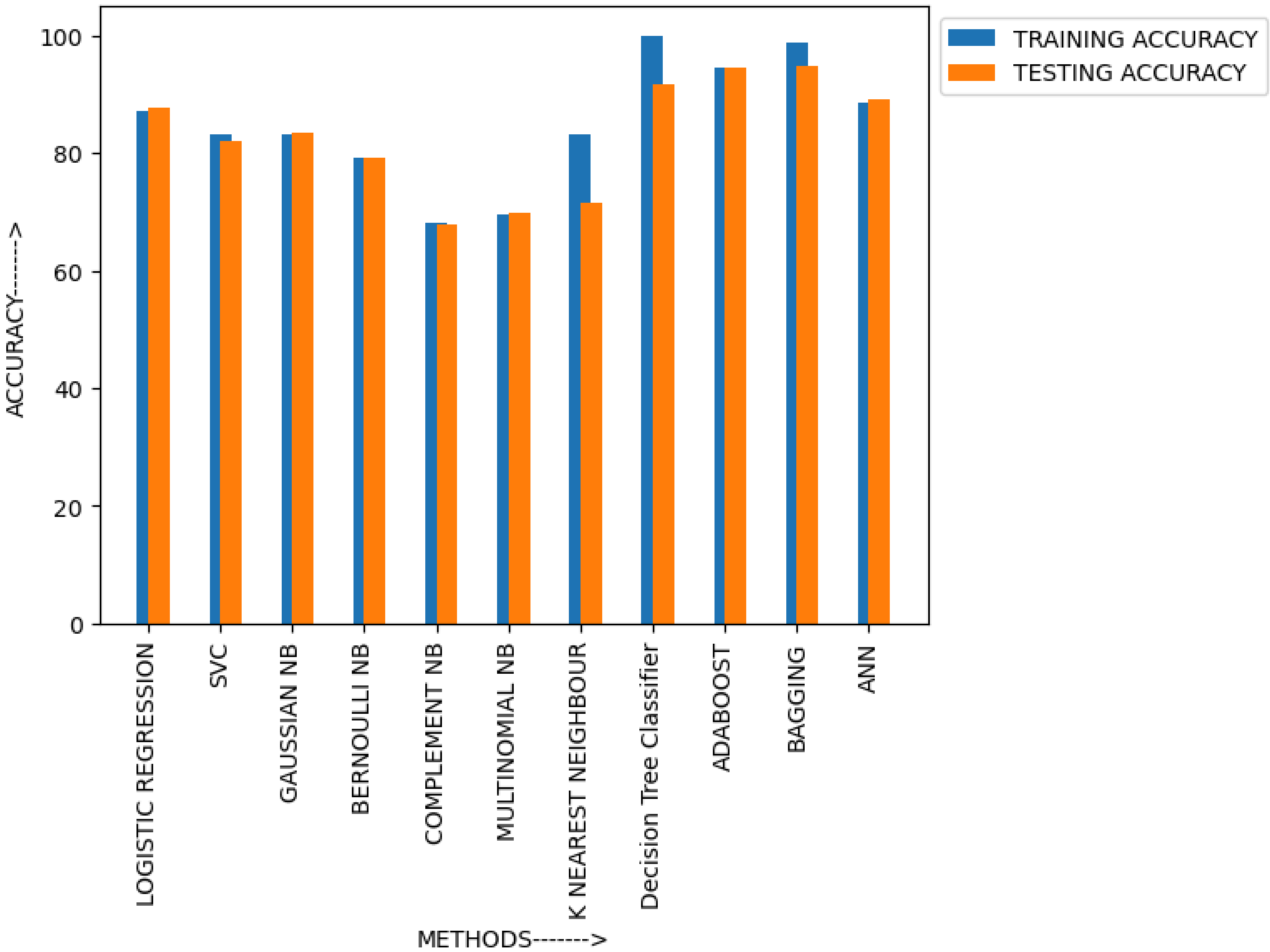
ACCURACY GRAPH:-

In [64]:
```
A={"METHODS":["LOGISTIC REGRESSION","SVC","GAUSSIAN NB","BERNOULLI NB","COMPLEMENT NB","MULTINOMIAL NB","K NEAREST NEI
A=pd.DataFrame(A)
A=np.around(A,2)
A
```

Out[64]:

	METHODS	TRAIN ACCURACY	TEST ACCURACY
0	LOGISTIC REGRESSION	87.24	87.71
1	SVC	83.22	82.09
2	GAUSSIAN NB	83.22	83.49
3	BERNOULLI NB	79.15	79.35
4	COMPLEMENT NB	68.07	67.95
5	MULTINOMIAL NB	69.69	69.95
6	K NEAREST NEIGHBOUR	83.24	71.50
7	Decision Tree Classifier	100.00	91.86
8	ADABOOST	94.55	94.52
9	BAGGING	98.82	94.74
10	ANN	88.70	89.05

In [65]:
```
plt.bar(A["METHODS"],A["TRAIN ACCURACY"],width=0.3,label="TRAINING ACCURACY")
plt.bar(A["METHODS"],A["TEST ACCURACY"],align="edge",width=0.3,label="TESTING ACCURACY")
plt.legend(bbox_to_anchor=[1,0,0,1])
plt.xlabel("METHODS------->")
plt.ylabel("ACCURACY------->")
plt.xticks(rotation=90)
plt.show()
```



CONCLUSION:

FROM THE ABOVE BAR CHART IT IS CLEAR THAT LOGISTIC REGRESSION AND ADABOAST ARE BEST

In [ ]:

```
```