

svc-knn-nb-dt-ensemble-learning-5

September 22, 2024

0.0.1 Why should I go for smart home devices?

Smart home devices gives convenience, energy savings, and good life with security. Making daily life more efficient and enjoyable

Target:- In this project discussion finding out

1. Less energy consumable devices
2. Their durability i.e. maximum life we call as device age
3. User preference with their efficiency
4. Conclusion from the above stu.

y. u ### Features (what we have):

1. Device type
2. Device usage hour per day
3. Energy consumption
4. Device age months
5. malfu

0.0.2 Approach inside:-

0.0.3 1. Less energy consumable devices =

- a. From the given data, I am going to analyze device usages hour per day of all devices for finding less energy per day hour usage device, I found that device having less usage hour per day which is 19.88% from all devices 2nd device is security system which consume 19.94% 3rd is light consume 20.00%, 4th is thermostat consume 20.09%, 5th is camera consume 20.

(So from all data I have found smart speaker 1108 entry data)

- b. From the given data, I am going to analyze device energy consumption of all devices, I found that smart speaker device having less consumption which is 4.87% from all devices Then 2nd device is light which consume 5.04%, 3rd is camera consume 5.08%, 4th is security system consume 5.1%, 5th is thermostat consume 5.14% (So from all data I have found smart speaker 1108 entry ### 2. Their durability i.e. maximum life we call as device age (which is depend on their malfunction incident)
- c. From the given data, I am going to analyze device age months and malfunction incident of all devices,
- I. I found that light device having less malfunction incident which is 2.02% but age months device is more less than other device, which is 29.91%

- II. But when compare with smart speaker which is having next to light malfunction incident is 2.03 % more than light but age months is more than other devices which is 30.59%

0.0.4 3. User preference with their efficiency

- a. From the given data, I am going to analyze user preferences and smart home efficiency of all devices,
- I. I found that device thermostat having more preference, which is 0.50 % by users and smart home efficient device 0.35 % but thermostat having more energy consumption having 5.14 % which is much more than all devices and per hour usages consumption which is 12.10% which is next to camer.
- II. But in case of thermostat malfunction incident is more than all devices, which is 2.14% and device age months is 30.54% which is next to smart speaker

0.0.5 4. Conclusion

1. From the above analysis and discussion I conclude that smart speaker is a smart efficient device than all device. 2 As comparing with age and malfunction devise I found light having less defective device and device age is less but smart speaker having more age than the light so 1st option is smart speaker and next is light
2. Thermostat having more age device but more malfunction incident which is costly and more energy consumption. I thought thermostat is not better option to smart efficient device
3. Sequence of smart efficient devices is
4. Smart speaker
5. Light
6. Security system
7. Thermostat
8. Camera....

data) %

malfunction incidence

```
[41]: import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
x=pd.read_csv(r"C:\Users\vidya\Downloads\smart_home_device_usage_data.csv")
x
```

```
[41]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	\
0	1	Smart Speaker	15.307188	1.961607	
1	2	Camera	19.973343	8.610689	
2	3	Security System	18.911535	2.651777	
3	4	Camera	7.011127	2.341653	
4	5	Camera	22.610684	4.859069	
...	

5398	5399	Thermostat	4.556314	5.871764
5399	5400	Lights	0.561856	1.555992
5400	5401	Smart Speaker	11.096236	7.677779
5401	5402	Security System	8.782169	7.467929
5402	5403	Thermostat	13.540381	9.043076

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
0	1	4	36	
1	1	0	29	
2	1	0	20	
3	0	3	15	
4	1	3	36	
...	
5398	1	0	28	
5399	1	4	24	
5400	0	0	42	
5401	0	2	28	
5402	0	0	30	

	SmartHomeEfficiency
0	1
1	1
2	1
3	0
4	1
...	...
5398	0
5399	0
5400	0
5401	1
5402	0

[5403 rows x 8 columns]

```
[42]: x.shape
```

```
[42]: (5403, 8)
```

```
[45]: x.columns
```

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

```
[77]: x["DeviceType"].unique()
```

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

```
[78]: x.describe()
```

```
[78]:
```

	UserID	UsageHoursPerDay	EnergyConsumption	UserPreferences \
count	5403.000000	5403.000000	5403.000000	5403.000000
mean	2702.000000	12.052992	5.054302	0.511753
std	1559.856083	6.714961	2.878941	0.499908
min	1.000000	0.501241	0.101562	0.000000
25%	1351.500000	6.297871	2.524968	0.000000
50%	2702.000000	11.903768	5.007047	1.000000
75%	4052.500000	17.791751	7.611912	1.000000
max	5403.000000	23.987326	9.998071	1.000000

	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
count	5403.000000	5403.000000	5403.000000
mean	2.066445	30.312234	0.376643
std	1.423291	16.990525	0.484589
min	0.000000	1.000000	0.000000
25%	1.000000	15.000000	0.000000
50%	2.000000	30.000000	0.000000
75%	3.000000	45.000000	1.000000
max	4.000000	59.000000	1.000000

```
[79]: o=x.groupby(["DeviceType"])[["EnergyConsumption"]].mean().reset_index().
      ↪sort_values(by="EnergyConsumption",ascending=True)
o
```

```
[79]:
```

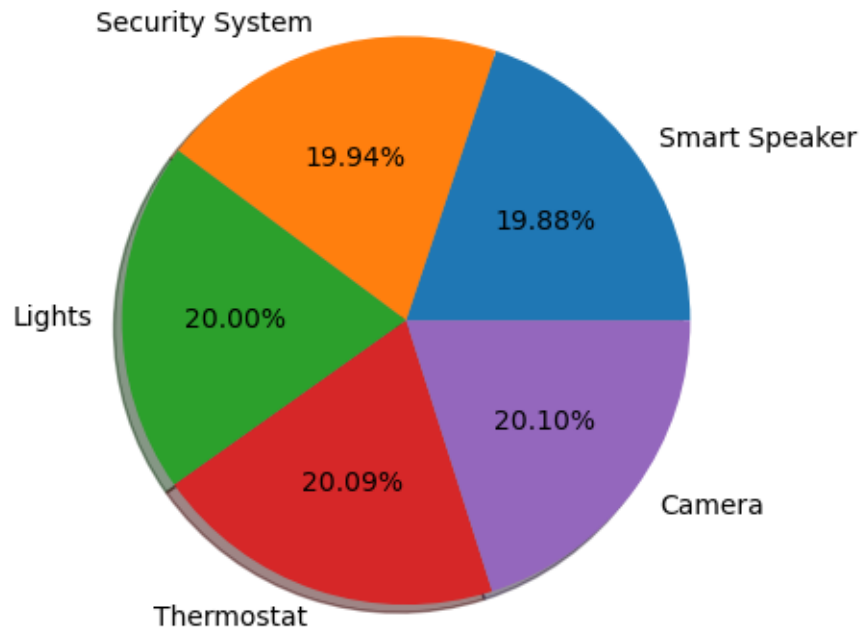
	DeviceType	EnergyConsumption
3	Smart Speaker	4.872036
1	Lights	5.044884
0	Camera	5.080666
2	Security System	5.138192
4	Thermostat	5.144356

```
[80]: o=x.groupby(["DeviceType"])[["UsageHoursPerDay"]].mean().reset_index().
      ↪sort_values(by="UsageHoursPerDay",ascending=True)
o
```

```
[80]:
```

	DeviceType	UsageHoursPerDay
3	Smart Speaker	11.979308
2	Security System	12.016149
1	Lights	12.052646
4	Thermostat	12.105753
0	Camera	12.113435

```
[81]: plt.pie(o["UsageHoursPerDay"], labels=o["DeviceType"], shadow=True, autopct="%.
      ↪2f%%")
      plt.show()
```



1 Device confirm = Smart speaker is having less usage house per day

```
[83]: i=x.loc[(x["DeviceType"]=="Smart Speaker")]
      i
```

```
[83]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption \
0	1	Smart Speaker	15.307188	1.961607
10	11	Smart Speaker	1.446710	7.723881
14	15	Smart Speaker	22.494525	1.468928
16	17	Smart Speaker	11.810032	8.228216
19	20	Smart Speaker	1.018554	1.344045
...
5383	5384	Smart Speaker	23.229510	4.061440
5389	5390	Smart Speaker	5.927129	0.364262
5390	5391	Smart Speaker	17.972310	4.712130
5395	5396	Smart Speaker	17.317435	8.839776
5400	5401	Smart Speaker	11.096236	7.677779

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
0	1	4	36	
10	0	3	54	
14	0	0	19	
16	1	2	3	
19	1	1	3	
...	
5383	0	1	39	
5389	0	1	44	
5390	0	0	40	
5395	1	0	13	
5400	0	0	42	

	SmartHomeEfficiency
0	1
10	0
14	1
16	1
19	1
...	...
5383	1
5389	0
5390	0
5395	0
5400	0

[1108 rows x 8 columns]

```
[84]: x.groupby(["DeviceType"])["MalfunctionIncidents"].mean().reset_index().
      ↪sort_values(by="MalfunctionIncidents",ascending=True)
```

```
[84]:   DeviceType  MalfunctionIncidents
1      Lights          2.021159
3  Smart Speaker          2.037906
2 Security System          2.048689
0      Camera          2.087193
4   Thermostat          2.140520
```

```
[85]: x.groupby(["DeviceType"])["DeviceAgeMonths"].mean().reset_index().
      ↪sort_values(by="DeviceAgeMonths",ascending=True)
```

```
[85]:   DeviceType  DeviceAgeMonths
1      Lights          29.912603
0      Camera          30.035422
2 Security System          30.485955
4   Thermostat          30.544755
```

3 Smart Speaker 30.593863

```
[86]: x.groupby(["DeviceType"])["UserPreferences"].mean().reset_index().
      ↪sort_values(by="UserPreferences",ascending=True)
```

```
[86]:
```

	DeviceType	UserPreferences
4	Thermostat	0.502406
2	Security System	0.503745
1	Lights	0.514259
0	Camera	0.518619
3	Smart Speaker	0.518953

```
[87]: x.groupby(["DeviceType"])["SmartHomeEfficiency"].mean().reset_index().
      ↪sort_values(by="SmartHomeEfficiency",ascending=True)
```

```
[87]:
```

	DeviceType	SmartHomeEfficiency
4	Thermostat	0.351299
2	Security System	0.375468
1	Lights	0.379945
0	Camera	0.386921
3	Smart Speaker	0.388087

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

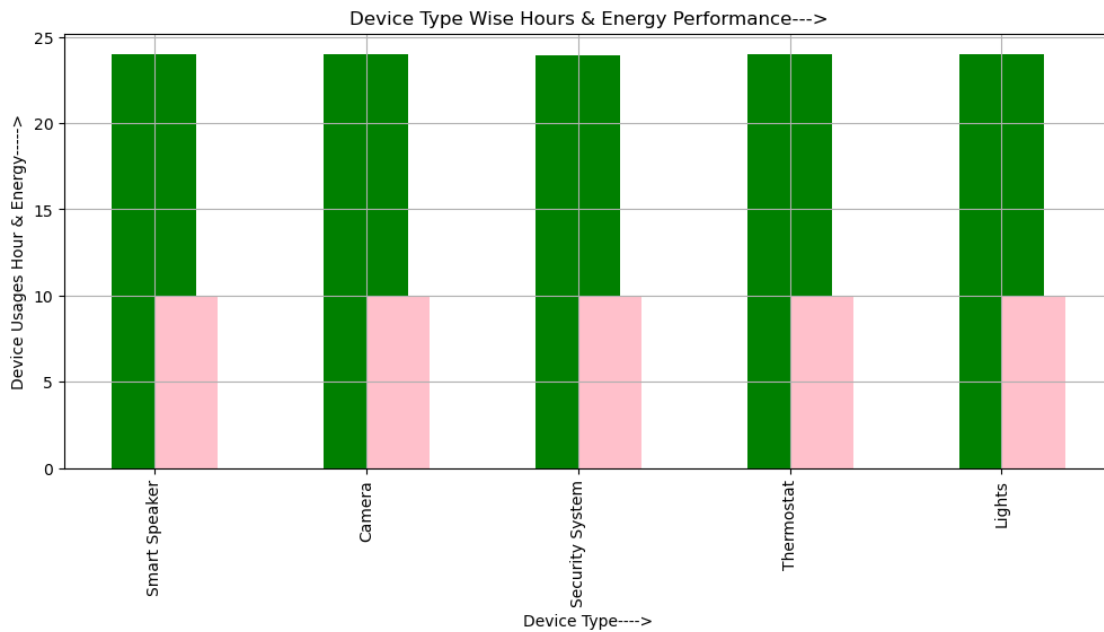
```
[88]: h=x.groupby(["DeviceType"]).agg({"UsageHoursPerDay":
      ↪["min","max"],"EnergyConsumption":["min","max"],"DeviceType":"count"}).
      ↪reset_index()
      h
```

```
[88]:
```

	DeviceType	UsageHoursPerDay		EnergyConsumption		
		min	max	min	max	\
0	Camera	0.505335	23.984732	0.113203	9.998071	
1	Lights	0.505664	23.967507	0.102385	9.996765	
2	Security System	0.509642	23.945298	0.101562	9.988564	
3	Smart Speaker	0.509436	23.987326	0.109336	9.995101	
4	Thermostat	0.501241	23.981372	0.113067	9.987115	

DeviceType		
	count	
0	1101	
1	1087	
2	1068	
3	1108	

```
[89]: plt.figure(figsize=(12,5))
plt.bar(x["DeviceType"],x["UsageHoursPerDay"],color="g",width=0.
↪4,align="center",label="Usages Hour Day")
plt.bar(x["DeviceType"],x["EnergyConsumption"],color="pink",width=0.
↪3,align="edge",label="Energy")
plt.xlabel("Device Type---->")
plt.ylabel("Device Usages Hour & Energy----->")
plt.xticks(rotation=90)
plt.title("Device Type Wise Hours & Energy Performance--->")
plt.grid()
plt.show()
```



2 Device Type wise Usages Hour & Energy confirm = Camera

```
[91]: t=x.loc[(x["DeviceType"]=="Camera")]
t.loc[(t["UsageHoursPerDay"].between(0,24))]
```

```
[91]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	UserPreferences	\
1	2	Camera	19.973343	8.610689	1	
3	4	Camera	7.011127	2.341653	0	
4	5	Camera	22.610684	4.859069	1	
9	10	Camera	17.468553	7.212756	1	
12	13	Camera	12.632658	7.169462	1	

...
5365	5366	Camera	9.616876	5.277574	0
5377	5378	Camera	13.517631	1.438874	1
5379	5380	Camera	7.209839	3.493130	0
5391	5392	Camera	13.001725	0.671065	1
5396	5397	Camera	19.301279	0.792446	1

	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
1	0	29	1
3	3	15	0
4	3	36	1
9	4	58	0
12	1	9	1
...
5365	1	29	1
5377	0	58	0
5379	2	35	1
5391	1	30	0
5396	1	33	1

[1101 rows x 8 columns]

```
[92]: t.loc[(x["EnergyConsumption"].between(0,10))]
```

```
[92]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	UserPreferences	\
1	2	Camera	19.973343	8.610689	1	
3	4	Camera	7.011127	2.341653	0	
4	5	Camera	22.610684	4.859069	1	
9	10	Camera	17.468553	7.212756	1	
12	13	Camera	12.632658	7.169462	1	
...	
5365	5366	Camera	9.616876	5.277574	0	
5377	5378	Camera	13.517631	1.438874	1	
5379	5380	Camera	7.209839	3.493130	0	
5391	5392	Camera	13.001725	0.671065	1	
5396	5397	Camera	19.301279	0.792446	1	

	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
1	0	29	1
3	3	15	0
4	3	36	1
9	4	58	0
12	1	9	1
...
5365	1	29	1
5377	0	58	0
5379	2	35	1

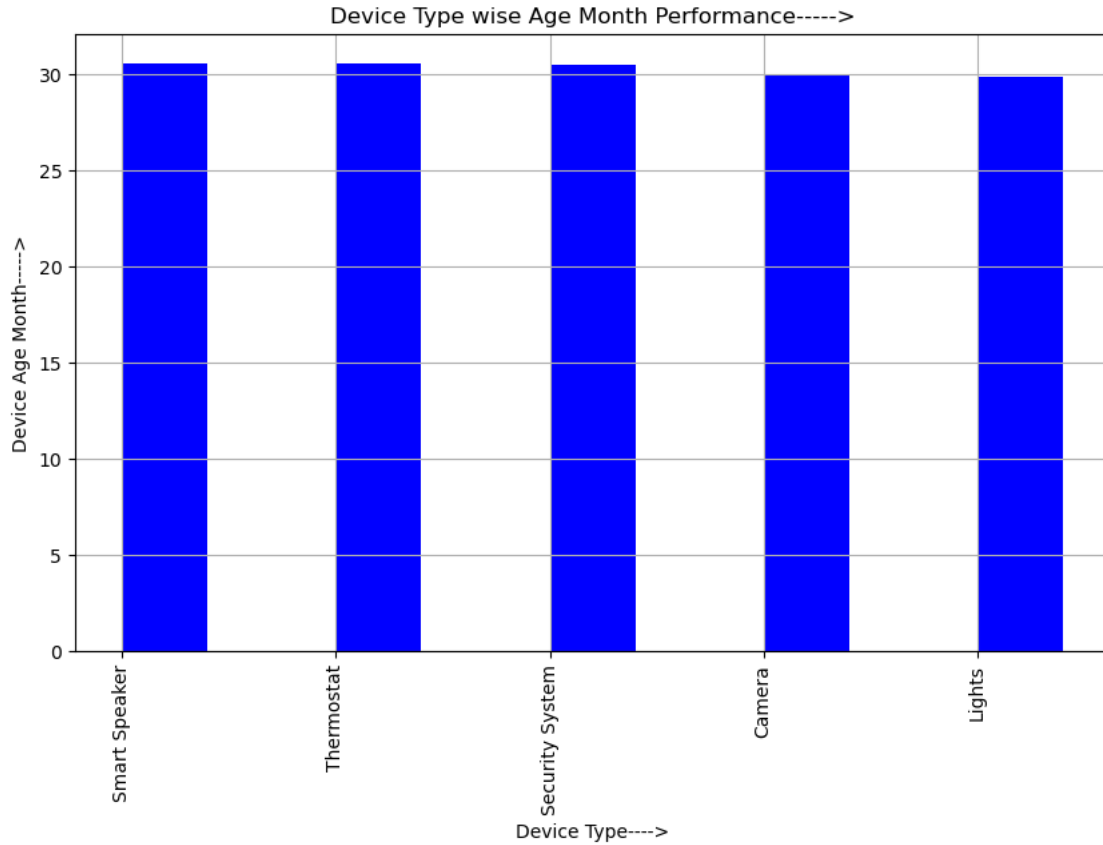
5391	1	30	0
5396	1	33	1

[1101 rows x 8 columns]

```
[93]: m=x.groupby(["DeviceType"])[["DeviceAgeMonths"]].mean().reset_index().
      ↪sort_values(by="DeviceAgeMonths",ascending=False)
      m
```

```
[93]:      DeviceType  DeviceAgeMonths
3    Smart Speaker      30.593863
4      Thermostat      30.544755
2  Security System      30.485955
0         Camera      30.035422
1         Lights      29.912603
```

```
[94]: plt.figure(figsize=(10,6))
      plt.bar(m["DeviceType"],m["DeviceAgeMonths"],color="b",width=0.
      ↪4,align="edge",label="Device Age Month")
      plt.title("Device Type wise Age Month Performance----->")
      plt.xlabel("Device Type----->")
      plt.ylabel("Device Age Month----->")
      plt.grid()
      plt.xticks(rotation=90)
      plt.show()
```



3 Devise Type wise Device Age Month confirm = 30 % MAX

```
[96]: d=x.loc[(x["DeviceAgeMonths"]==30)]
d
```

```
[96]:   UserID    DeviceType  UsageHoursPerDay  EnergyConsumption  \
13      14      Thermostat         14.145163           7.385760
56      57  Smart Speaker         12.799932           6.377145
65      66  Smart Speaker          1.702030           4.702013
136     137  Smart Speaker          9.884316           8.494920
152     153      Lights         13.391828           9.339436
...     ...           ...           ...           ...
5170    5171  Smart Speaker         21.185917           8.206446
5274    5275      Thermostat         13.368882           7.631937
5320    5321      Thermostat         20.996806           6.489874
5391    5392      Camera          13.001725           0.671065
5402    5403      Thermostat         13.540381           9.043076
```

```
UserPreferences  MalfunctionIncidents  DeviceAgeMonths  \
```

13	0	2	30
56	1	3	30
65	0	1	30
136	0	2	30
152	0	3	30
...
5170	0	4	30
5274	1	3	30
5320	0	3	30
5391	1	1	30
5402	0	0	30

	SmartHomeEfficiency
13	0
56	1
65	0
136	0
152	0
...	...
5170	0
5274	1
5320	0
5391	0
5402	0

[97 rows x 8 columns]

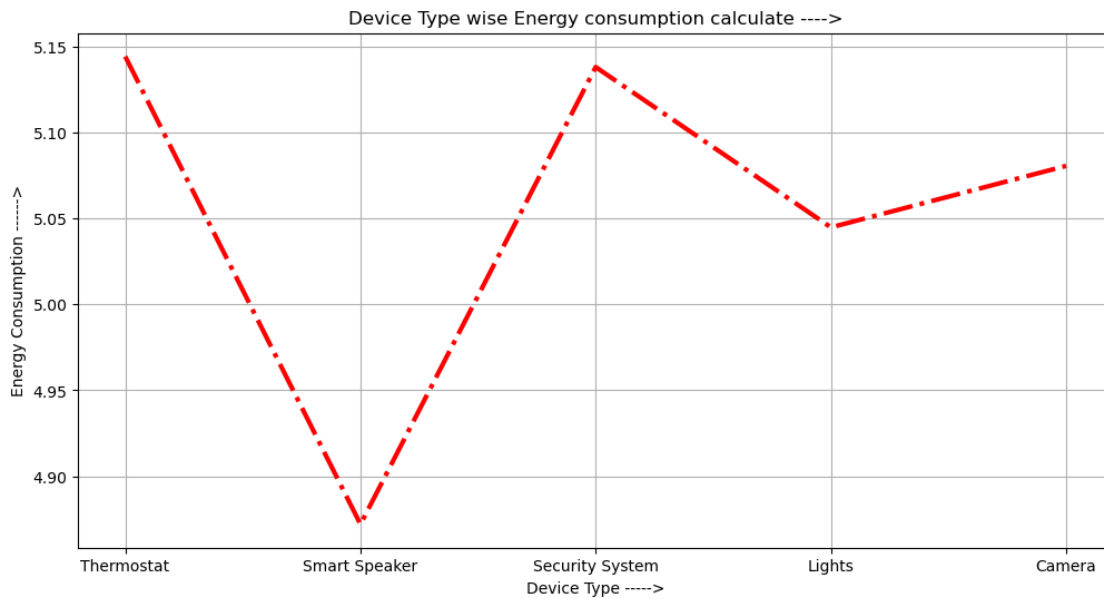
```
[97]: z=x.groupby(["DeviceType"])[["EnergyConsumption"]].mean().reset_index().
      ↪sort_values(by="DeviceType",ascending=False)
z
```

```
[97]:      DeviceType  EnergyConsumption
4      Thermostat      5.144356
3    Smart Speaker      4.872036
2 Security System      5.138192
1         Lights      5.044884
0         Camera      5.080666
```

3.1 Device Type Final = Camera having Less Energy Consumption

```
[99]: plt.figure(figsize=(12,6))
plt.plot(z["DeviceType"],z["EnergyConsumption"],color="r",lw=3,ls="--",
      ↪",markersize=6,label="Energy Consu")
plt.title("Device Type wise Energy consumption calculate ---->")
plt.xlabel("Device Type ----->")
plt.ylabel("Energy Consumption ----->")
plt.grid()
```

```
plt.show()
```



```
[100]: x.groupby(["DeviceType"])[["UserPreferences", "UsageHoursPerDay"]].mean().
        ↪reset_index()
```

```
[100]:
```

	DeviceType	UserPreferences	UsageHoursPerDay
0	Camera	0.518619	12.113435
1	Lights	0.514259	12.052646
2	Security System	0.503745	12.016149
3	Smart Speaker	0.518953	11.979308
4	Thermostat	0.502406	12.105753

3.2 device type Final = Camera having more user Preferences

```
[102]: x.groupby(["DeviceType"])[["MalfunctionIncidents", "DeviceAgeMonths"]].mean().
        ↪reset_index()
```

```
[102]:
```

	DeviceType	MalfunctionIncidents	DeviceAgeMonths
0	Camera	2.087193	30.035422
1	Lights	2.021159	29.912603
2	Security System	2.048689	30.485955
3	Smart Speaker	2.037906	30.593863
4	Thermostat	2.140520	30.544755

3.3 Device Type confirm =Smart Speaker because device Age month more

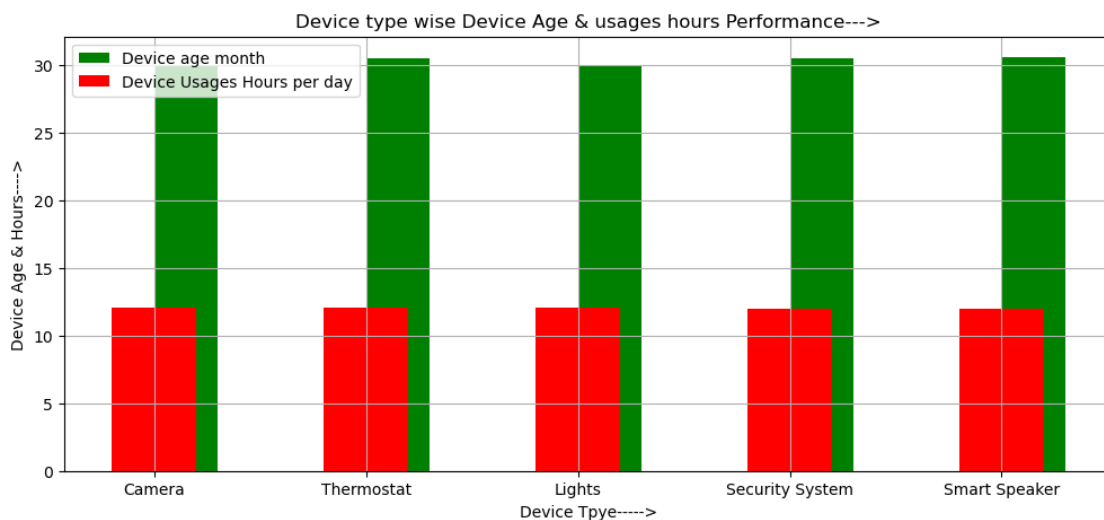
```
[104]: s=x.groupby(["DeviceType"]).agg({"DeviceAgeMonths":"mean","UsageHoursPerDay":
    ↪ "mean"}).reset_index().sort_values(by="UsageHoursPerDay",ascending=False)
s
```

```
[104]:
```

	DeviceType	DeviceAgeMonths	UsageHoursPerDay
0	Camera	30.035422	12.113435
4	Thermostat	30.544755	12.105753
1	Lights	29.912603	12.052646
2	Security System	30.485955	12.016149
3	Smart Speaker	30.593863	11.979308

3.3.1 Smart Speaker Final = because device age month more & Usages Hour Per Day Less

```
[106]: plt.figure(figsize=(12,5))
plt.bar(s["DeviceType"],s["DeviceAgeMonths"],color="g",width=0.
    ↪ 3,align="edge",label="Device age month")
plt.bar(s["DeviceType"],s["UsageHoursPerDay"],color="r",width=0.
    ↪ 4,align="center",label="Device Usages Hours per day")
plt.title("Device type wise Device Age & usages hours Performance---->")
plt.xlabel("Device Tpye----->")
plt.ylabel("Device Age & Hours----->")
plt.grid()
plt.legend()
plt.show()
```



```
[107]: d.loc[(x["DeviceAgeMonths"]==31)]
```

```
[107]: Empty DataFrame
       Columns: [UserID, DeviceType, UsageHoursPerDay, EnergyConsumption,
       UserPreferences, MalfunctionIncidents, DeviceAgeMonths, SmartHomeEfficiency]
       Index: []
```

```
[108]: x["MalfunctionIncidents"].unique()
```

```
[108]: array([4, 0, 3, 2, 1], dtype=int64)
```

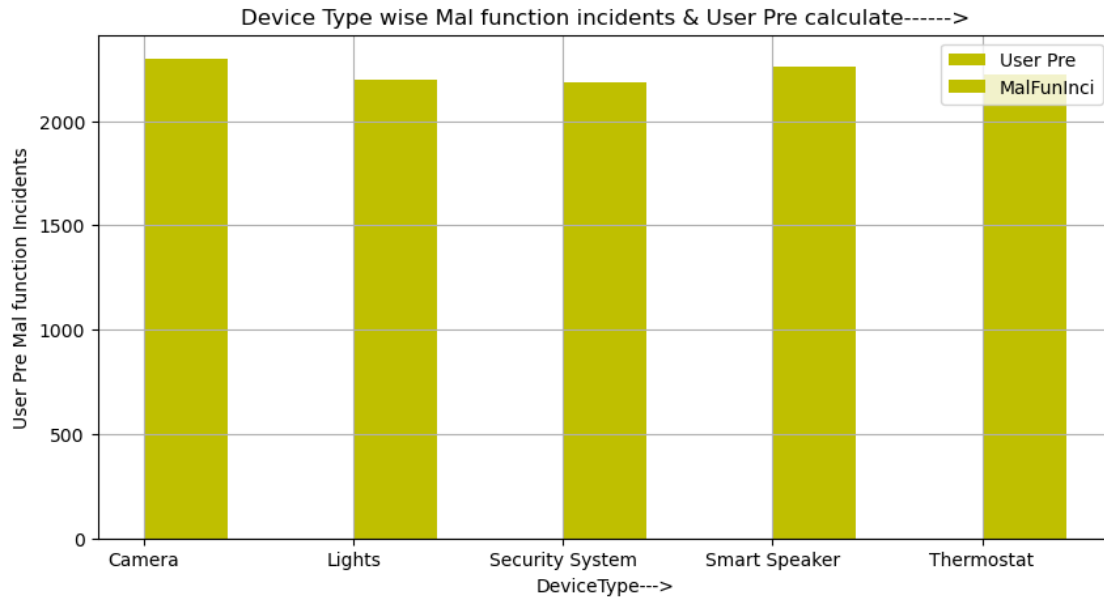
```
[109]: a=x.groupby(["DeviceType"])[["UserPreferences","MalfunctionIncidents"]].sum().
       ↪reset_index()
       a
```

```
[109]:
```

	DeviceType	UserPreferences	MalfunctionIncidents
0	Camera	571	2298
1	Lights	559	2197
2	Security System	538	2188
3	Smart Speaker	575	2258
4	Thermostat	522	2224

4 device Final = Thermostat because MalfunctionIncidents are Less

```
[111]: plt.figure(figsize=(10,5))
       plt.bar(a["DeviceType"],a["UserPreferences"],color="y",width=0.
       ↪4,align="edge",label="User Pre")
       plt.bar(a["DeviceType"],a["MalfunctionIncidents"],color="y",width=0.
       ↪4,align="edge",label="MalFunInci")
       plt.title("Device Type wise Mal function incidents & User Pre calculate----->")
       plt.xlabel("DeviceType---->")
       plt.ylabel("User Pre Mal function Incidents")
       plt.legend()
       plt.grid()
       plt.show()
```



```
[112]: y=x.loc[(x["DeviceType"]=="Thermostat")]
y.loc[(x["MalfunctionIncidents"].between(0,2))]
```

```
[112]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	\
5	6	Thermostat	3.422127	5.038625	
13	14	Thermostat	14.145163	7.385760	
15	16	Thermostat	16.297891	9.665162	
27	28	Thermostat	9.452368	0.281722	
43	44	Thermostat	18.933529	7.707831	
...	
5359	5360	Thermostat	1.616667	9.457098	
5375	5376	Thermostat	7.856096	1.091419	
5388	5389	Thermostat	13.472427	6.728036	
5398	5399	Thermostat	4.556314	5.871764	
5402	5403	Thermostat	13.540381	9.043076	

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
5	1	0	3	
13	0	2	30	
15	1	0	38	
27	1	0	47	
43	0	0	18	
...	
5359	1	0	54	
5375	0	2	8	
5388	1	2	2	
5398	1	0	28	

5402	0	0	30
------	---	---	----

	SmartHomeEfficiency
5	1
13	0
15	1
27	1
43	0
...	...
5359	0
5375	1
5388	1
5398	0
5402	0

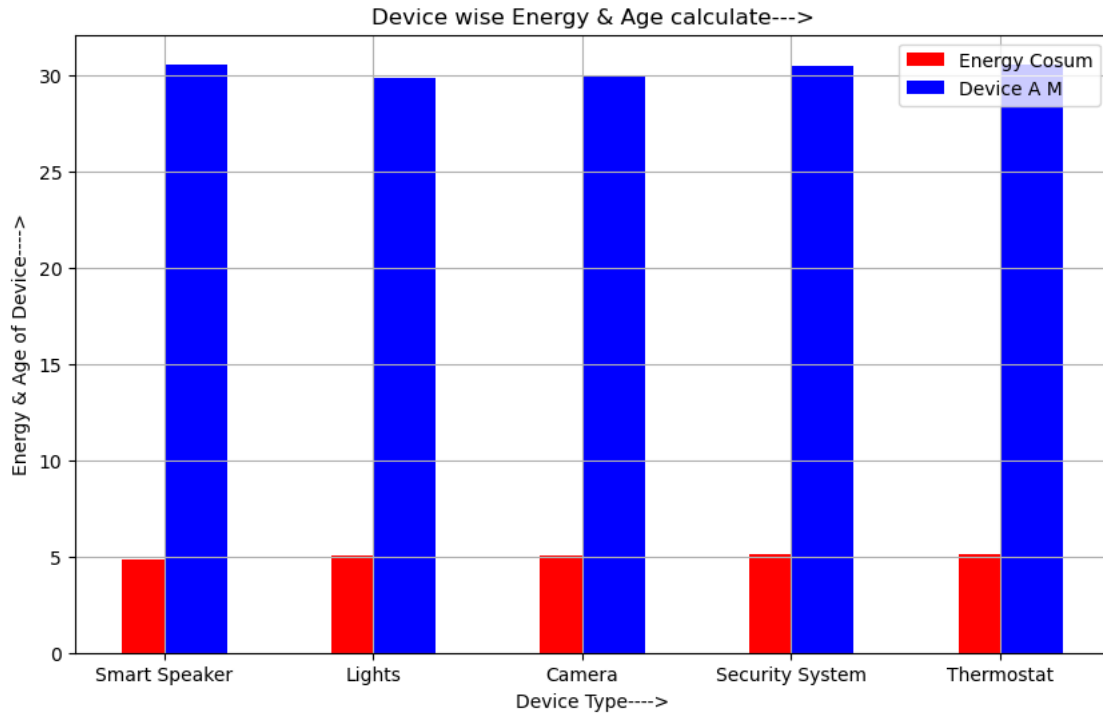
[571 rows x 8 columns]

```
[113]: ss=x.groupby(["DeviceType"])[["EnergyConsumption","DeviceAgeMonths"]].mean().
        ↪reset_index().sort_values(by="EnergyConsumption",ascending=True)
ss
```

```
[113]:
```

	DeviceType	EnergyConsumption	DeviceAgeMonths
3	Smart Speaker	4.872036	30.593863
1	Lights	5.044884	29.912603
0	Camera	5.080666	30.035422
2	Security System	5.138192	30.485955
4	Thermostat	5.144356	30.544755

```
[114]: plt.figure(figsize=(10,6))
plt.bar(ss["DeviceType"],ss["EnergyConsumption"],color="r",width=0.
        ↪4,align="center",label="Energy Cosum")
plt.bar(ss["DeviceType"],ss["DeviceAgeMonths"],color="b",width=0.
        ↪3,align="edge",label="Device A M")
plt.xlabel("Device Type---->")
plt.ylabel("Energy & Age of Device---->")
plt.title("Device wise Energy & Age calculate---->")
plt.legend()
plt.grid()
plt.show()
```



5 Device Type Final = Lights because Energy Consumption is Less

```
[116]: q=x.groupby(["DeviceType","DeviceAgeMonths"])[["EnergyConsumption"]].mean().
        ↪reset_index().sort_values(by="EnergyConsumption",ascending=True)
q
```

```
[116]:
```

	DeviceType	DeviceAgeMonths	EnergyConsumption
133	Security System	16	2.996148
105	Lights	47	3.068667
221	Smart Speaker	45	3.259841
162	Security System	45	3.307480
93	Lights	35	3.337385
..
247	Thermostat	12	6.579902
76	Lights	18	6.587448
124	Security System	7	6.652444
33	Camera	34	6.795095
242	Thermostat	7	6.838405

[295 rows x 3 columns]

```
[117]: y=x.loc[(x["DeviceType"]=="Security System")]
      j=y.loc[(y["DeviceAgeMonths"]==16)]
      j
```

```
[117]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	\
154	155	Security System	12.710874	6.960421	
167	168	Security System	16.226647	3.785228	
244	245	Security System	0.973239	1.745385	
689	690	Security System	3.305454	4.968932	
1503	1504	Security System	4.413655	0.535319	
2001	2002	Security System	12.859745	1.262875	
2306	2307	Security System	1.354008	0.819555	
3602	3603	Security System	12.067080	1.946923	
3821	3822	Security System	20.882834	4.102201	
3910	3911	Security System	7.864141	4.881238	
3985	3986	Security System	2.166530	0.948076	
4177	4178	Security System	17.433781	0.233096	
4204	4205	Security System	15.814475	4.788043	
4548	4549	Security System	3.422115	1.601503	
5037	5038	Security System	1.869984	5.554348	
5273	5274	Security System	6.945153	3.805218	

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
154	0	2	16	
167	1	1	16	
244	1	1	16	
689	0	4	16	
1503	1	2	16	
2001	1	2	16	
2306	1	0	16	
3602	1	2	16	
3821	1	2	16	
3910	1	0	16	
3985	1	0	16	
4177	1	1	16	
4204	0	4	16	
4548	1	4	16	
5037	0	1	16	
5273	1	2	16	

	SmartHomeEfficiency
154	0
167	1
244	1
689	0
1503	1
2001	1

2306	1
3602	1
3821	1
3910	1
3985	1
4177	1
4204	0
4548	1
5037	0
5273	0

6 Device Type confirm = Security System because low Energy Consumption

```
[119]: y=pd.get_dummies(x["DeviceType"],drop_first=False).replace({True:1,False:0})
y
```

```
[119]:
```

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

[5403 rows x 5 columns]

```
[120]: F=pd.concat([x,y],axis=1)
F
```

```
[120]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	\
0	1	Smart Speaker	15.307188	1.961607	
1	2	Camera	19.973343	8.610689	
2	3	Security System	18.911535	2.651777	
3	4	Camera	7.011127	2.341653	
4	5	Camera	22.610684	4.859069	
...	
5398	5399	Thermostat	4.556314	5.871764	
5399	5400	Lights	0.561856	1.555992	
5400	5401	Smart Speaker	11.096236	7.677779	
5401	5402	Security System	8.782169	7.467929	

5402	5403	Thermostat	13.540381	9.043076
------	------	------------	-----------	----------

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
0	1	4	36	
1	1	0	29	
2	1	0	20	
3	0	3	15	
4	1	3	36	
...	
5398	1	0	28	
5399	1	4	24	
5400	0	0	42	
5401	0	2	28	
5402	0	0	30	

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

	Thermostat
0	0
1	0
2	0
3	0
4	0
...	...
5398	1
5399	0
5400	0
5401	0
5402	1

[5403 rows x 13 columns]

```
[121]: F.drop(columns="DeviceType", inplace=True)
F
```

```
[121]:
```

	UserID	UsageHoursPerDay	EnergyConsumption	UserPreferences	\
0	1	15.307188	1.961607	1	
1	2	19.973343	8.610689	1	
2	3	18.911535	2.651777	1	
3	4	7.011127	2.341653	0	
4	5	22.610684	4.859069	1	
...	
5398	5399	4.556314	5.871764	1	
5399	5400	0.561856	1.555992	1	
5400	5401	11.096236	7.677779	0	
5401	5402	8.782169	7.467929	0	
5402	5403	13.540381	9.043076	0	

	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency	Camera	\
0	4	36	1	0	
1	0	29	1	1	
2	0	20	1	0	
3	3	15	0	1	
4	3	36	1	1	
...	
5398	0	28	0	0	
5399	4	24	0	0	
5400	0	42	0	0	
5401	2	28	1	0	
5402	0	30	0	0	

	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 x 12 columns]

```
[122]: F.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5403 entries, 0 to 5402
Data columns (total 12 columns):
#   Column              Non-Null Count  Dtype
#   ...
```

```

---  -----
0  UserID          5403 non-null  int64
1  UsageHoursPerDay 5403 non-null  float64
2  EnergyConsumption 5403 non-null  float64
3  UserPreferences  5403 non-null  int64
4  MalfunctionIncidents 5403 non-null  int64
5  DeviceAgeMonths  5403 non-null  int64
6  SmartHomeEfficiency 5403 non-null  int64
7  Camera           5403 non-null  int64
8  Lights            5403 non-null  int64
9  Security System   5403 non-null  int64
10 Smart Speaker     5403 non-null  int64
11 Thermostat        5403 non-null  int64
dtypes: float64(2), int64(10)
memory usage: 506.7 KB

```

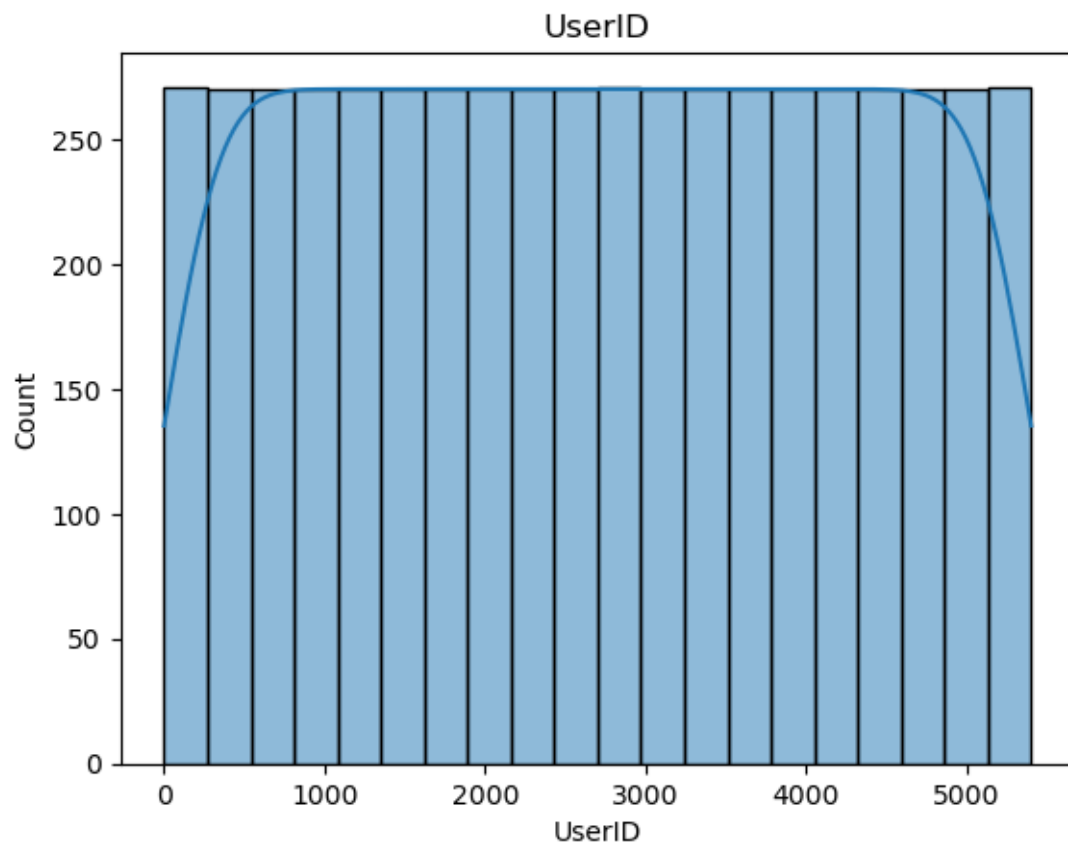
```
[123]: F.columns
```

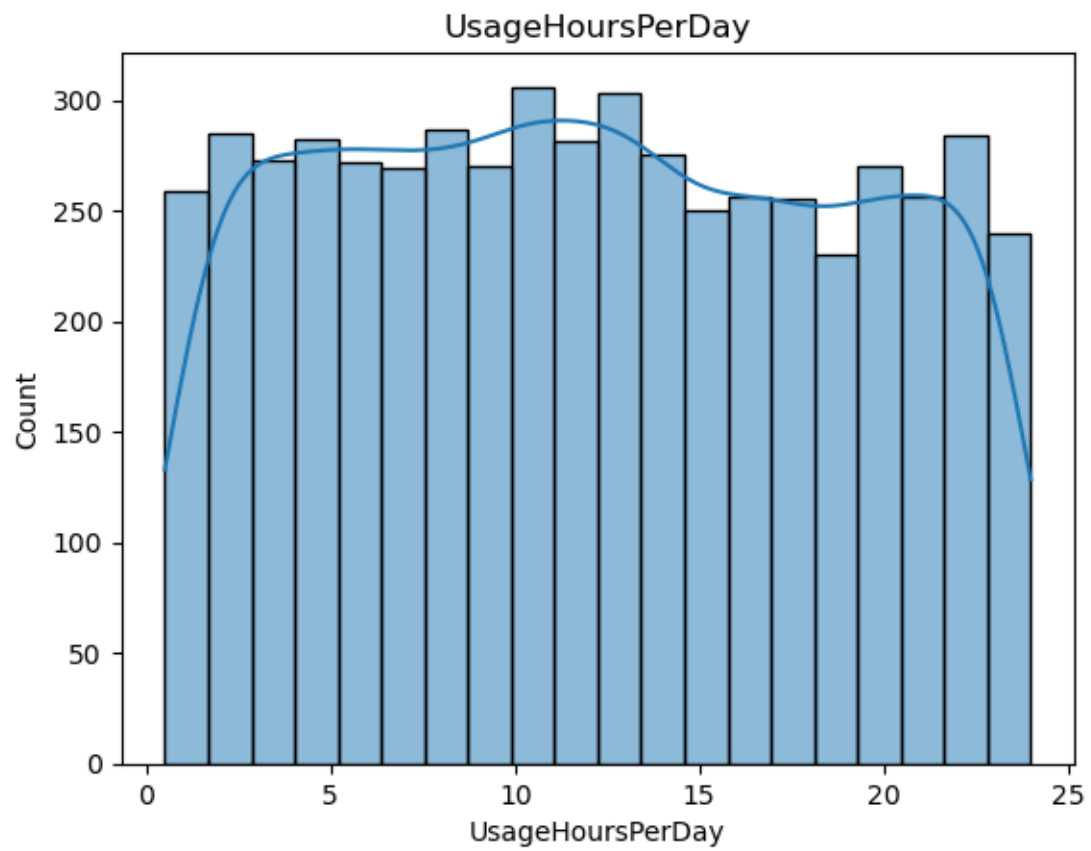
```
[123]: Index(['UserID', 'UsageHoursPerDay', 'EnergyConsumption', 'UserPreferences',
            'MalfunctionIncidents', 'DeviceAgeMonths', 'SmartHomeEfficiency',
            'Camera', 'Lights', 'Security System', 'Smart Speaker', 'Thermostat'],
            dtype='object')
```

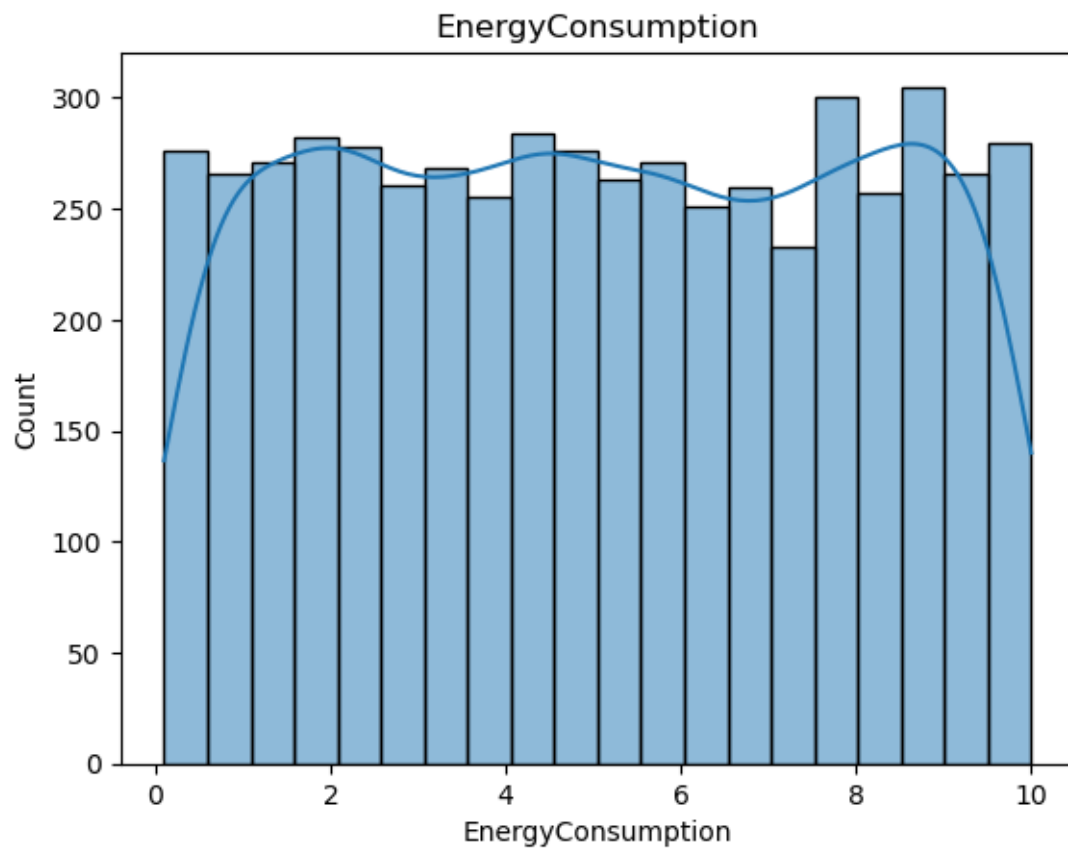
```
[124]: F["UserID"].unique()
```

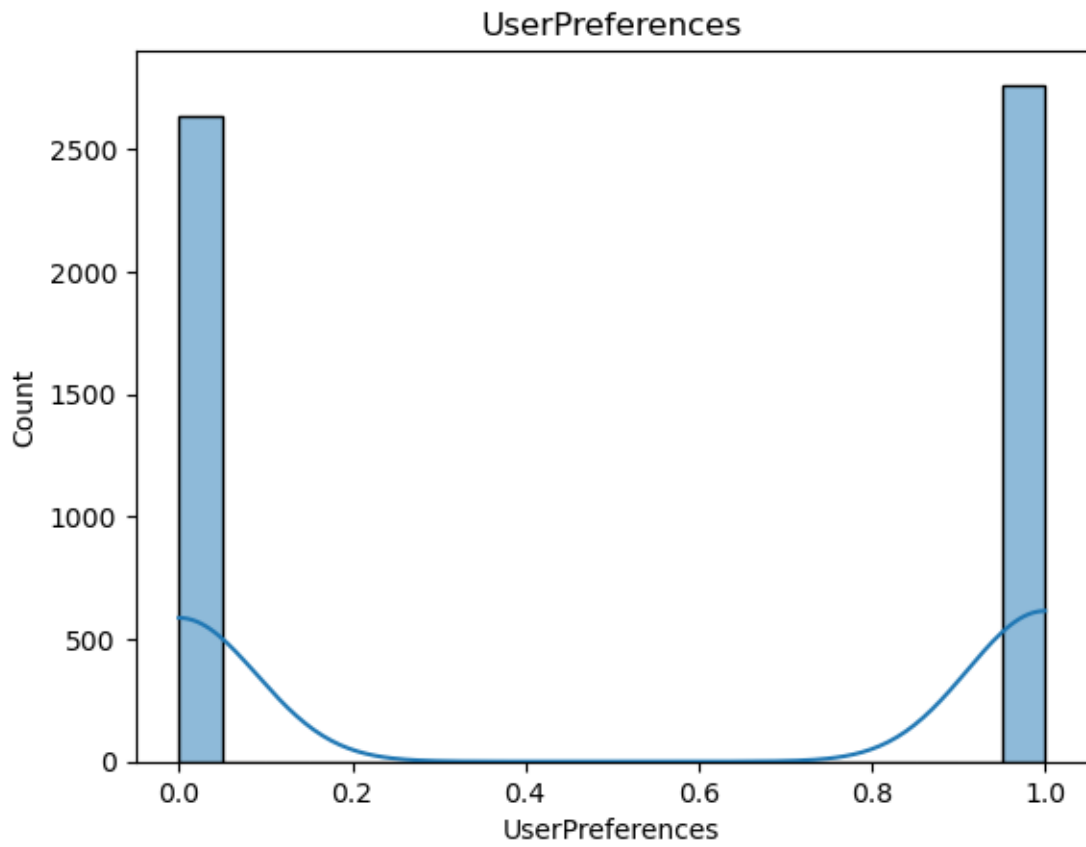
```
[124]: array([ 1,  2,  3, ..., 5401, 5402, 5403], dtype=int64)
```

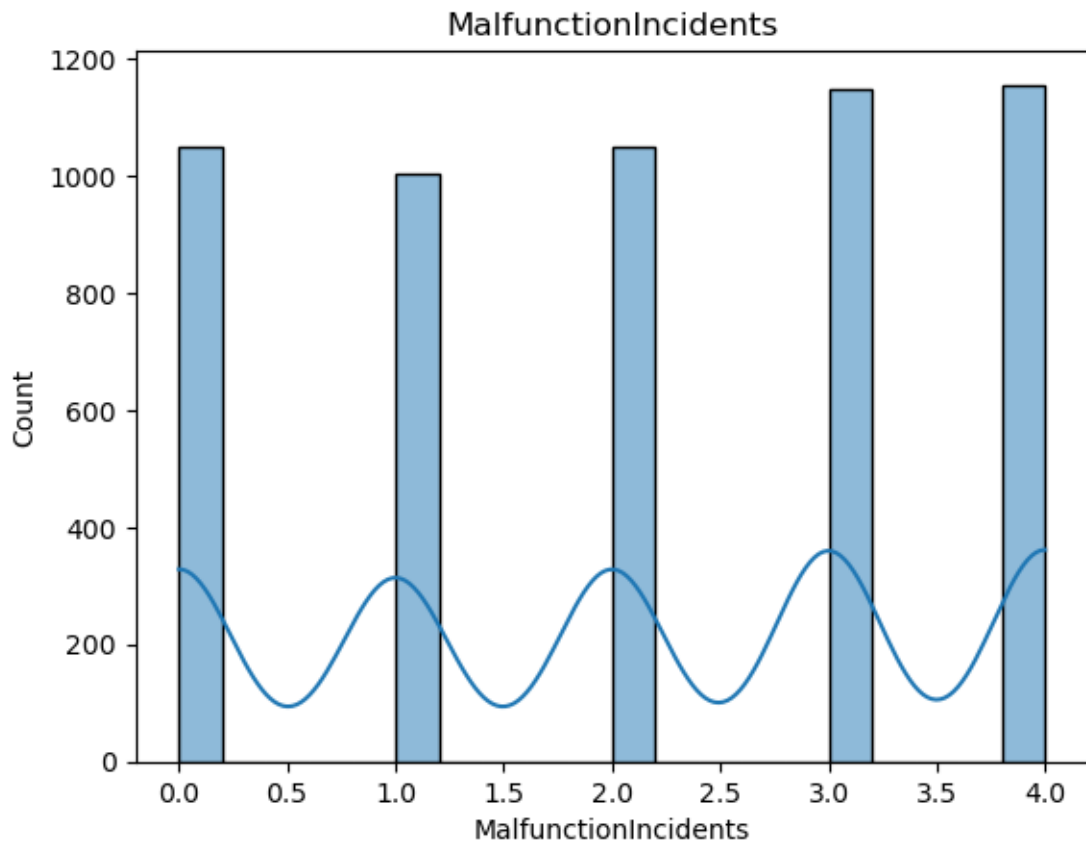
```
[125]: import matplotlib.pyplot as plt
import seaborn as sns
for i in F.columns:
    sns.histplot(F[i], bins=20, kde=True)
    plt.title(i)
    plt.show()
```

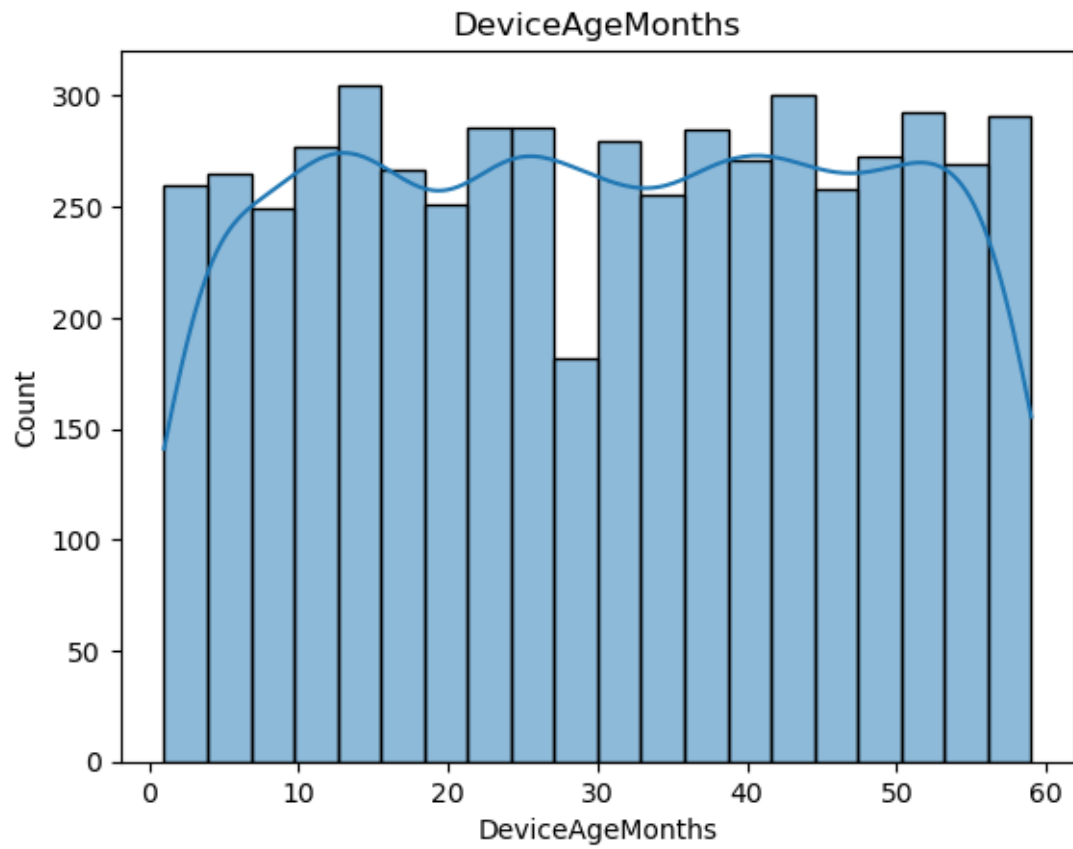


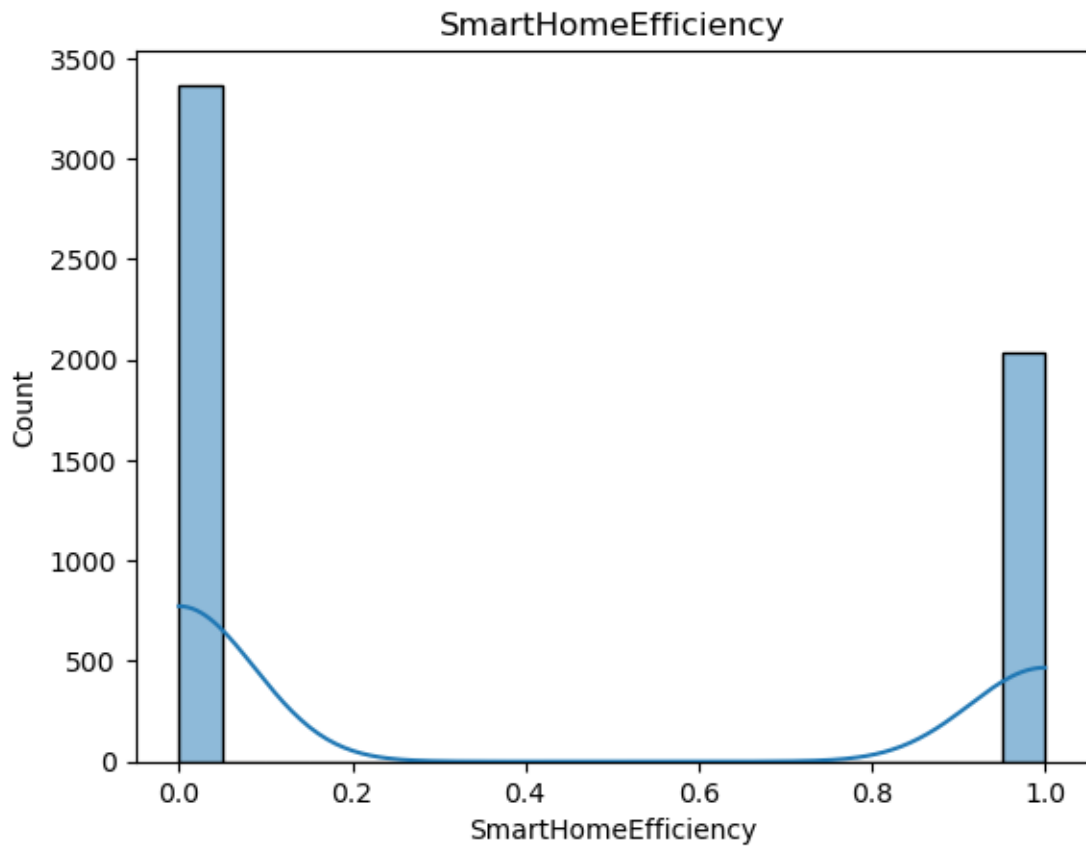


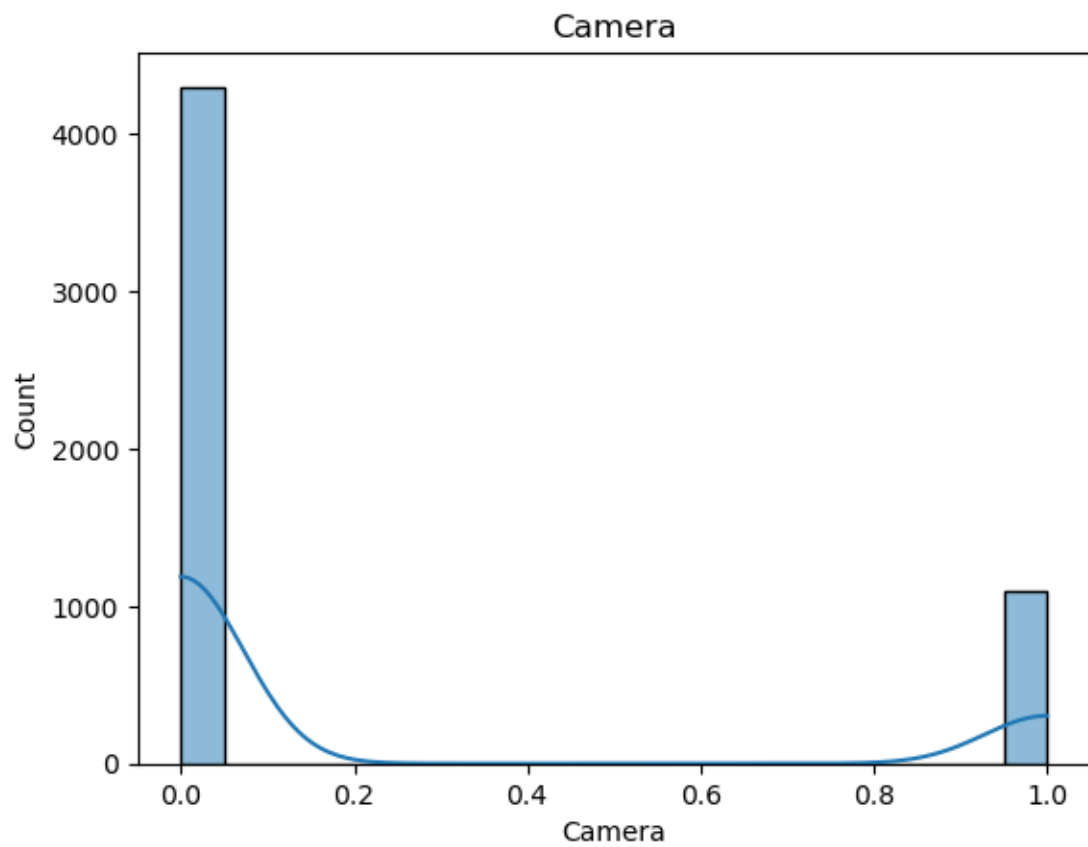


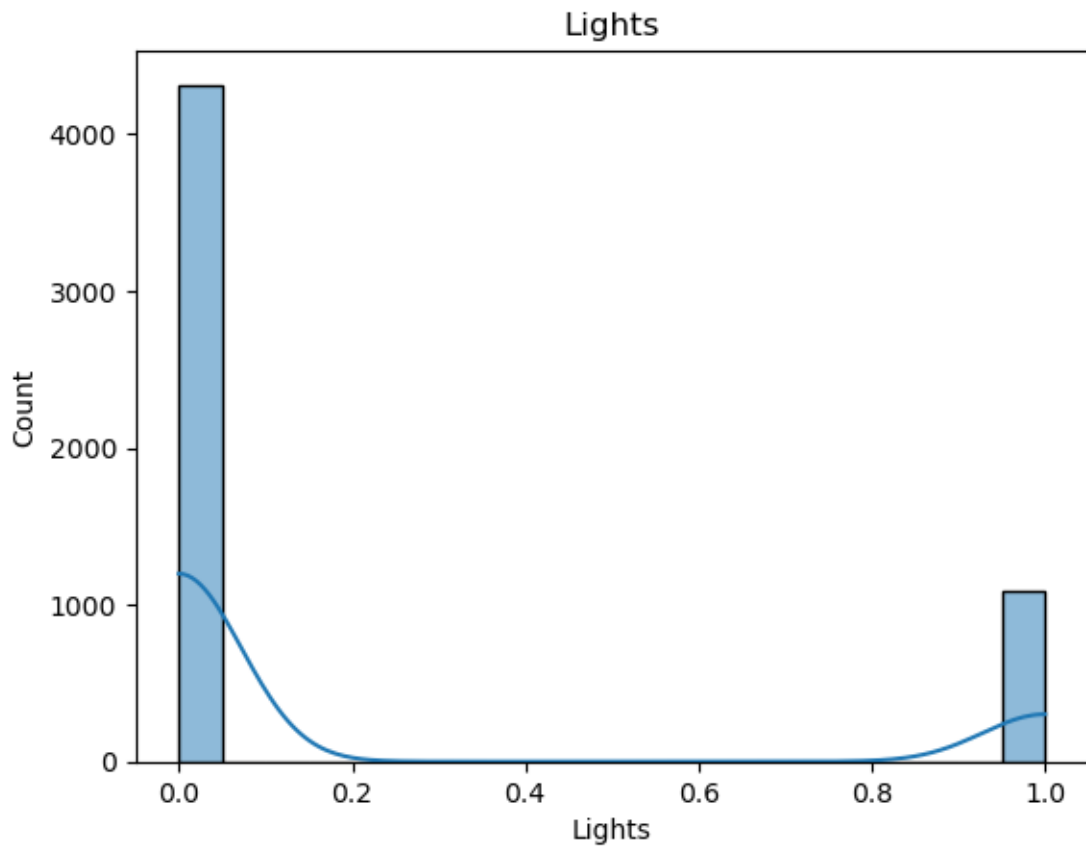


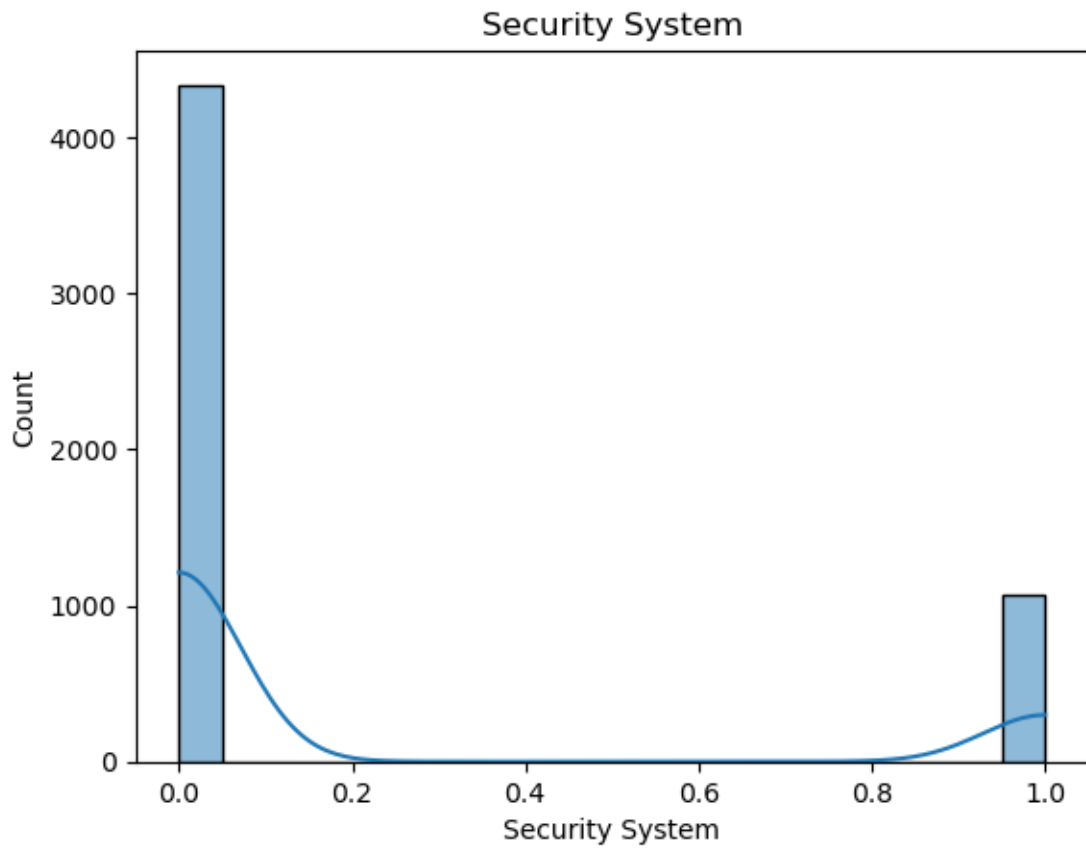


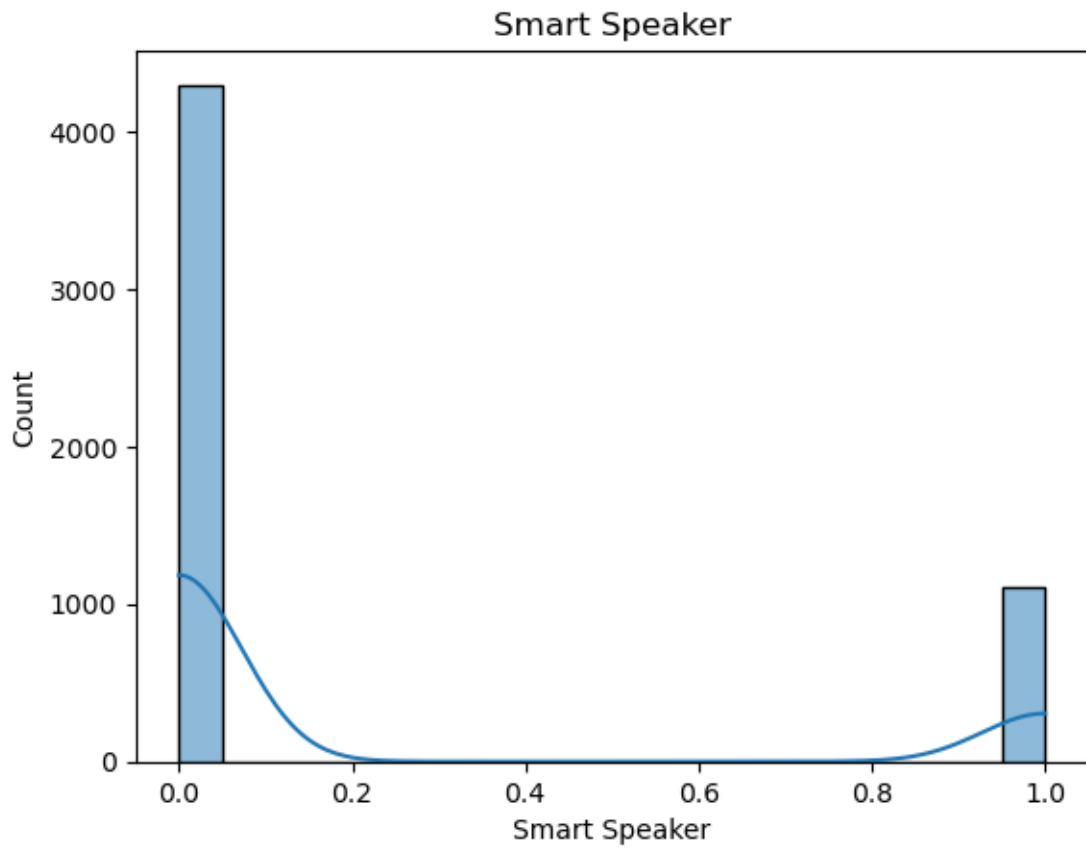


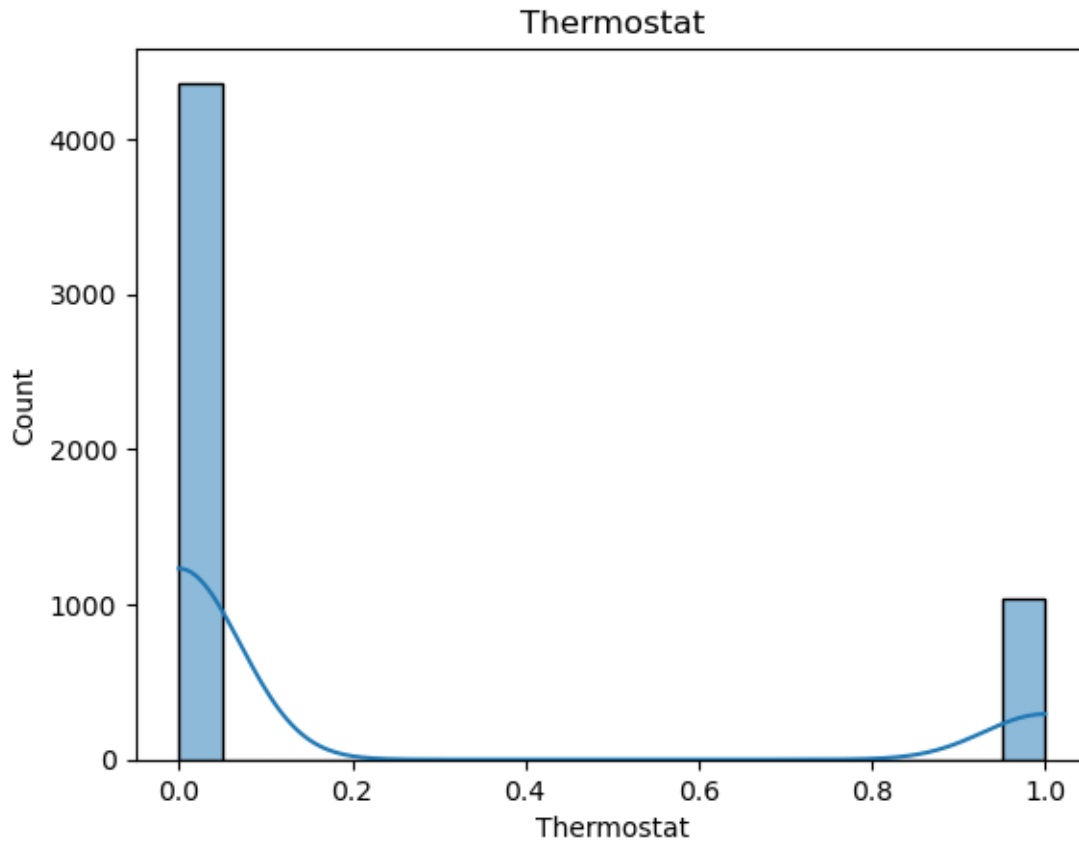










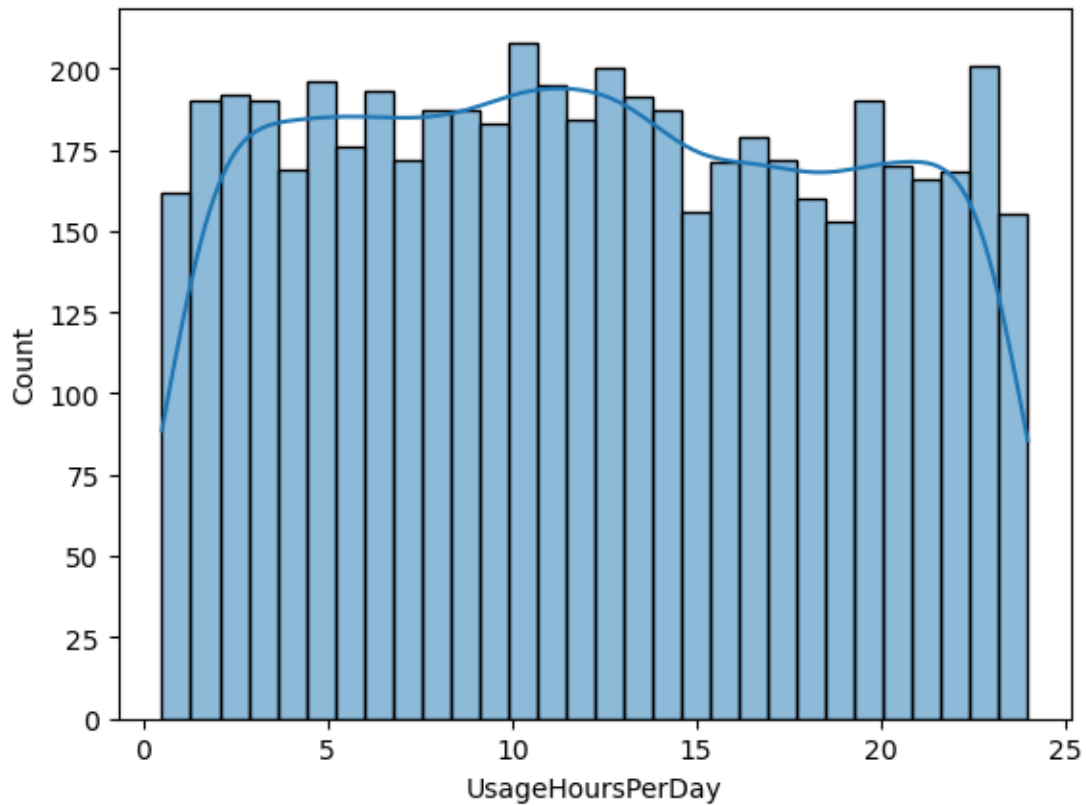


```
[126]: F.isnull().sum()
```

```
[126]: UserID          0
UsageHoursPerDay    0
EnergyConsumption  0
UserPreferences    0
MalfunctionIncidents 0
DeviceAgeMonths    0
SmartHomeEfficiency 0
Camera             0
Lights             0
Security System    0
Smart Speaker      0
Thermostat         0
dtype: int64
```

```
[127]: import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.histplot(x["UsageHoursPerDay"],bins=30,kde=True)
```

```
plt.show()
```



```
[128]: F["UsageHoursPerDay"].mean()
```

```
[128]: 12.052992010466317
```

```
[129]: F["UsageHoursPerDay"].median()
```

```
[129]: 11.903768445051607
```

```
[130]: F["UsageHoursPerDay"].mode()[0]
```

```
[130]: 0.5012414329089748
```

```
[131]: F["UsageHoursPerDay"].sum()
```

```
[131]: 65122.31583254952
```

```
[132]: F["UsageHoursPerDay"].min()
```

```
[132]: 0.5012414329089748
```

```
[133]: F["UsageHoursPerDay"].max()
```

```
[133]: 23.98732600490232
```

```
[134]: F["UsageHoursPerDay"].var()
```

```
[134]: 45.09069733238142
```

```
[135]: F["UsageHoursPerDay"].std()
```

```
[135]: 6.714960709667736
```

```
[136]: import warnings
warnings.filterwarnings("ignore")
for i in F.columns:
    print(i)
    Q1=F[[i]].quantile(0.25)
    Q2=F[[i]].quantile(0.5)
    Q3=F[[i]].quantile(0.75)
    print("Q1=",Q1[0])
    print("Q2=",Q2[0])
    print("Q3=",Q3[0])
    IQR=Q3[0]-Q1[0]
    print("IQR=",IQR)
    upp=Q3[0]+1.5*IQR
    low=Q1[0]-1.5*IQR
    print("LOW=",low)
    print("UPP=",upp)
    sns.boxplot(F[i])
    plt.show()
    s=F.loc[(F[i]>=low)&(F[i]<=upp)]
```

UserID

Q1= 1351.5

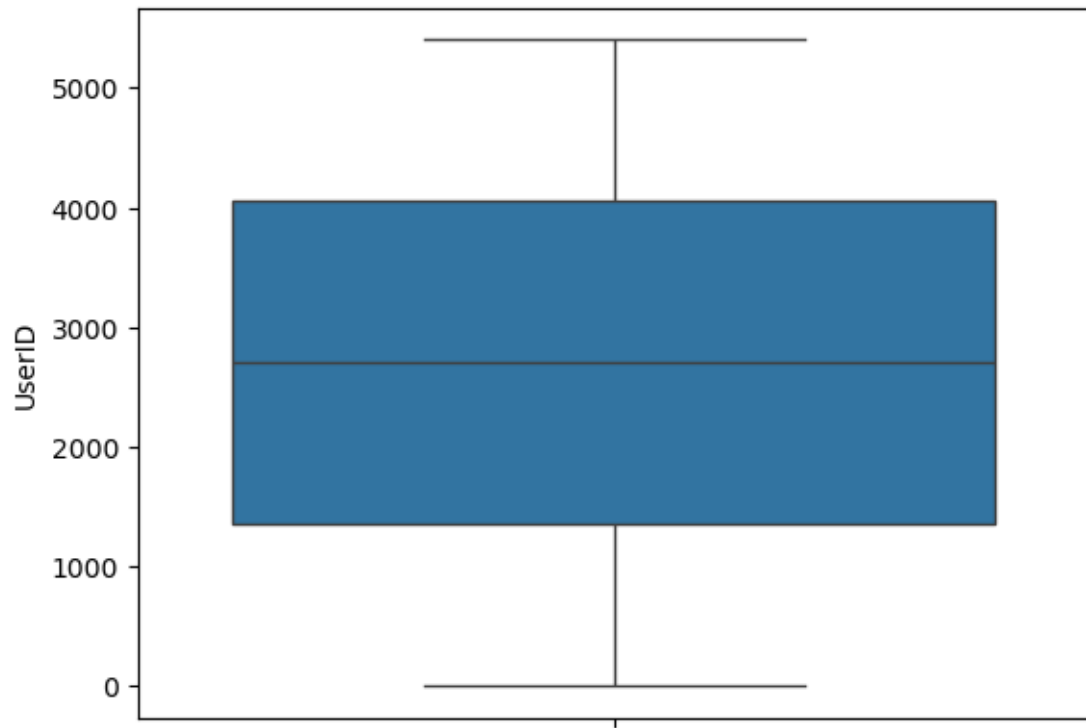
Q2= 2702.0

Q3= 4052.5

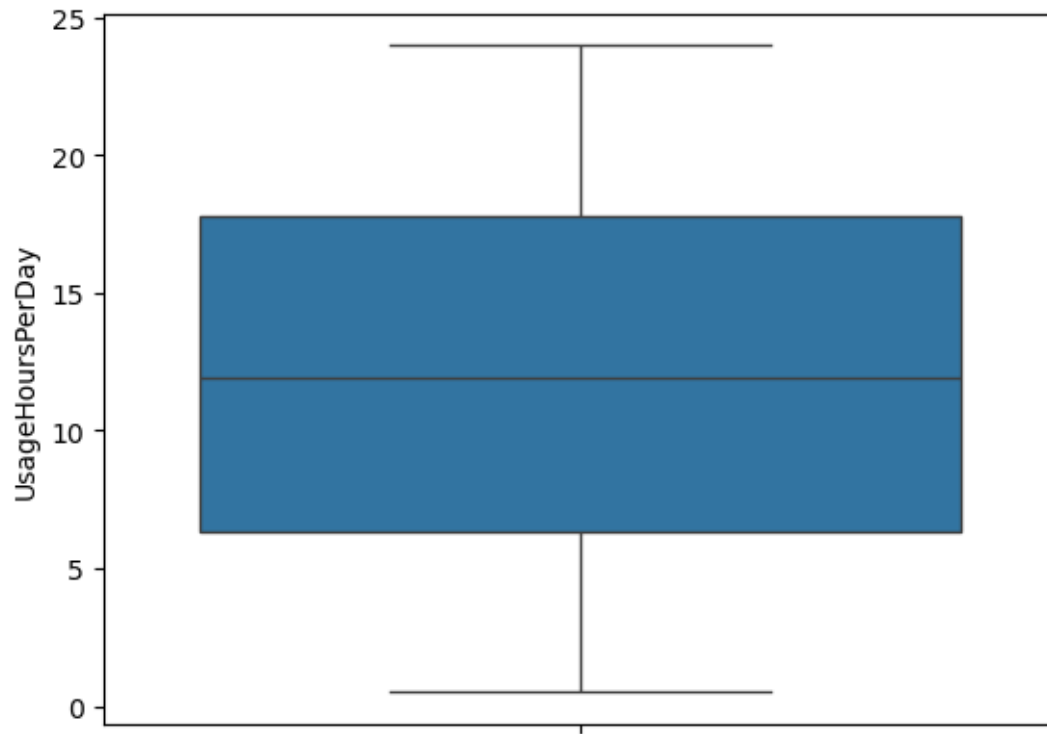
IQR= 2701.0

LOW= -2700.0

UPP= 8104.0



UsageHoursPerDay
Q1= 6.297871242333693
Q2= 11.903768445051607
Q3= 17.79175111953669
IQR= 11.493879877202998
LOW= -10.942948573470803
UPP= 35.032570935341184



EnergyConsumption

Q1= 2.5249681425950814

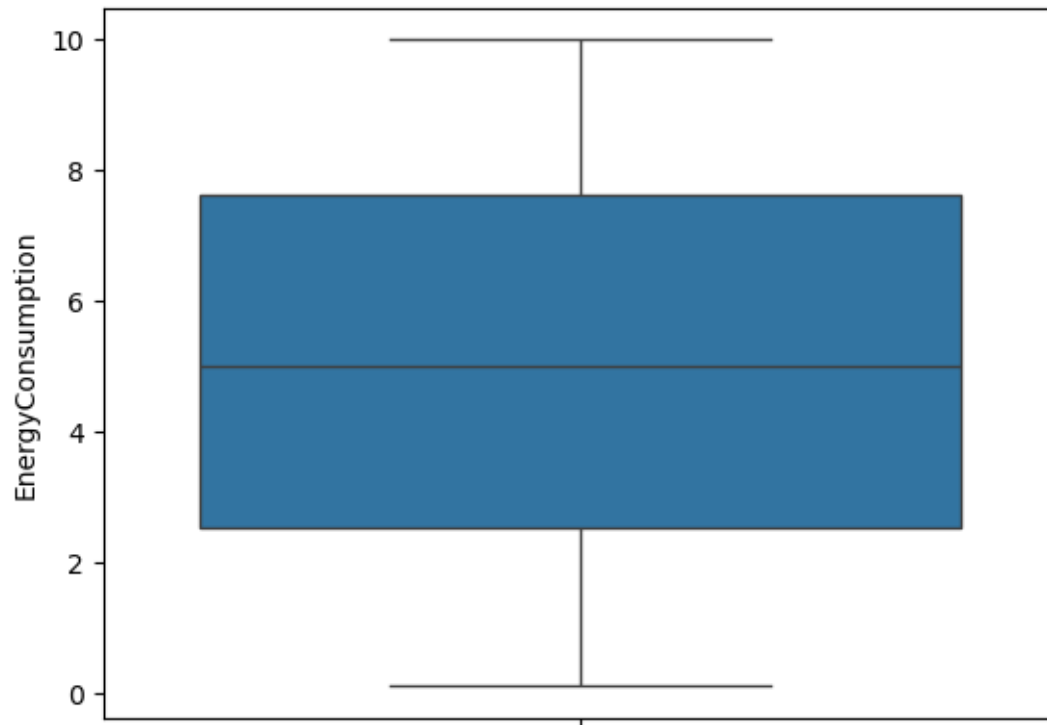
Q2= 5.007047305947374

Q3= 7.6119115723606425

IQR= 5.086943429765562

LOW= -5.1054470020532605

UPP= 15.242326717008986



UserPreferences

Q1= 0.0

Q2= 1.0

Q3= 1.0

IQR= 1.0

LOW= -1.5

UPP= 2.5



MalfunctionIncidents

Q1= 1.0

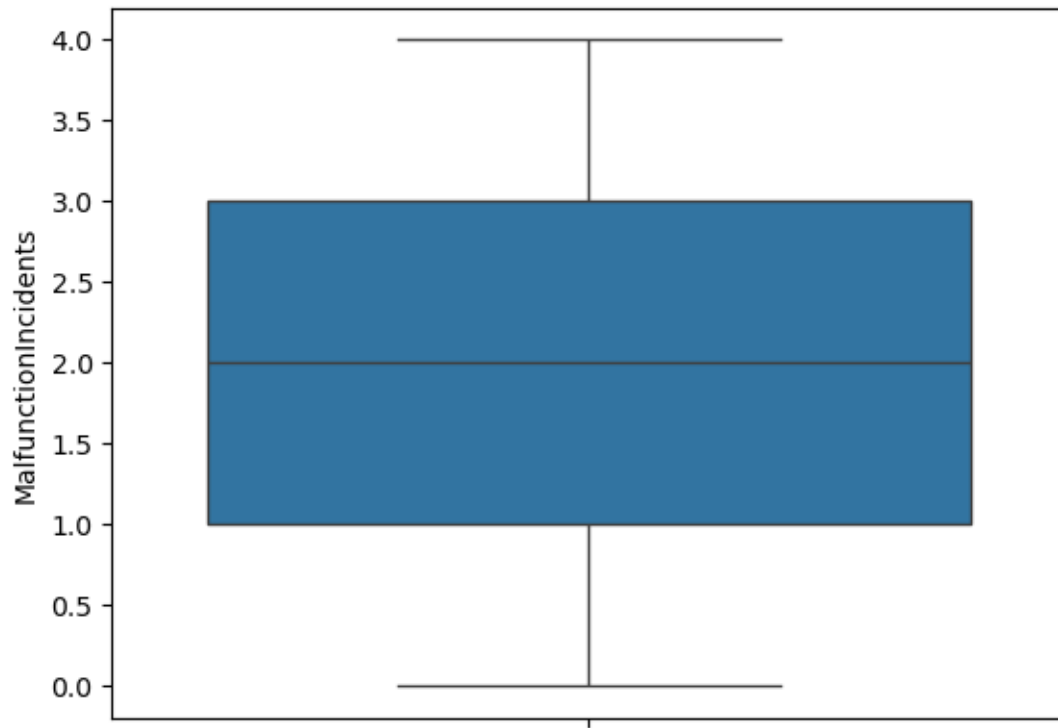
Q2= 2.0

Q3= 3.0

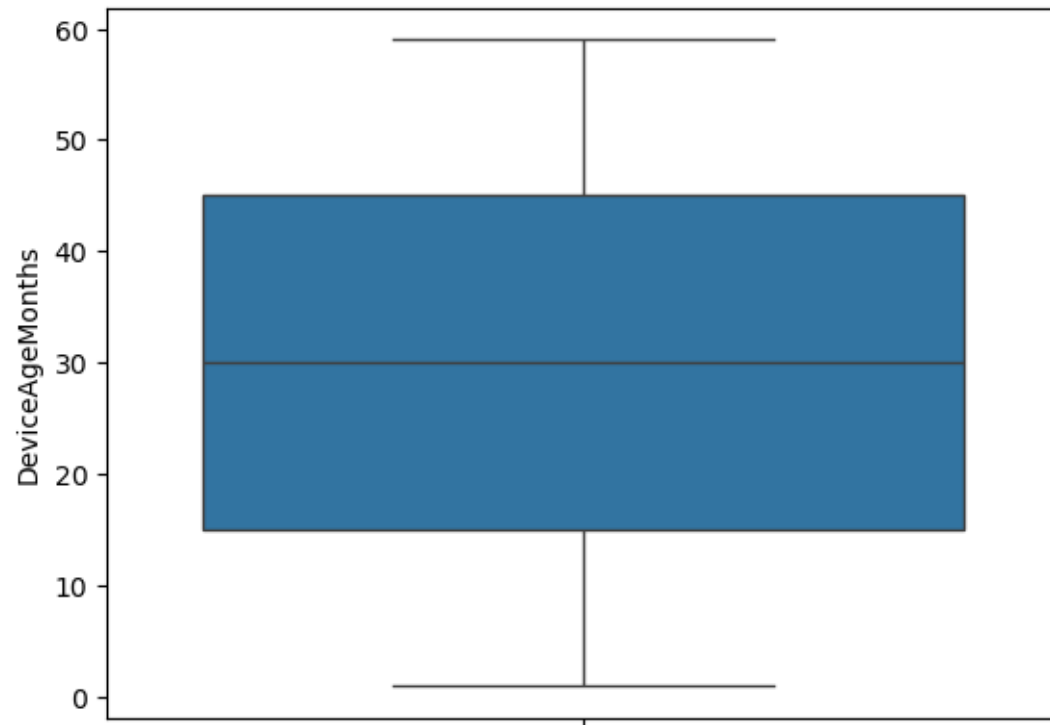
IQR= 2.0

LOW= -2.0

UPP= 6.0



DeviceAgeMonths
Q1= 15.0
Q2= 30.0
Q3= 45.0
IQR= 30.0
LOW= -30.0
UPP= 90.0



SmartHomeEfficiency

Q1= 0.0

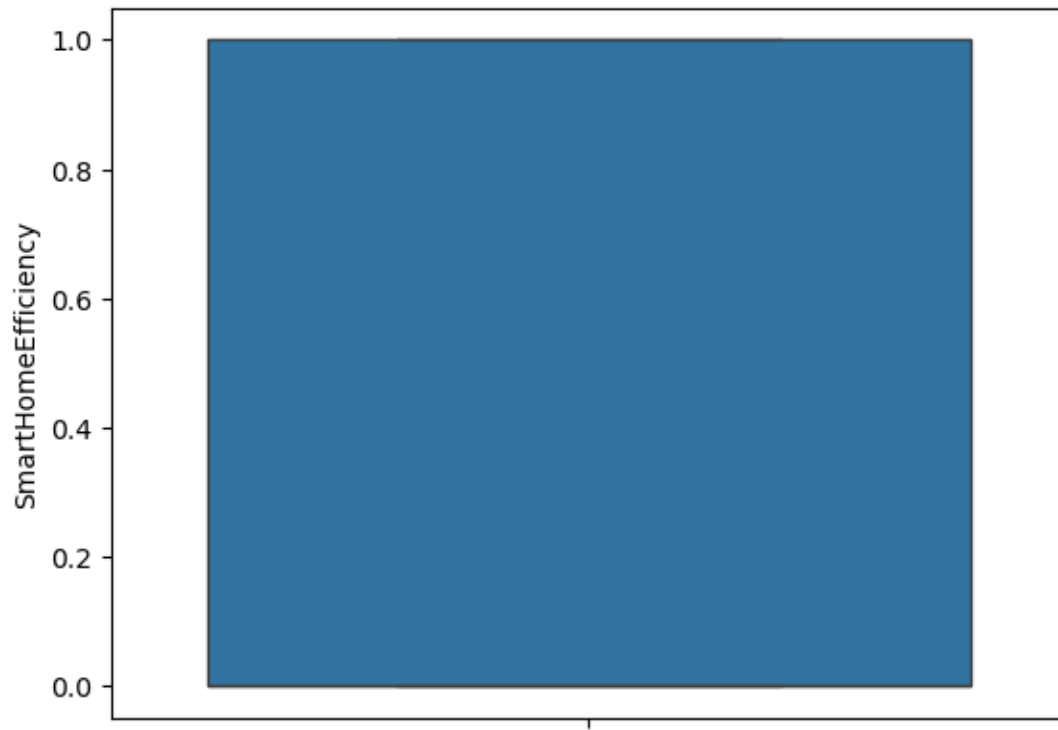
Q2= 0.0

Q3= 1.0

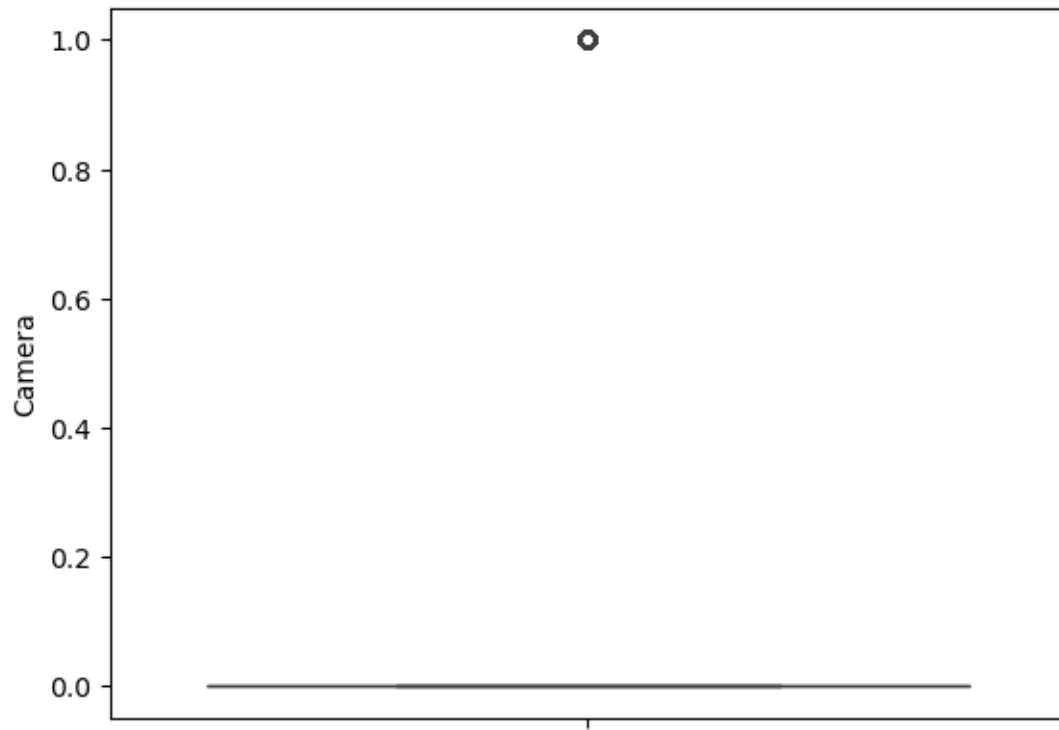
IQR= 1.0

LOW= -1.5

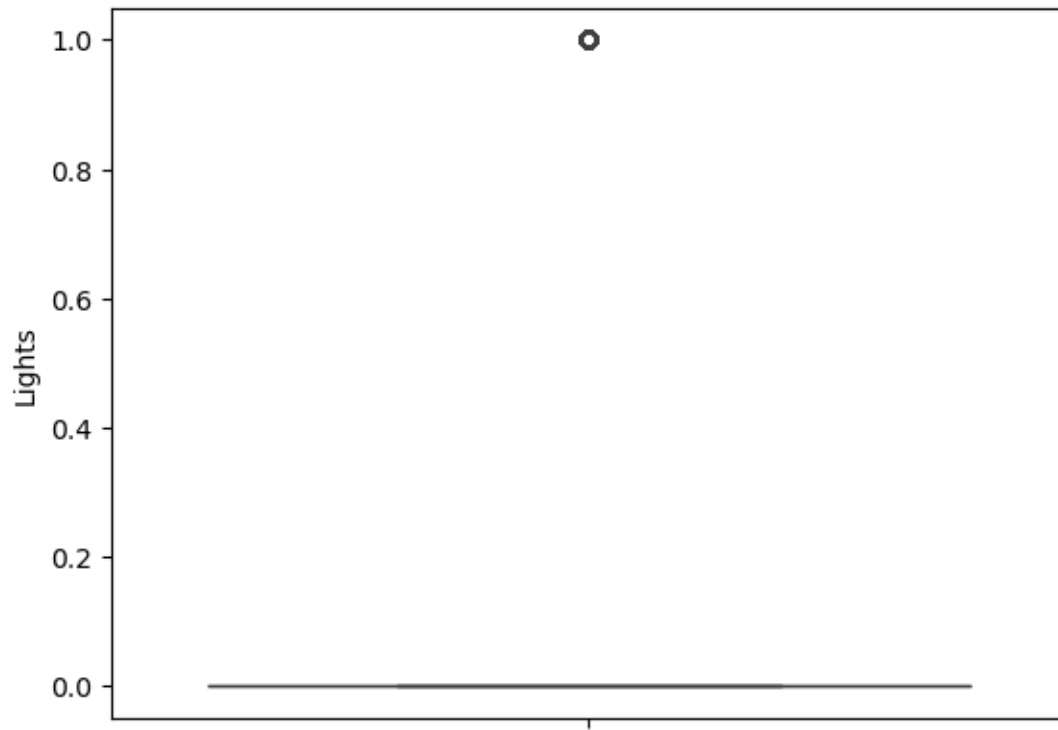
UPP= 2.5



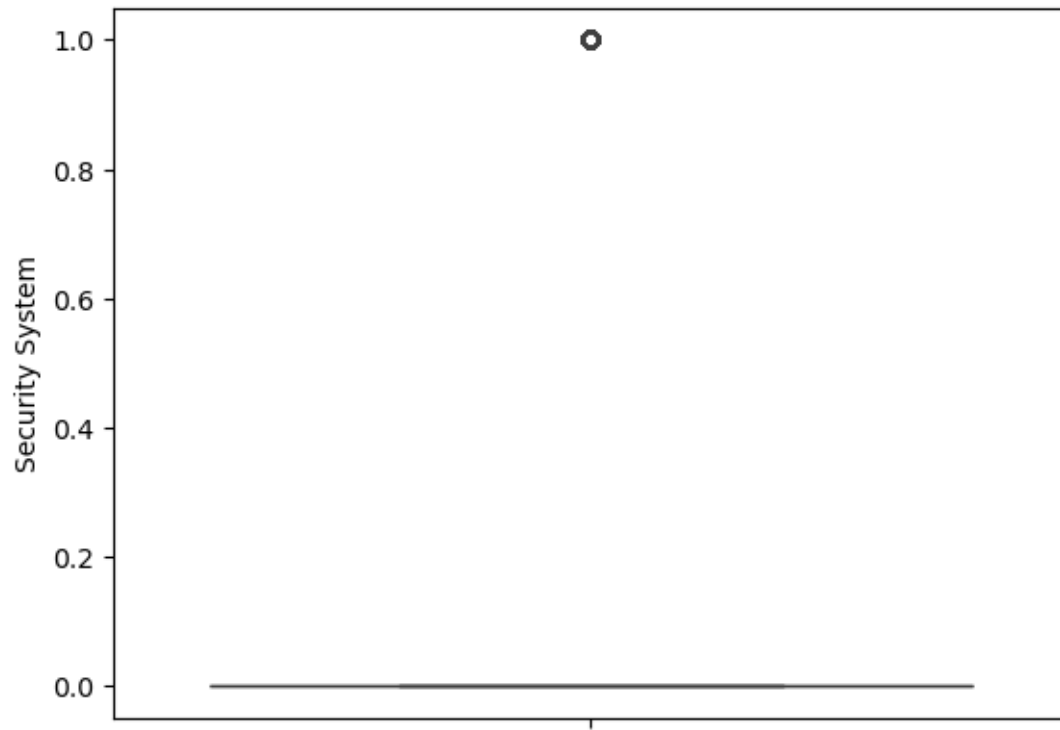
Camera
Q1= 0.0
Q2= 0.0
Q3= 0.0
IQR= 0.0
LOW= 0.0
UPP= 0.0



Lights
Q1= 0.0
Q2= 0.0
Q3= 0.0
IQR= 0.0
LOW= 0.0
UPP= 0.0



Security System
Q1= 0.0
Q2= 0.0
Q3= 0.0
IQR= 0.0
LOW= 0.0
UPP= 0.0



Smart Speaker

Q1= 0.0

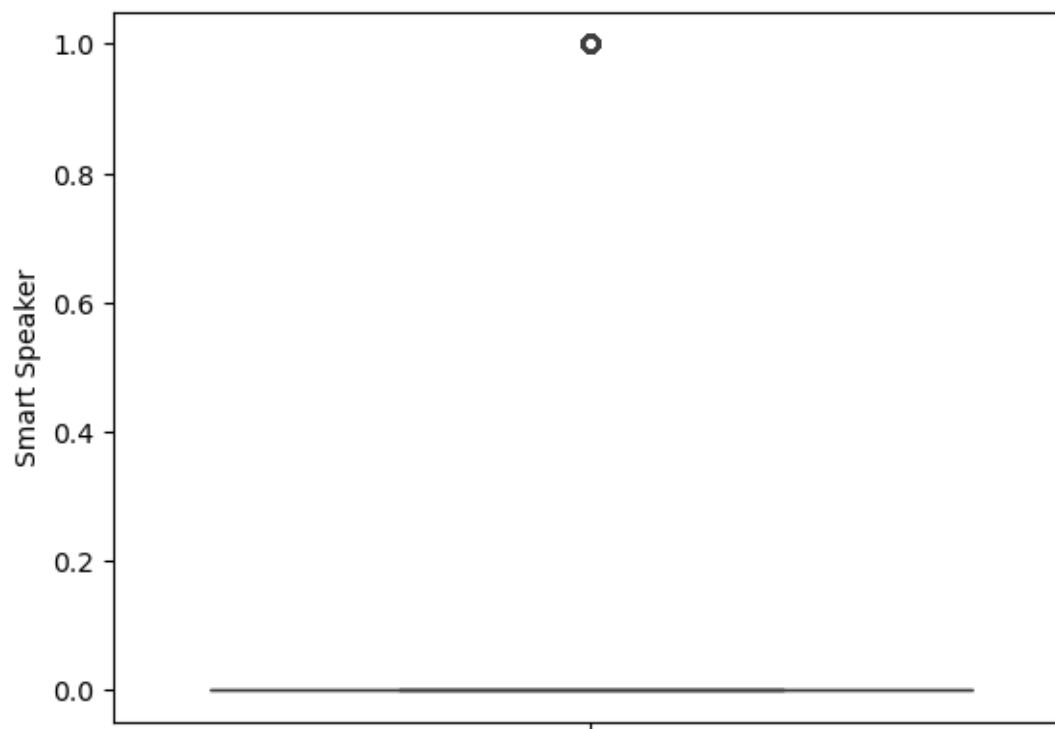
Q2= 0.0

Q3= 0.0

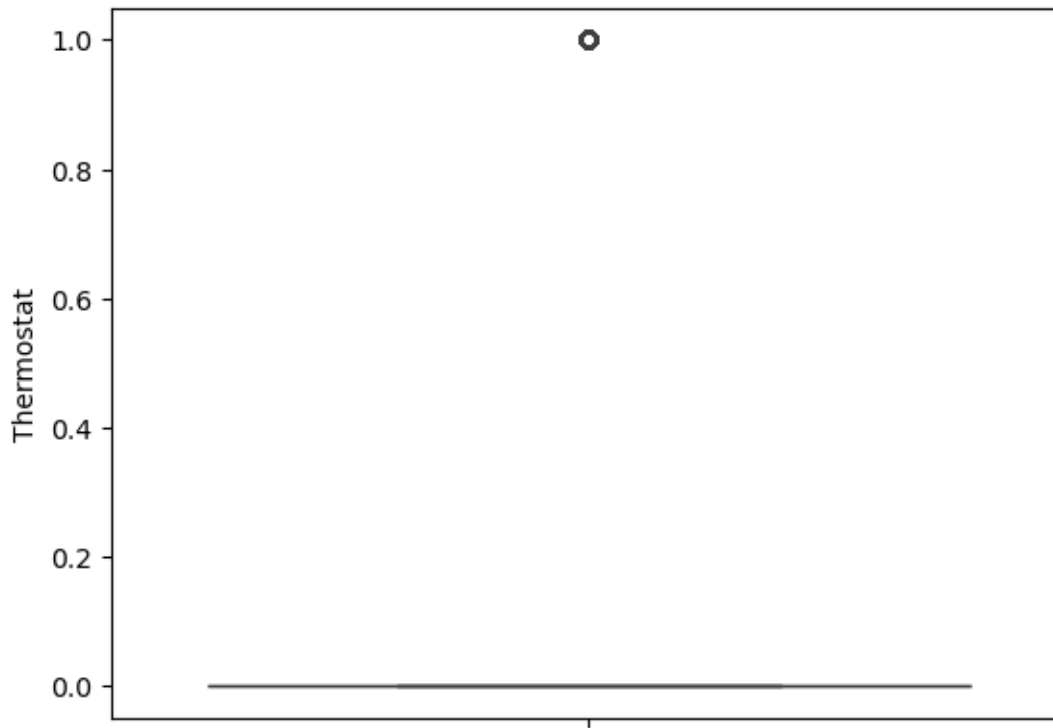
IQR= 0.0

LOW= 0.0

UPP= 0.0



Thermostat
Q1= 0.0
Q2= 0.0
Q3= 0.0
IQR= 0.0
LOW= 0.0
UPP= 0.0



[137]: s

```
[137]:      UserID  UsageHoursPerDay  EnergyConsumption  UserPreferences  \
0         1         15.307188          1.961607          1
1         2         19.973343          8.610689          1
2         3         18.911535          2.651777          1
3         4          7.011127          2.341653          0
4         5         22.610684          4.859069          1
...      ...
5396      5397         19.301279          0.792446          1
5397      5398          8.633520          4.249140          0
5399      5400          0.561856          1.555992          1
5400      5401         11.096236          7.677779          0
5401      5402          8.782169          7.467929          0

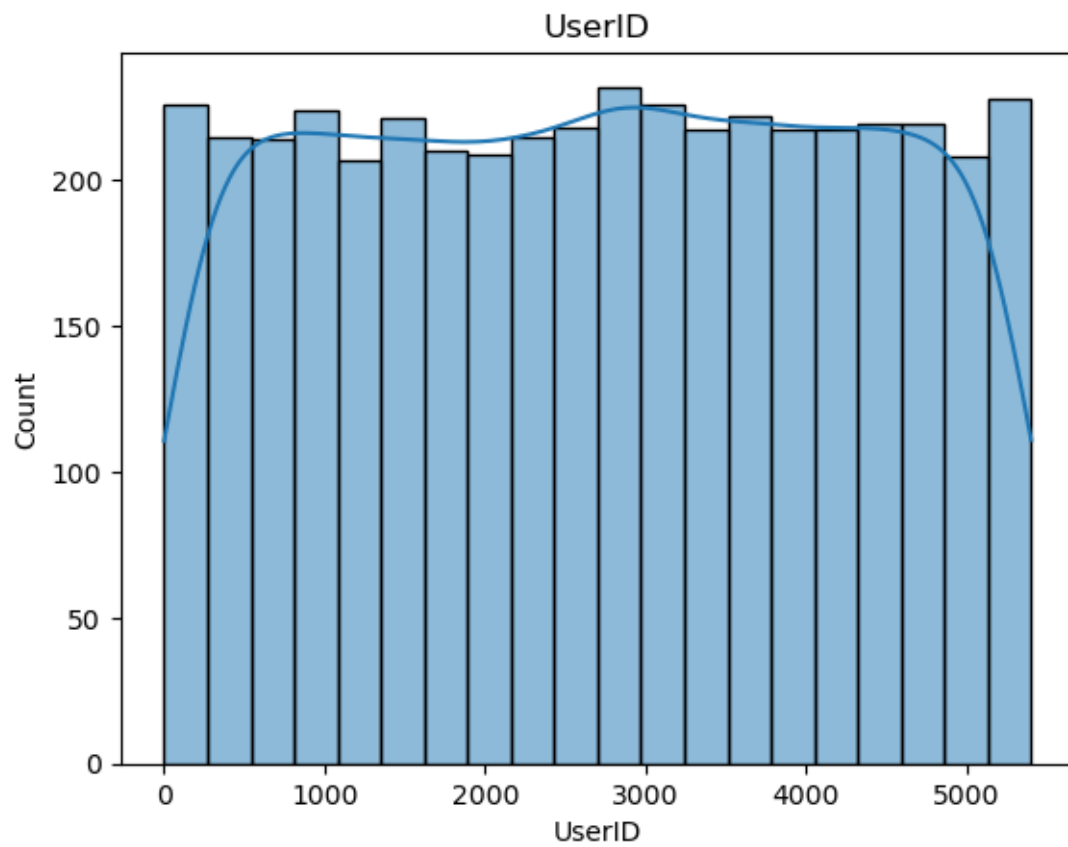
      MalfunctionIncidents  DeviceAgeMonths  SmartHomeEfficiency  Camera  \
0              4              36              1              0
1              0              29              1              1
2              0              20              1              0
3              3              15              0              1
4              3              36              1              1
...      ...
5396              1              33              1              1
```

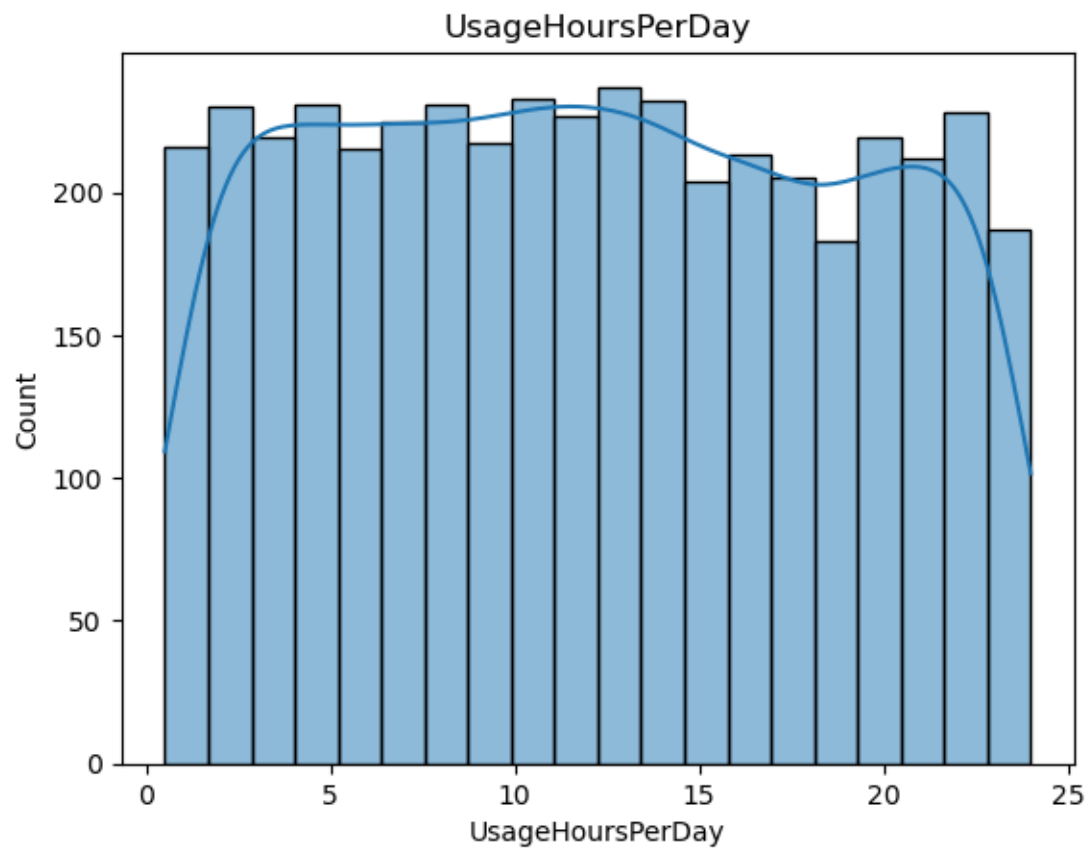
5397	0	32	0	0
5399	4	24	0	0
5400	0	42	0	0
5401	2	28	1	0

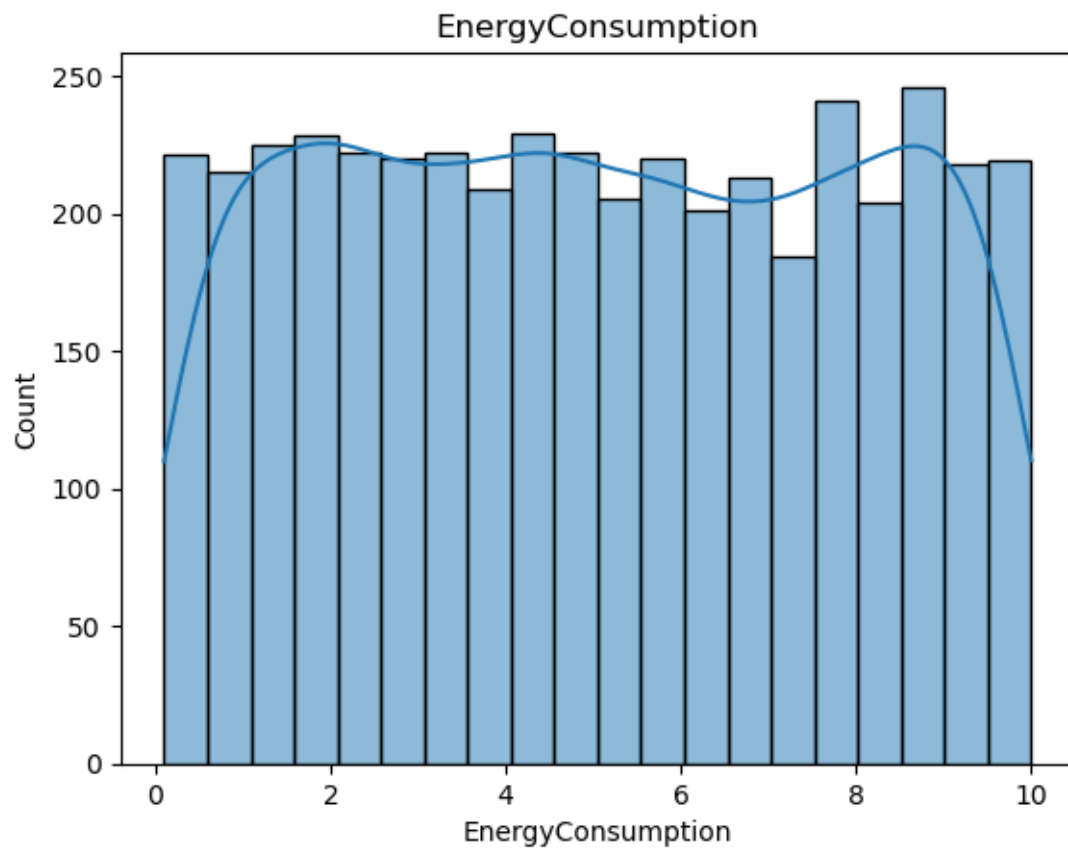
	Lights	Security System	Smart Speaker	Thermostat
0	0	0	1	0
1	0	0	0	0
2	0	1	0	0
3	0	0	0	0
4	0	0	0	0
...
5396	0	0	0	0
5397	1	0	0	0
5399	1	0	0	0
5400	0	0	1	0
5401	0	1	0	0

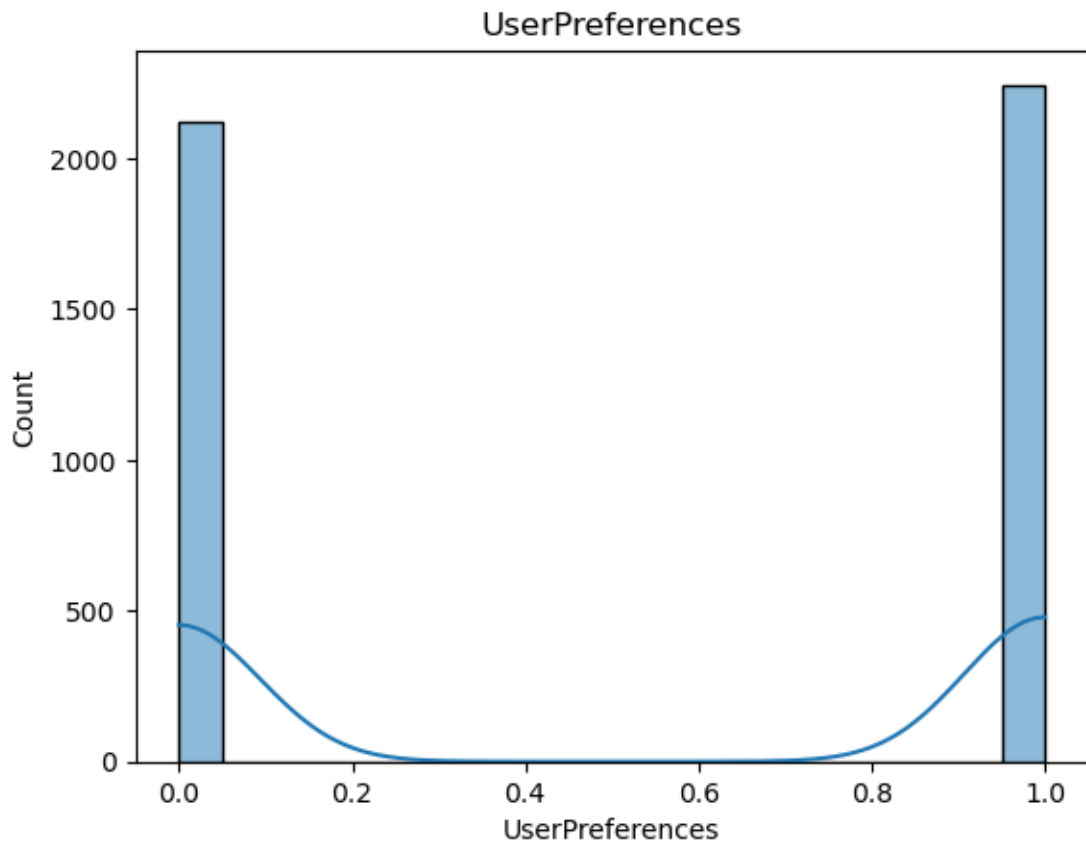
[4364 rows x 12 columns]

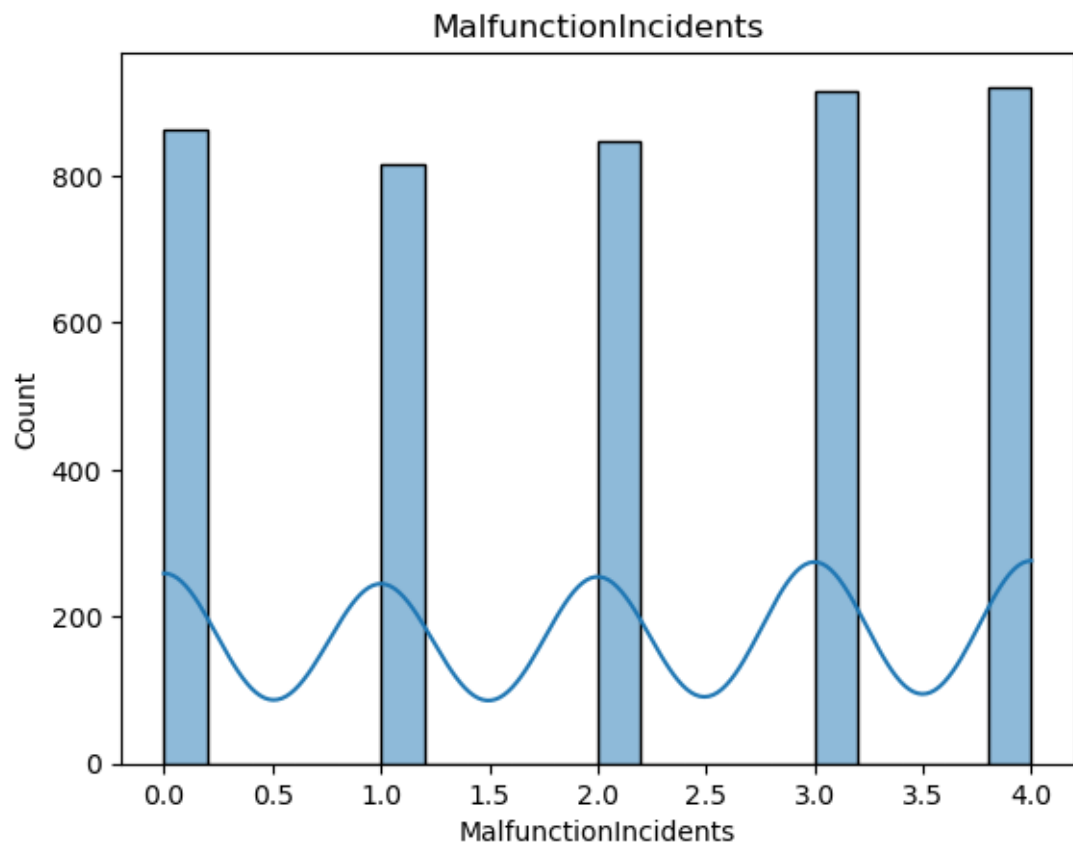
```
[138]: import matplotlib.pyplot as plt
import seaborn as sns
for i in s.columns:
    sns.histplot(s[i],bins=20,kde=True)
    plt.title(i)
    plt.show()
```

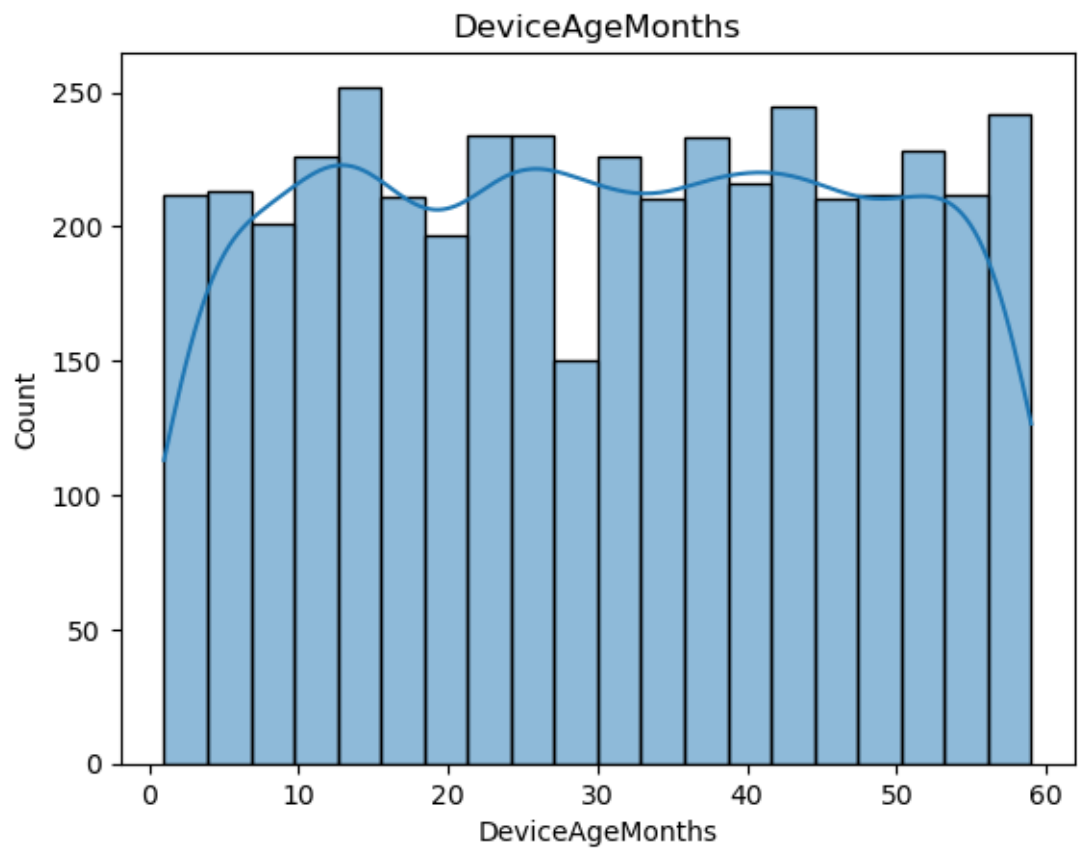


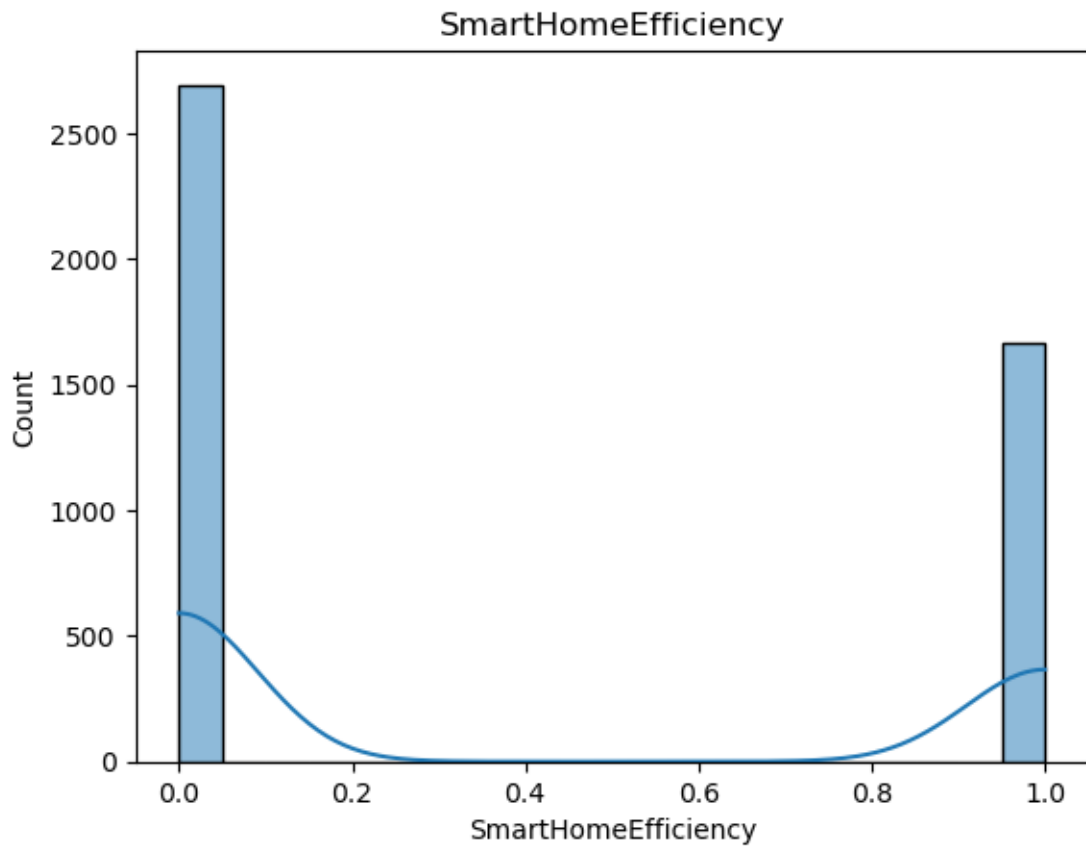


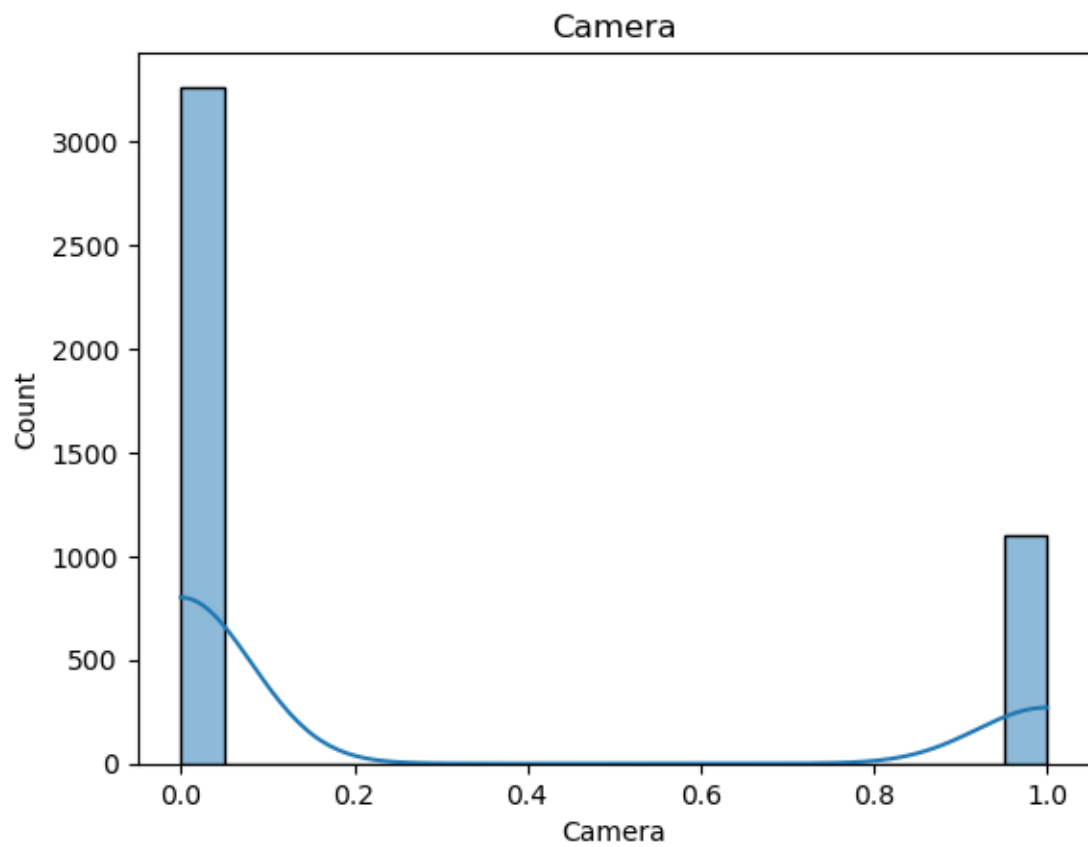


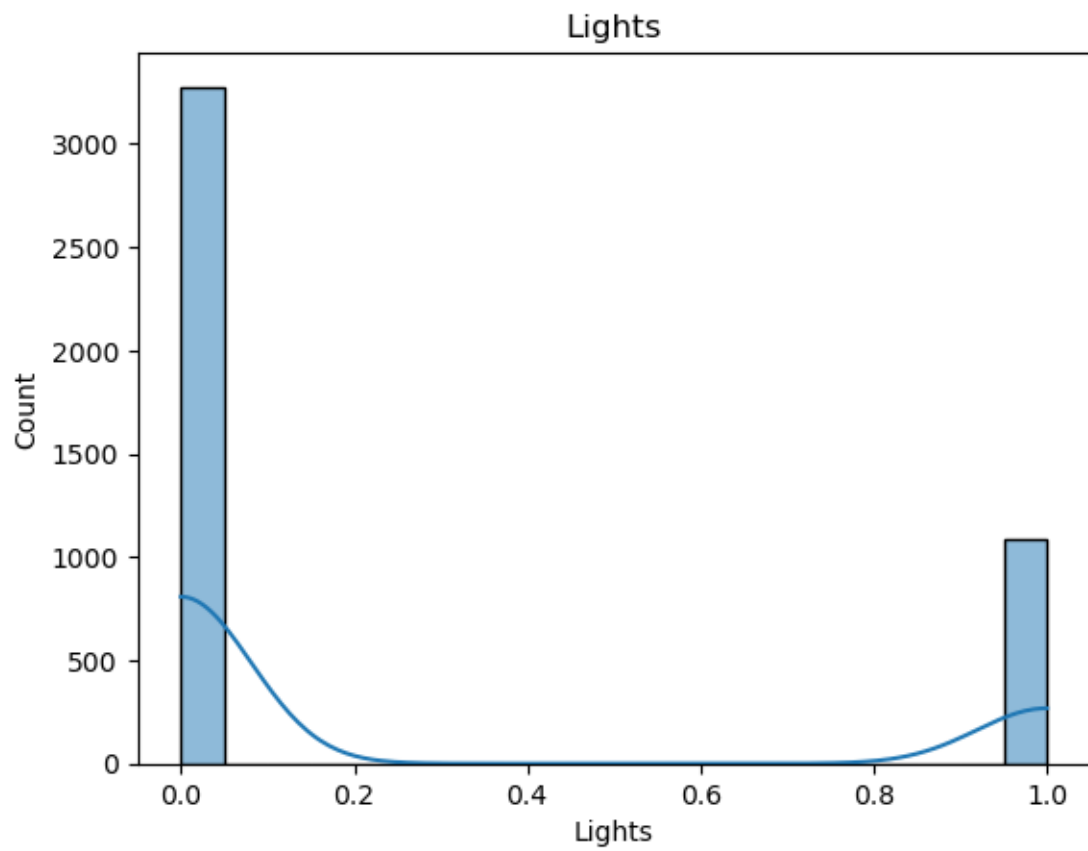


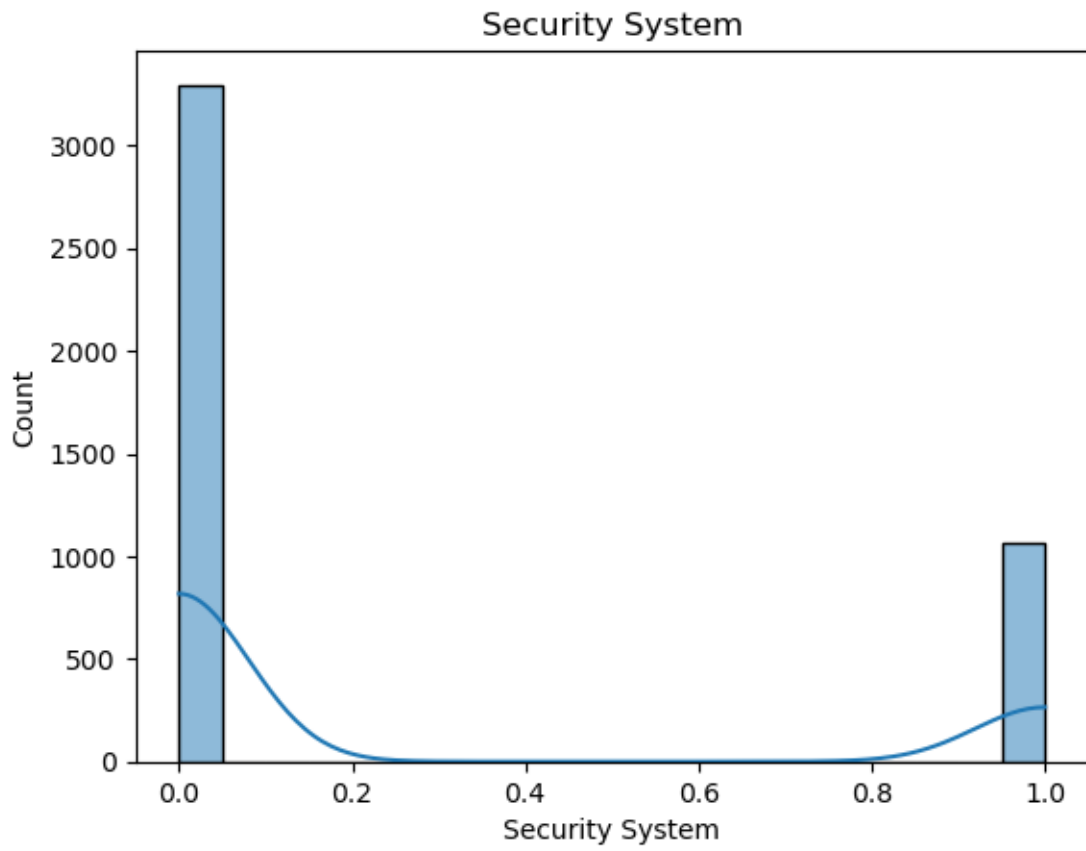


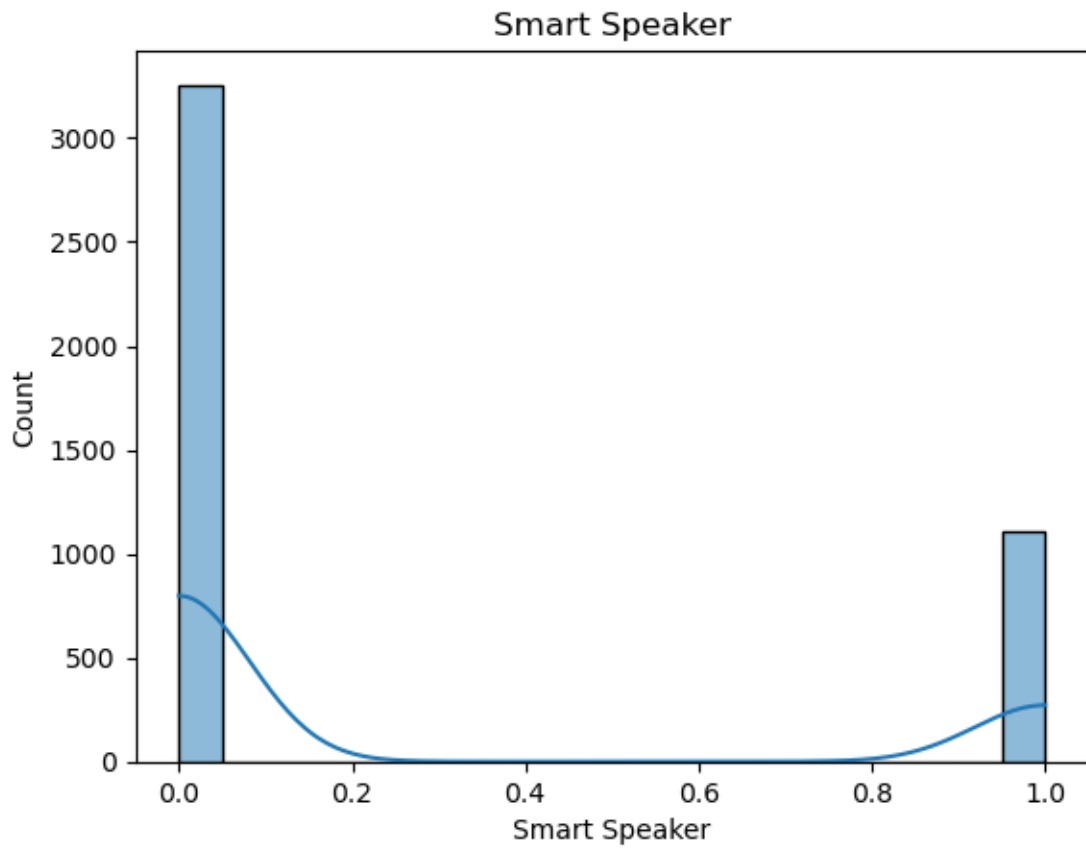


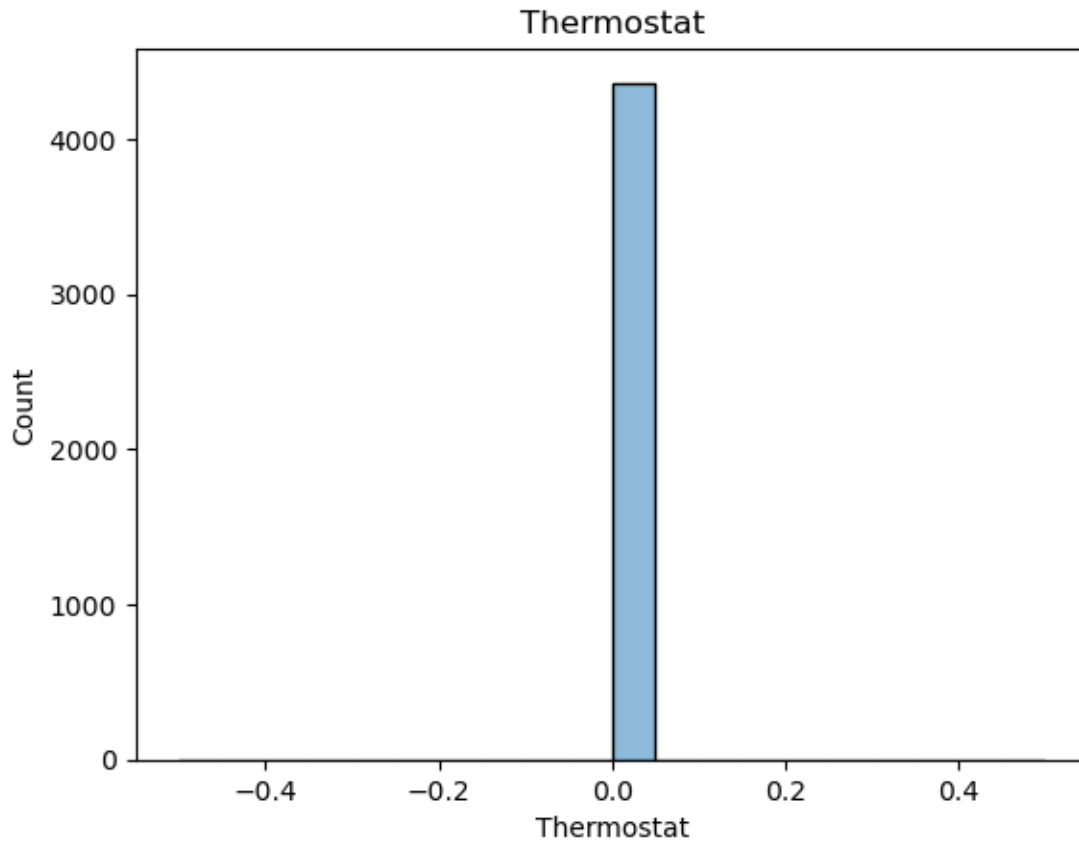












```
[139]: for i in s.columns:
        print(i.upper())
        sum=s[i].sum()
        print("sum:",sum)
        mean=s[i].mean()
        print("mean:",mean)
        median=s[i].median()
        print("median:",median)
        mode=s[i].mode()[0]
        print("mode:",mode)
        min=s[i].min()
        print("min:",min)
        max=s[i].max()
        print("max:",max)
        std=s[i].var()
        print("std:",std)
        var=s[i].var()
        print("var:",var)
        print("_"*30)
        plt.show()
```

USERID

sum: 11813932
mean: 2707.133822181485
median: 2732.5
mode: 1
min: 1
max: 5402
std: 2433928.7618262344
var: 2433928.7618262344

USAGEHOURSPERDAY

sum: 52544.438568160374
mean: 12.040430469330975
median: 11.915358879084705
mode: 0.5053353981290052
min: 0.5053353981290052
max: 23.98732600490232
std: 45.140528007364715
var: 45.140528007364715

ENERGYCONSUMPTION

sum: 21963.40730917837
mean: 5.0328614365669955
median: 4.968829676983313
mode: 0.1015616713227616
min: 0.1015616713227616
max: 9.998070926924637
std: 8.266604441984045
var: 8.266604441984045

USERPREFERENCES

sum: 2243
mean: 0.5139780018331805
median: 1.0
mode: 1
min: 0
max: 1
std: 0.24986187070551405
var: 0.24986187070551405

MALFUNCTIONINCIDENTS

sum: 8941
mean: 2.048808432630614
median: 2.0
mode: 4
min: 0
max: 4
std: 2.030851204182858

var: 2.030851204182858

DEVICEAGEMONTHS

sum: 132041
mean: 30.256874427131073
median: 30.0
mode: 13
min: 1
max: 59
std: 288.16526329754504
var: 288.16526329754504

SMARTHOMEEFFICIENCY

sum: 1670
mean: 0.38267644362969755
median: 0.0
mode: 0
min: 0
max: 1
std: 0.23628932824624083
var: 0.23628932824624083

CAMERA

sum: 1101
mean: 0.2522914757103575
median: 0.0
mode: 0
min: 0
max: 1
std: 0.18868372341115514
var: 0.18868372341115514

LIGHTS

sum: 1087
mean: 0.24908340971585702
median: 0.0
mode: 0
min: 0
max: 1
std: 0.1870837345035399
var: 0.1870837345035399

SECURITY SYSTEM

sum: 1068
mean: 0.2447296058661778
median: 0.0
mode: 0
min: 0


```
max: 1
std: 0.18487939054203606
var: 0.18487939054203606
```

```
-----
SMART SPEAKER
```

```
sum: 1108
mean: 0.2538955087076077
median: 0.0
mode: 0
min: 0
max: 1
std: 0.18947599733025922
var: 0.18947599733025922
```

```
-----
THERMOSTAT
```

```
sum: 0
mean: 0.0
median: 0.0
mode: 0
min: 0
max: 0
std: 0.0
var: 0.0
```

```
[140]: s["Smart Speaker"].nunique()
```

```
[140]: 2
```

```
[141]: F["Smart Speaker"].value_counts()
```

```
[141]: Smart Speaker
0      4295
1       1108
Name: count, dtype: int64
```

```
[142]: s["Smart Speaker"].value_counts()
```

```
[142]: Smart Speaker
0      3256
1       1108
Name: count, dtype: int64
```

```
[143]: F["SmartHomeEfficiency"].value_counts()
```

```
[143]: SmartHomeEfficiency
0       3368
```

```
1    2035
Name: count, dtype: int64
```

```
[144]: s["SmartHomeEfficiency"].value_counts()
```

```
[144]: SmartHomeEfficiency
0     2694
1     1670
Name: count, dtype: int64
```

```
[145]: s.corr()
```

```
[145]:
```

	UserID	UsageHoursPerDay	EnergyConsumption	\
UserID	1.000000	-0.004086	-0.012594	
UsageHoursPerDay	-0.004086	1.000000	0.026804	
EnergyConsumption	-0.012594	0.026804	1.000000	
UserPreferences	0.022984	-0.000396	0.013514	
MalfunctionIncidents	-0.007615	0.004248	-0.010932	
DeviceAgeMonths	0.004980	0.017997	-0.011321	
SmartHomeEfficiency	0.047688	0.188698	-0.179222	
Camera	-0.004935	0.006312	0.009659	
Lights	-0.022023	0.001047	0.002409	
Security System	0.022982	-0.002057	0.020856	
Smart Speaker	0.004107	-0.005308	-0.032634	
Thermostat	NaN	NaN	NaN	

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
UserID	0.022984	-0.007615	0.004980	
UsageHoursPerDay	-0.000396	0.004248	0.017997	
EnergyConsumption	0.013514	-0.010932	-0.011321	
UserPreferences	1.000000	-0.007232	-0.024126	
MalfunctionIncidents	-0.007232	1.000000	-0.023807	
DeviceAgeMonths	-0.024126	-0.023807	1.000000	
SmartHomeEfficiency	0.604322	-0.121928	-0.199738	
Camera	0.005394	0.015648	-0.007579	
Lights	0.000324	-0.011176	-0.011682	
Security System	-0.011654	-0.000048	0.007683	
Smart Speaker	0.005807	-0.004463	0.011582	
Thermostat	NaN	NaN	NaN	

	SmartHomeEfficiency	Camera	Lights	\
UserID	0.047688	-0.004935	-0.022023	
UsageHoursPerDay	0.188698	0.006312	0.001047	
EnergyConsumption	-0.179222	0.009659	0.002409	
UserPreferences	0.604322	0.005394	0.000324	
MalfunctionIncidents	-0.121928	0.015648	-0.011176	
DeviceAgeMonths	-0.199738	-0.007579	-0.011682	

SmartHomeEfficiency	1.000000	0.005073	-0.003237
Camera	0.005073	1.000000	-0.334550
Lights	-0.003237	-0.334550	1.000000
Security System	-0.008442	-0.330657	-0.327845
Smart Speaker	0.006493	-0.338854	-0.335973
Thermostat	NaN	NaN	NaN

	Security System	Smart Speaker	Thermostat
UserID	0.022982	0.004107	NaN
UsageHoursPerDay	-0.002057	-0.005308	NaN
EnergyConsumption	0.020856	-0.032634	NaN
UserPreferences	-0.011654	0.005807	NaN
MalfunctionIncidents	-0.000048	-0.004463	NaN
DeviceAgeMonths	0.007683	0.011582	NaN
SmartHomeEfficiency	-0.008442	0.006493	NaN
Camera	-0.330657	-0.338854	NaN
Lights	-0.327845	-0.335973	NaN
Security System	1.000000	-0.332062	NaN
Smart Speaker	-0.332062	1.000000	NaN
Thermostat	NaN	NaN	NaN

```
[146]: F=s.drop("SmartHomeEfficiency",axis=1)
      T=s["SmartHomeEfficiency"]
```

```
[147]: F.head()
```

```
[147]:
```

	UserID	UsageHoursPerDay	EnergyConsumption	UserPreferences	\
0	1	15.307188	1.961607	1	
1	2	19.973343	8.610689	1	
2	3	18.911535	2.651777	1	
3	4	7.011127	2.341653	0	
4	5	22.610684	4.859069	1	

	MalfunctionIncidents	DeviceAgeMonths	Camera	Lights	Security System	\
0	4	36	0	0	0	
1	0	29	1	0	0	
2	0	20	0	0	1	
3	3	15	1	0	0	
4	3	36	1	0	0	

	Smart Speaker	Thermostat
0	1	0
1	0	0
2	0	0
3	0	0
4	0	0

```
[148]: T
```

```
[148]: 0      1
      1      1
      2      1
      3      0
      4      1
      ..
     5396     1
     5397     0
     5399     0
     5400     0
     5401     1
      Name: SmartHomeEfficiency, Length: 4364, dtype: int64
```

```
[149]: from sklearn.model_selection import train_test_split
      X_train,X_test,y_train,y_test=train_test_split(F,T,train_size=0.80)
```

```
[150]: X_train.shape
```

```
[150]: (3491, 11)
```

```
[151]: y_train.shape
```

```
[151]: (3491,)
```

```
[152]: T.unique()
```

```
[152]: array([1, 0], dtype=int64)
```

```
[153]: import warnings
      warnings.filterwarnings("ignore")
      from sklearn.linear_model import LogisticRegression
      L=LogisticRegression()
      from sklearn.model_selection import GridSearchCV
      params={"C": [0.1,0.01,0.2,0.04,0.001], "penalty": ["l1", "l2"]}
      log=GridSearchCV(L,param_grid=params,scoring="accuracy",cv=5)
```

```
[154]: log.fit(X_train,y_train)
```

```
[154]: GridSearchCV(cv=5, estimator=LogisticRegression(),
      param_grid={'C': [0.1, 0.01, 0.2, 0.04, 0.001],
      'penalty': ['l1', 'l2']},
      scoring='accuracy')
```

```
[155]: log.best_params_
```

```
[155]: {'C': 0.04, 'penalty': 'l2'}
```

```
[156]: model=log.best_estimator_  
model
```

```
[156]: LogisticRegression(C=0.04)
```

```
[157]: model.score(X_train,y_train)
```

```
[157]: 0.8627900315095961
```

```
[158]: model.score(X_test,y_test)
```

```
[158]: 0.861397479954181
```

```
[159]: from sklearn.neighbors import KNeighborsClassifier  
A=KNeighborsClassifier()  
from sklearn.model_selection import GridSearchCV  
knn=GridSearchCV(A,param_grid={"n_neighbors": [3,5,7,9]},scoring="accuracy",cv=5)
```

```
[160]: knn.fit(X_train,y_train)
```

```
[160]: GridSearchCV(cv=5, estimator=KNeighborsClassifier(),  
                param_grid={'n_neighbors': [3, 5, 7, 9]}, scoring='accuracy')
```

```
[161]: knn.best_params_
```

```
[161]: {'n_neighbors': 5}
```

```
[162]: model2=knn.best_estimator_  
model2
```

```
[162]: KNeighborsClassifier()
```

```
[163]: model2.score(X_train,y_train)
```

```
[163]: 0.7419077628186765
```

```
[164]: model2.score(X_test,y_test)
```

```
[164]: 0.5807560137457045
```

```
[165]: from sklearn.naive_bayes import   
      ↪ GaussianNB, MultinomialNB, BernoulliNB, ComplementNB  
Gaussian=GaussianNB()  
Multinomial=MultinomialNB()  
Bernoulli=BernoulliNB()
```

```
Complement=ComplementNB()
```

```
[166]: Gaussian.fit(X_train,y_train)
```

```
[166]: GaussianNB()
```

```
[167]: Gaussian.score(X_train,y_train)
```

```
[167]: 0.8341449441420796
```

```
[168]: Gaussian.score(X_test,y_test)
```

```
[168]: 0.8384879725085911
```

```
[169]: Multinomial.fit(X_train,y_train)
```

```
[169]: MultinomialNB()
```

```
[170]: Multinomial.score(X_train,y_train)
```

```
[170]: 0.6264680607275852
```

```
[171]: Multinomial.score(X_test,y_test)
```

```
[171]: 0.6185567010309279
```

```
[172]: Bernoulli.fit(X_train,y_train)
```

```
[172]: BernoulliNB()
```

```
[173]: Bernoulli.score(X_train,y_train)
```

```
[173]: 0.791177313090805
```

```
[174]: Bernoulli.score(X_test,y_test)
```

```
[174]: 0.7869415807560137
```

```
[175]: Complement.fit(X_train,y_train)
```

```
[175]: ComplementNB()
```

```
[176]: Complement.score(X_train,y_train)
```

```
[176]: 0.6218848467487826
```

```
[177]: Complement.score(X_test,y_test)
```

```
[177]: 0.6071019473081328
```

```
[178]: from sklearn.naive_bayes import GaussianNB,BernoulliNB,ComplementNB
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
```

```
[179]: models={"Gaussian":GaussianNB(),
            "Bernoulli":BernoulliNB(),
            "Complement":ComplementNB(),
            "SVC":SVC(),
            "KNN":KNeighborsClassifier(),
            "Logistic":LogisticRegression(),
            }
```

```
[180]: models.keys()
```

```
[180]: dict_keys(['Gaussian', 'Bernoulli', 'Complement', 'SVC', 'KNN', 'Logistic'])
```

```
[181]: models.values()
```

```
[181]: dict_values([GaussianNB(), BernoulliNB(), ComplementNB(), SVC(),
KNeighborsClassifier(), LogisticRegression()])
```

```
[182]: models.items()
```

```
[182]: dict_items([('Gaussian', GaussianNB()), ('Bernoulli', BernoulliNB()),
('Complement', ComplementNB()), ('SVC', SVC()), ('KNN', KNeighborsClassifier()),
('Logistic', LogisticRegression())])
```

```
[183]: from sklearn.metrics import confusion_matrix,classification_report
```

```
[184]: Data=[]
for i,j in models.items():
    j.fit(X_train,y_train)
    TR=j.score(X_train,y_train)
    TE=j.score(X_test,y_test)
    pred=j.predict(X_test)
    Data.append([i,TR,TE])
    print(i.capitalize())
    print(classification_report(y_test,pred))
    print(confusion_matrix(y_test,pred))
    print("_"*80)
```

Gaussian

precision recall f1-score support

0	0.93	0.79	0.86	536
1	0.74	0.91	0.81	337
accuracy			0.84	873
macro avg	0.83	0.85	0.84	873
weighted avg	0.86	0.84	0.84	873

```
[[426 110]
 [ 31 306]]
```

Bernoulli

	precision	recall	f1-score	support
0	0.93	0.71	0.80	536
1	0.66	0.91	0.77	337
accuracy			0.79	873
macro avg	0.80	0.81	0.79	873
weighted avg	0.83	0.79	0.79	873

```
[[379 157]
 [ 29 308]]
```

Complement

	precision	recall	f1-score	support
0	0.71	0.61	0.66	536
1	0.49	0.60	0.54	337
accuracy			0.61	873
macro avg	0.60	0.61	0.60	873
weighted avg	0.63	0.61	0.61	873

```
[[328 208]
 [135 202]]
```

Svc

	precision	recall	f1-score	support
0	0.61	1.00	0.76	536
1	0.00	0.00	0.00	337
accuracy			0.61	873
macro avg	0.31	0.50	0.38	873
weighted avg	0.38	0.61	0.47	873

```
[[536  0]
 [337  0]]
```



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

0         0.65        0.69        0.67         536
1         0.45        0.40        0.42         337

 accuracy
macro avg         0.55        0.55        0.55         873
weighted avg         0.57        0.58        0.58         873

[[372 164]
 [202 135]]
-----
```

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

0         0.90        0.88        0.89         536
1         0.81        0.85        0.83         337

 accuracy
macro avg         0.86        0.86        0.86         873
weighted avg         0.87        0.86        0.87         873

[[469  67]
 [ 51 286]]
-----
```

```
[185]: Data
```

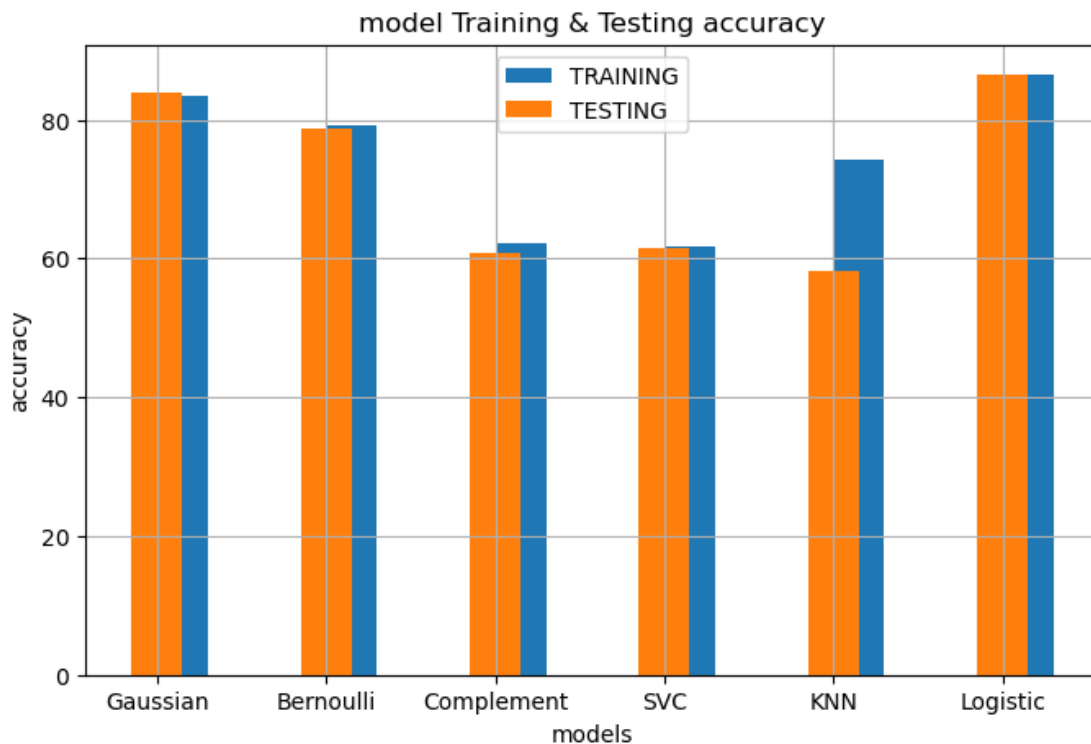
```
[185]: [['Gaussian', 0.8341449441420796, 0.8384879725085911],
        ['Bernoulli', 0.791177313090805, 0.7869415807560137],
        ['Complement', 0.6218848467487826, 0.6071019473081328],
        ['SVC', 0.6181609853910054, 0.6139747995418099],
        ['KNN', 0.7419077628186765, 0.5807560137457045],
        ['Logistic', 0.8645087367516471, 0.8648339060710195]]
```

```
[186]: Result=pd.DataFrame(Data,columns=("models name", "Training Accuracy", "Testing_
Accuracy"))
Result
```

```
[186]:  models name  Training Accuracy  Testing Accuracy
0    Gaussian          0.834145          0.838488
1  Bernoulli          0.791177          0.786942
2  Complement          0.621885          0.607102
3         SVC          0.618161          0.613975
4         KNN          0.741908          0.580756
```

5 Logistic 0.864509 0.864834

```
[187]: import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.bar(Result["models name"],Result["Training Accuracy"]*100,width=0.
        ↪3,align="edge",label="TRAINING")
plt.bar(Result["models name"],Result["Testing Accuracy"]*100,width=0.
        ↪3,align="center",label="TESTING")
plt.grid()
plt.legend()
plt.xlabel("models")
plt.ylabel("accuracy")
plt.title("model Training & Testing accuracy")
plt.show()
```



6.1 Decision Tree

```
[189]: from sklearn.tree import DecisionTreeClassifier
D=DecisionTreeClassifier(max_depth=10,criterion="gini",min_samples_split=20)
from sklearn.model_selection import GridSearchCV
params={"max_depth": [10,2,3,1,4,9,8], "criterion":
        ↪["gini", "entropy"], "min_samples_split": [11,15,10,8,4,9]}
```

```
G=GridSearchCV(D,param_grid=params,scoring="accuracy",cv=5)
```

```
[190]: G.fit(X_train,y_train)
```

```
[190]: GridSearchCV(cv=5,
                  estimator=DecisionTreeClassifier(max_depth=10,
                                                    min_samples_split=20),
                  param_grid={'criterion': ['gini', 'entropy'],
                              'max_depth': [10, 2, 3, 1, 4, 9, 8],
                              'min_samples_split': [11, 15, 10, 8, 4, 9]},
                  scoring='accuracy')
```

```
[191]: G.best_params_
```

```
[191]: {'criterion': 'entropy', 'max_depth': 8, 'min_samples_split': 15}
```

```
[192]: DecisionTree=G.best_estimator_
DecisionTree
```

```
[192]: DecisionTreeClassifier(criterion='entropy', max_depth=8, min_samples_split=15)
```

```
[193]: DecisionTree.score(X_train,y_train)*100
```

```
[193]: 97.45058722429103
```

```
[194]: DecisionTree.score(X_test,y_test)*100
```

```
[194]: 95.1890034364261
```

```
[195]: pred=DecisionTree.predict(X_test)
pred
```

```
[195]: array([0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0,
         0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
         0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0,
         0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0,
         0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
         1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1,
         0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
         0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0,
         0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0,
         0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
         1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
         0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1,
         0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1,
         0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
```

```

0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1,
1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1,
0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0,
1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1,
0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0,
1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0,
0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,
0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0,
0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1,
0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1,
1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0,
0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0,
1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0,
1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1,
0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0,
0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1,
0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1,
0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0,
0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0,
0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0,
1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1,
0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1,
1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0], dtype=int64)

```

```

[196]: from sklearn.metrics import
       ↪ confusion_matrix, classification_report, accuracy_score

```

```

[197]: confusion_matrix(y_test, pred)

```

```

[197]: array([[519, 17],
              [ 25, 312]], dtype=int64)

```

```

[198]: print(classification_report(y_test, pred))

```

	precision	recall	f1-score	support
0	0.95	0.97	0.96	536
1	0.95	0.93	0.94	337
accuracy			0.95	873
macro avg	0.95	0.95	0.95	873
weighted avg	0.95	0.95	0.95	873

```

[199]: accuracy_score(y_test, pred)*100

```

```
[199]: 95.1890034364261
```

```
[200]: DecisionTree={"DecisionTree":DecisionTreeClassifier()}
```

```
[201]: DecisionTree.keys()
```

```
[201]: dict_keys(['DecisionTree'])
```

```
[202]: DecisionTree.values()
```

```
[202]: dict_values([DecisionTreeClassifier()])
```

```
[203]: DecisionTree.items()
```

```
[203]: dict_items([('DecisionTree', DecisionTreeClassifier())])
```

```
[204]: Data=[]
for i,j in DecisionTree.items():
    j.fit(X_train,y_train)
    TR=j.score(X_train,y_train)
    TE=j.score(X_test,y_test)
    pred=j.predict(X_test)
    Data.append([i,TR,TE])
    print(i.capitalize())
    print(classification_report(y_test,pred))
    print(confusion_matrix(y_test,pred))
    print("_"*80)
```

```
Decisiontree
              precision    recall  f1-score   support

         0           0.96       0.96       0.96         536
         1           0.94       0.94       0.94         337

 accuracy                   0.95         873
 macro avg           0.95       0.95       0.95         873
 weighted avg        0.95       0.95       0.95         873
```

```
[[514  22]
 [ 20 317]]
```

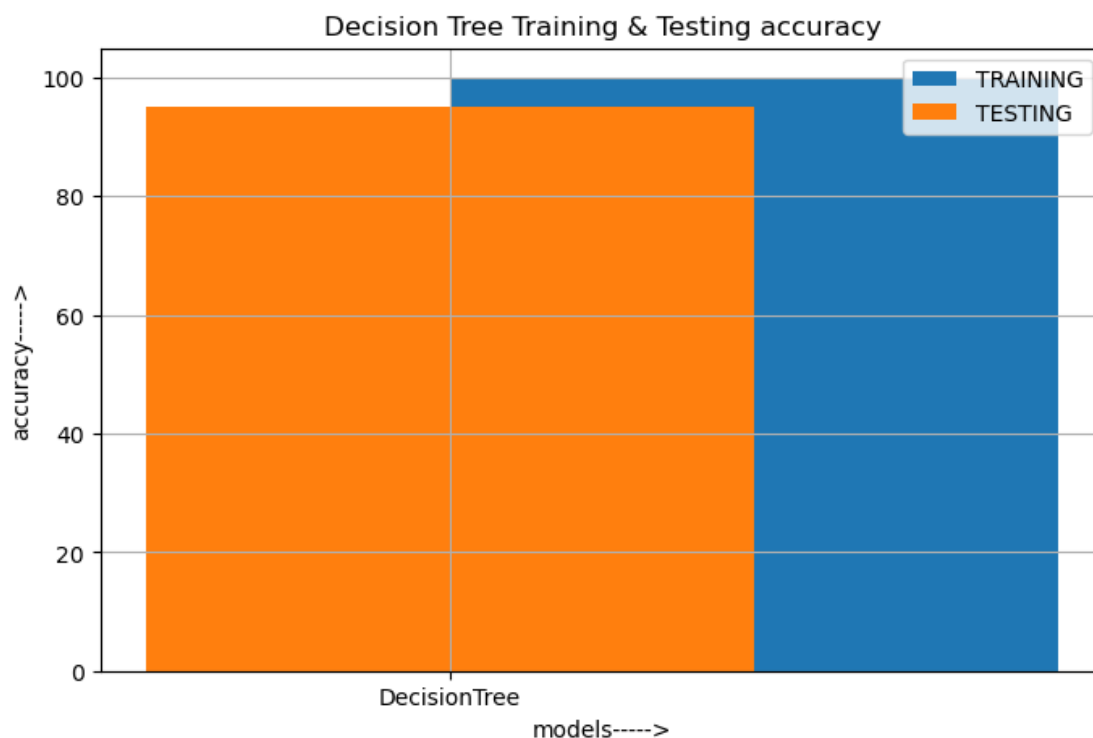
```
[205]: Data
```

```
[205]: [['DecisionTree', 1.0, 0.9518900343642611]]
```

```
[206]: Result=pd.DataFrame(Data,columns=("models name","Training Accuracy","Testing_
↪Accuracy"))
Result
```

```
[206]:      models name  Training Accuracy  Testing Accuracy
0  DecisionTree          1.0          0.95189
```

```
[207]: import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.bar(Result["models name"],Result["Training Accuracy"]*100,width=0.
↪3,align="edge",label="TRAINING")
plt.bar(Result["models name"],Result["Testing Accuracy"]*100,width=0.
↪3,align="center",label="TESTING")
plt.grid()
plt.legend()
plt.xlabel("models----->")
plt.ylabel("accuracy----->")
plt.title("Decision Tree Training & Testing accuracy")
plt.show()
```



6.2 Ensemble Learning

```
[209]: from sklearn.ensemble import RandomForestClassifier ## RFC are only use
      ↪ Decision Tree
      RFC=RandomForestClassifier(n_estimators=10)
      RFC.fit(X_train,y_train)
```

```
[209]: RandomForestClassifier(n_estimators=10)
```

```
[210]: RFC.score(X_train,y_train)*100
```

```
[210]: 99.62761386422228
```

```
[211]: RFC.score(X_test,y_test)*100
```

```
[211]: 95.1890034364261
```

```
[212]: from sklearn.ensemble import BaggingClassifier
      from sklearn.svm import SVC
      Bg=BaggingClassifier(estimator=SVC(),n_estimators=10)
```

```
[213]: Bg.fit(X_train,y_train)
```

```
[213]: BaggingClassifier(estimator=SVC())
```

```
[214]: Bg.score(X_train,y_train)*100
```

```
[214]: 61.81609853910054
```

```
[215]: Bg.score(X_test,y_test)*100
```

```
[215]: 61.39747995418099
```

```
[216]: from sklearn.ensemble import VotingClassifier
      A=VotingClassifier(estimators=[("LogReg",LogisticRegression()),
      ("SVC",SVC()),
      ("NB",GaussianNB())])
```

```
[217]: A.fit(X_train,y_train)
```

```
[217]: VotingClassifier(estimators=[('LogReg', LogisticRegression()), ('SVC', SVC()),
      ('NB', GaussianNB())])
```

```
[218]: A.score(X_train,y_train)*100
```

```
[218]: 86.53680893726727
```

```
[219]: A.score(X_test,y_test)*100
```

```
[219]: 86.94158075601375
```

```
[220]: from sklearn.ensemble import StackingClassifier
stacking=StackingClassifier(estimators=[("NB",GaussianNB()),
                                       ("SVC",SVC()),
                                       ("KNN",KNeighborsClassifier()),
                                       ("DT",DecisionTreeClassifier()),
                                       ("LogR",LogisticRegression())],
                           final_estimator=LogisticRegression())
```

```
[221]: stacking.fit(X_train,y_train)
```

```
[221]: StackingClassifier(estimators=[('NB', GaussianNB()), ('SVC', SVC()),
                                   ('KNN', KNeighborsClassifier()),
                                   ('DT', DecisionTreeClassifier()),
                                   ('LogR', LogisticRegression())],
                       final_estimator=LogisticRegression())
```

```
[222]: stacking.score(X_train,y_train)*100
```

```
[222]: 100.0
```

```
[223]: stacking.score(X_test,y_test)*100
```

```
[223]: 95.53264604810997
```

```
[224]: models={"RandomForestClassifier":RandomForestClassifier(n_estimators=10),
          "Bagging":BaggingClassifier(estimator=SVC(),n_estimators=10),
          "Voting":VotingClassifier(estimators=[("LogReg",LogisticRegression()),
                                                ("SVC",SVC()),
                                                ("NB",GaussianNB())]),
          "stacking":StackingClassifier(estimators=[("NB",GaussianNB()),
                                                    ("SVC",SVC()),
                                                    ("KNN",KNeighborsClassifier()),
                                                    ("DT",DecisionTreeClassifier()),
                                                    ("LogR",LogisticRegression())],
                                       final_estimator=LogisticRegression())}
```

```
[225]: models.values()
```

```
[225]: dict_values([RandomForestClassifier(n_estimators=10),
BaggingClassifier(estimator=SVC()), VotingClassifier(estimators=[('LogReg',
LogisticRegression()), ('SVC', SVC()),
                                   ('NB', GaussianNB())]),
StackingClassifier(estimators=[('NB', GaussianNB()), ('SVC', SVC()),
```



```

        ('KNN', KNeighborsClassifier()),
        ('DT', DecisionTreeClassifier()),
        ('LogR', LogisticRegression())],
        final_estimator=LogisticRegression())])

```

```
[226]: models.keys()
```

```
[226]: dict_keys(['RandomForestClassifier', 'Bagging', 'Voting', 'stacking'])
```

```
[227]: models.items()
```

```
[227]: dict_items([('RandomForestClassifier', RandomForestClassifier(n_estimators=10)),
('Bagging', BaggingClassifier(estimator=SVC())), ('Voting',
VotingClassifier(estimators=[('LogReg', LogisticRegression()), ('SVC', SVC()),
('NB', GaussianNB())])), ('stacking',
StackingClassifier(estimators=[('NB', GaussianNB()), ('SVC', SVC()),
('KNN', KNeighborsClassifier()),
('DT', DecisionTreeClassifier()),
('LogR', LogisticRegression())],
final_estimator=LogisticRegression()))])
```

```
[228]: from sklearn.metrics import confusion_matrix, classification_report
```

```
[229]: Data=[]
for i,j in models.items():
    j.fit(X_train,y_train)
    TR=j.score(X_train,y_train)
    TE=j.score(X_test,y_test)
    pred=j.predict(X_test)
    Data.append([i,TR,TE])
    print(i.capitalize())
    print(classification_report(y_test,pred))
    print(confusion_matrix(y_test,pred))
    print("_"*80)
```

```

Randomforestclassifier
      precision    recall  f1-score   support

      0       0.94      0.96      0.95        536
      1       0.94      0.90      0.92        337

 accuracy          0.94          0.94          0.94          873
 macro avg       0.94      0.93      0.94          873
 weighted avg    0.94      0.94      0.94          873

```

```

[[516  20]
 [ 33 304]]

```

Bagging

	precision	recall	f1-score	support
0	0.61	1.00	0.76	536
1	0.00	0.00	0.00	337
accuracy			0.61	873
macro avg	0.31	0.50	0.38	873
weighted avg	0.38	0.61	0.47	873

```
[[536  0]
 [337  0]]
```

Voting

	precision	recall	f1-score	support
0	0.90	0.88	0.89	536
1	0.82	0.85	0.83	337
accuracy			0.87	873
macro avg	0.86	0.87	0.86	873
weighted avg	0.87	0.87	0.87	873

```
[[474 62]
 [ 52 285]]
```

Stacking

	precision	recall	f1-score	support
0	0.96	0.96	0.96	536
1	0.94	0.94	0.94	337
accuracy			0.95	873
macro avg	0.95	0.95	0.95	873
weighted avg	0.95	0.95	0.95	873

```
[[515 21]
 [ 20 317]]
```

[230]: Data

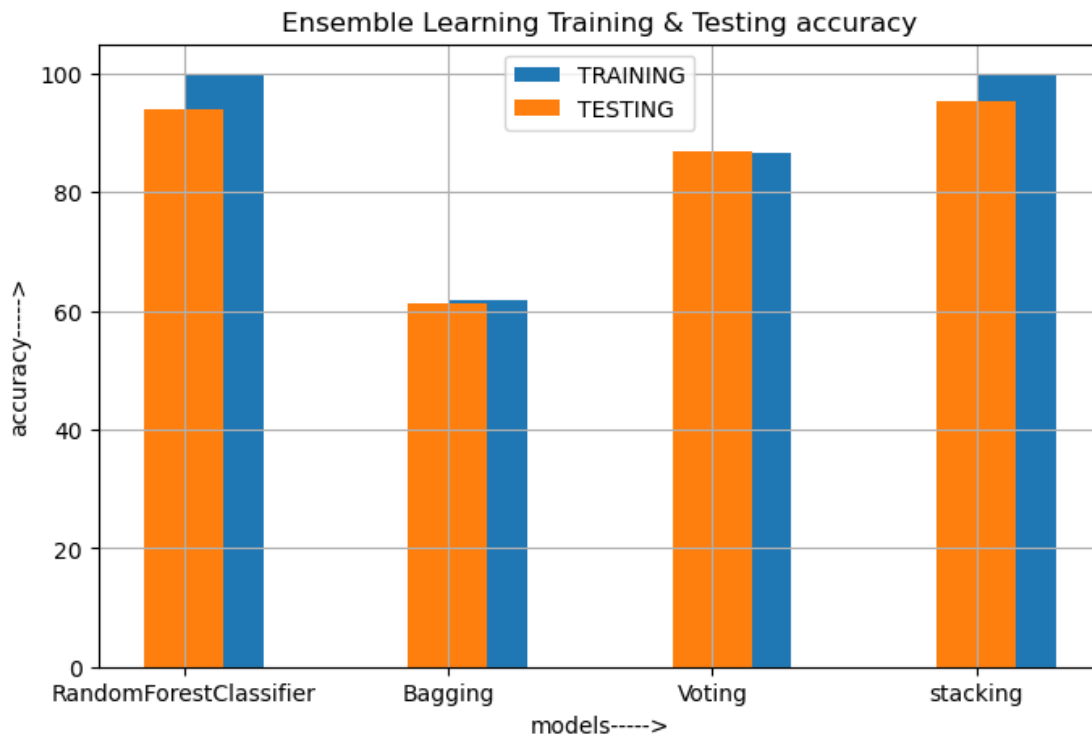
```
[230]: [['RandomForestClassifier', 0.9977083930105987, 0.9392898052691867],
        ['Bagging', 0.6181609853910054, 0.6139747995418099],
        ['Voting', 0.8653680893726726, 0.8694158075601375],
        ['stacking', 1.0, 0.9530355097365406]]
```

```
[231]: Result=pd.DataFrame(Data,columns=("models name","Training Accuracy","Testing_Accuracy"))
Result
```

```
[231]:
```

	models name	Training Accuracy	Testing Accuracy
0	RandomForestClassifier	0.997708	0.939290
1	Bagging	0.618161	0.613975
2	Voting	0.865368	0.869416
3	stacking	1.000000	0.953036

```
[232]: import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.bar(Result["models name"],Result["Training Accuracy"]*100,width=0.3,align="edge",label="TRAINING")
plt.bar(Result["models name"],Result["Testing Accuracy"]*100,width=0.3,align="center",label="TESTING")
plt.grid()
plt.legend()
plt.xlabel("models----->")
plt.ylabel("accuracy----->")
plt.title("Ensemble Learning Training & Testing accuracy")
plt.show()
```



7 AdaBoost

```
[234]: from sklearn.ensemble import AdaBoostClassifier
```

```
[235]: A=AdaBoostClassifier(n_estimators=50)
A.fit(X_train,y_train)
```

```
[235]: AdaBoostClassifier()
```

```
[236]: A.score(X_train,y_train)*100
```

```
[236]: 94.35691778859926
```

```
[237]: A.score(X_test,y_test)*100
```

```
[237]: 94.38717067583046
```

8 PCL

```
[240]: x=pd.read_csv(r"C:\Users\vidya\Downloads\smart_home_device_usage_data.csv")
x
```

```
[240]:
```

	UserID	DeviceType	UsageHoursPerDay	EnergyConsumption	\
0	1	Smart Speaker	15.307188	1.961607	
1	2	Camera	19.973343	8.610689	
2	3	Security System	18.911535	2.651777	
3	4	Camera	7.011127	2.341653	
4	5	Camera	22.610684	4.859069	
...	
5398	5399	Thermostat	4.556314	5.871764	
5399	5400	Lights	0.561856	1.555992	
5400	5401	Smart Speaker	11.096236	7.677779	
5401	5402	Security System	8.782169	7.467929	
5402	5403	Thermostat	13.540381	9.043076	

	UserPreferences	MalfunctionIncidents	DeviceAgeMonths	\
0	1	4	36	
1	1	0	29	
2	1	0	20	
3	0	3	15	
4	1	3	36	
...	
5398	1	0	28	
5399	1	4	24	
5400	0	0	42	
5401	0	2	28	

5402	0	0	30
------	---	---	----

	SmartHomeEfficiency
0	1
1	1
2	1
3	0
4	1
...	...
5398	0
5399	0
5400	0
5401	1
5402	0

[5403 rows x 8 columns]

```
[242]: x.drop(columns="DeviceType",inplace=True)
x
```

```
[242]:
```

	UserID	UsageHoursPerDay	EnergyConsumption	UserPreferences	\
0	1	15.307188	1.961607		1
1	2	19.973343	8.610689		1
2	3	18.911535	2.651777		1
3	4	7.011127	2.341653		0
4	5	22.610684	4.859069		1
...	
5398	5399	4.556314	5.871764		1
5399	5400	0.561856	1.555992		1
5400	5401	11.096236	7.677779		0
5401	5402	8.782169	7.467929		0
5402	5403	13.540381	9.043076		0

	MalfunctionIncidents	DeviceAgeMonths	SmartHomeEfficiency
0	4	36	1
1	0	29	1
2	0	20	1
3	3	15	0
4	3	36	1
...
5398	0	28	0
5399	4	24	0
5400	0	42	0
5401	2	28	1
5402	0	30	0

[5403 rows x 7 columns]

```
[269]: from sklearn.decomposition import PCA
A=PCA(n_components=5)
x1=A.fit_transform(x)
x2=pd.DataFrame(x1)
A.explained_variance_ratio_.sum()*100
```

[269]: 99.99998135075101

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