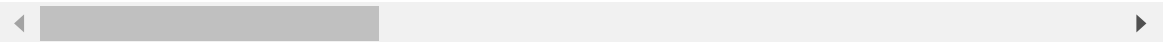


```
In [1]: 1 import pandas as pd
        2 import matplotlib.pyplot as plt
        3 X=pd.read_csv(r"C:\Users\Admin\Downloads\alzheimers_disease_data.csv")
        4 X
```

```
Out[1]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsur
0	4751	73	0	0	2	22.927749	0	13.2
1	4752	89	0	0	0	26.827681	0	4.5
2	4753	73	0	3	1	17.795882	0	19.5
3	4754	74	1	0	1	33.800817	1	12.2
4	4755	89	0	0	0	20.716974	0	18.4
...	...	...	...	...	...	...	...	...
2144	6895	61	0	0	1	39.121757	0	1.5
2145	6896	75	0	0	2	17.857903	0	18.7
2146	6897	77	0	0	1	15.476479	0	4.5
2147	6898	78	1	3	1	15.299911	0	8.6
2148	6899	72	0	0	2	33.289738	0	7.8

2149 rows × 35 columns



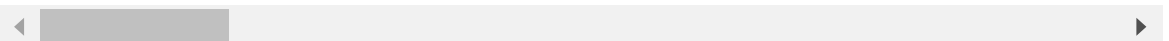
```
In [2]: 1 pd.set_option("Display.max_columns",100)
```

```
In [3]: 1 X
```

```
Out[3]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsur
0	4751	73	0	0	2	22.927749	0	13.2
1	4752	89	0	0	0	26.827681	0	4.5
2	4753	73	0	3	1	17.795882	0	19.5
3	4754	74	1	0	1	33.800817	1	12.2
4	4755	89	0	0	0	20.716974	0	18.4
...	...	...	...	...	...	...	...	...
2144	6895	61	0	0	1	39.121757	0	1.5
2145	6896	75	0	0	2	17.857903	0	18.7
2146	6897	77	0	0	1	15.476479	0	4.5
2147	6898	78	1	3	1	15.299911	0	8.6
2148	6899	72	0	0	2	33.289738	0	7.8

2149 rows × 35 columns



```
In [4]: 1 X.shape
```

```
Out[4]: (2149, 35)
```

```
In [5]: 1 X.isnull().sum()
```

```
Out[5]: PatientID          0
        Age                0
        Gender             0
        Ethnicity          0
        EducationLevel     0
        BMI                0
        Smoking            0
        AlcoholConsumption 0
        PhysicalActivity    0
        DietQuality         0
        SleepQuality        0
        FamilyHistoryAlzheimers 0
        CardiovascularDisease 0
        Diabetes           0
        Depression         0
        HeadInjury         0
        Hypertension        0
        SystolicBP          0
        DiastolicBP         0
        CholesterolTotal    0
        CholesterolLDL      0
        CholesterolHDL      0
        CholesterolTriglycerides 0
        MMSE               0
        FunctionalAssessment 0
        MemoryComplaints    0
        BehavioralProblems  0
        ADL                0
        Confusion           0
        Disorientation       0
        PersonalityChanges  0
        DifficultyCompletingTasks 0
        Forgetfulness       0
        Diagnosis           0
        DoctorInCharge      0
        dtype: int64
```

```
In [6]: 1 X[['Age', 'Diagnosis']].value_counts()
```

```
Out[6]: Age  Diagnosis
72  0          61
88  0          56
68  0          55
67  0          53
76  0          51
    ..
64  1          19
74  1          18
69  1          17
79  1          16
86  1          15
Name: count, Length: 62, dtype: int64
```

```
In [7]: 1 X[['Age', 'Diagnosis']].min()
```

```
Out[7]: Age          60  
Diagnosis      0  
dtype: int64
```

```
In [8]: 1 X[['Age', 'Diagnosis']].max()
```

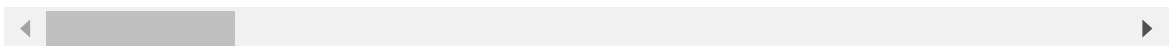
```
Out[8]: Age          90  
Diagnosis      1  
dtype: int64
```

```
In [9]: 1 X1=X.loc[(X['BehavioralProblems']==1)&(X['Diagnosis']==1)]  
2 X1
```

```
Out[9]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
19	4770	68	0	0	3	20.041400	0	18.4
20	4771	82	1	0	0	36.223099	0	4.1
24	4775	64	1	0	1	15.457688	1	9.7
46	4797	71	0	1	1	15.648055	0	17.8
48	4799	87	0	1	2	33.476971	1	15.8
...	...	...	...	...	...	...	...	...
2088	6839	64	1	0	2	39.218489	1	0.8
2126	6877	75	1	1	1	35.832125	0	13.0
2132	6883	65	1	0	1	18.517832	0	8.2
2136	6887	83	1	2	2	19.006926	0	13.9
2145	6896	75	0	0	2	17.857903	0	18.7

203 rows × 35 columns

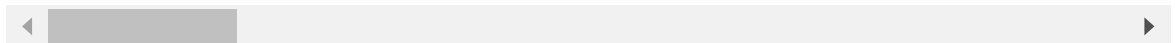


```
In [10]: 1 X.loc[(X['DifficultyCompletingTasks']==1)&(X['Diagnosis']==1)]
```

```
Out[10]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	
	45	4796	68	1	0	1	26.804164	0	19.6
	58	4809	83	1	1	2	28.997201	0	14.8
	65	4816	90	1	1	1	28.191097	0	10.4
	72	4823	89	1	1	1	28.443777	0	4.3
	78	4829	82	1	3	2	15.908275	0	16.3
	...	...	...	...	...	...	...	...	...
	2130	6881	81	1	2	0	22.630945	1	2.3
	2136	6887	83	1	2	2	19.006926	0	13.9
	2138	6889	71	0	0	2	36.796170	0	16.1
	2142	6893	88	0	0	0	20.097600	0	4.0
	2143	6894	66	1	2	1	32.013806	1	9.3

124 rows × 35 columns

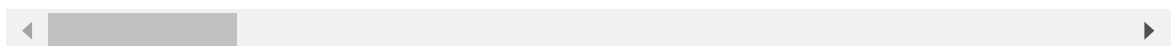


```
In [11]: 1 X2=X.loc[(X['ADL']<=5)&(X['Diagnosis']==1)]
          2 X2
```

```
Out[11]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	
	7	4758	75	0	0	1	18.776009	0	13.7
	13	4764	78	1	0	1	28.870652	1	10.1
	15	4766	69	0	0	1	18.045917	0	8.7
	16	4767	63	1	1	2	22.822896	1	4.4
	17	4768	65	1	0	1	16.333283	1	4.1
	...	...	...	...	...	...	...	...	...
	2135	6886	60	1	0	2	15.435244	0	15.6
	2138	6889	71	0	0	2	36.796170	0	16.1
	2143	6894	66	1	2	1	32.013806	1	9.3
	2144	6895	61	0	0	1	39.121757	0	1.3
	2147	6898	78	1	3	1	15.299911	0	8.6

567 rows × 35 columns

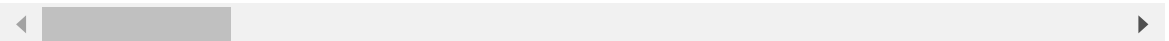


```
In [12]: 1 X.loc[(X['FunctionalAssessment']<=5)&(X['Diagnosis']==1)]
```

```
Out[12]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
7	4758	75	0	0	1	18.776009	0	13.7
13	4764	78	1	0	1	28.870652	1	10.1
15	4766	69	0	0	1	18.045917	0	8.7
17	4768	65	1	0	1	16.333283	1	4.1
19	4770	68	0	0	3	20.041400	0	18.4
...	...	...	...	...	...	...	...	...
2133	6884	87	0	0	0	35.580967	0	17.7
2136	6887	83	1	2	2	19.006926	0	13.9
2143	6894	66	1	2	1	32.013806	1	9.3
2144	6895	61	0	0	1	39.121757	0	1.3
2146	6897	77	0	0	1	15.476479	0	4.5

584 rows × 35 columns

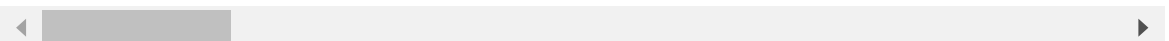


```
In [13]: 1 x=X.loc[X['Diagnosis']==1]
          2 x
```

```
Out[13]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
7	4758	75	0	0	1	18.776009	0	13.7
13	4764	78	1	0	1	28.870652	1	10.1
15	4766	69	0	0	1	18.045917	0	8.7
16	4767	63	1	1	2	22.822896	1	4.4
17	4768	65	1	0	1	16.333283	1	4.1
...	...	...	...	...	...	...	...	...
2143	6894	66	1	2	1	32.013806	1	9.3
2144	6895	61	0	0	1	39.121757	0	1.3
2145	6896	75	0	0	2	17.857903	0	18.7
2146	6897	77	0	0	1	15.476479	0	4.5
2147	6898	78	1	3	1	15.299911	0	8.6

760 rows × 35 columns



```
In [14]: 1 x['Age'].value_counts().reset_index()
```

```
Out[14]:
```

	Age	count
0	61	32
1	90	31
2	71	31
3	76	30
4	78	29
5	68	29
6	84	29
7	63	28
8	88	28
9	70	27
10	89	27
11	83	27
12	60	26
13	75	26
14	66	26
15	62	25
16	73	24
17	80	24
18	67	24
19	87	24
20	65	24
21	77	23
22	72	21
23	85	21
24	81	20
25	82	19
26	64	19
27	74	18
28	69	17
29	79	16
30	86	15

```
In [15]: 1 X[['CholesterolTotal', 'CholesterolLDL', 'CholesterolHDL']].max()
```

```
Out[15]: CholesterolTotal    299.993352
CholesterolLDL      199.965665
CholesterolHDL       99.980324
dtype: float64
```

```
In [16]: 1 X[['CholesterolTotal', 'CholesterolLDL', 'CholesterolHDL']].min()
```

```
Out[16]: CholesterolTotal    150.093316  
CholesterolLDL          50.230707  
CholesterolHDL          20.003434  
dtype: float64
```

```
In [17]: 1 X[['CholesterolTotal', 'CholesterolLDL', 'CholesterolHDL', 'Diagnosis']].min()
```

```
Out[17]:
```

	index	0
0	CholesterolTotal	225.197519
1	CholesterolLDL	124.335944
2	CholesterolHDL	59.463533
3	Diagnosis	0.353653

```
In [18]: 1 X.groupby(['CholesterolTotal', 'CholesterolLDL', 'CholesterolHDL'])[['Diagnosis']].min()
```

```
Out[18]:
```

	CholesterolTotal	CholesterolLDL	CholesterolHDL	Diagnosis
	150.093316	69.067758	35.440518	1
	150.135572	137.630223	37.583055	1
	150.192183	105.857772	79.163699	1
	150.212650	119.251101	83.997809	1
	150.287014	163.424986	58.714098	1
	...	...	...	...
	299.868482	88.110915	81.983039	1
	299.873259	164.452648	62.757367	1
	299.890133	96.737082	97.516957	1
	299.959991	120.918658	90.372018	1
	299.993352	64.182129	51.410637	1

2149 rows × 1 columns

In [19]:

```
1 A=X.loc[(X['CholesterolTotal']>=240)&(X['CholesterolLDL']>=160)&(X['CholesterolHDL']>=100)]
2 A
```

Out[19]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
14	4765	64	1	0	2	27.942863	0	2.1
120	4871	70	0	0	1	39.637153	0	3.6
131	4882	60	0	1	1	16.196569	0	4.7
248	4999	66	1	1	0	35.235847	0	17.5
325	5076	88	1	0	1	18.165057	1	18.4
344	5095	72	0	1	2	26.880676	0	4.4
398	5149	68	1	0	2	23.290559	0	5.2
435	5186	71	1	0	2	24.050077	0	1.3
450	5201	61	1	3	3	34.940999	0	10.2
513	5264	84	1	0	1	27.948006	0	0.9
524	5275	62	0	3	2	34.150320	0	19.7
739	5490	88	1	0	1	23.936827	0	16.8
807	5558	79	1	2	1	25.091602	0	4.5
832	5583	66	0	0	2	39.159497	0	9.9
883	5634	84	0	0	0	39.586924	1	18.6
951	5702	90	1	0	1	27.276350	0	3.2
1064	5815	78	1	0	1	22.268722	0	9.7
1096	5847	74	0	0	2	30.536551	1	10.8
1321	6072	82	0	0	2	26.191381	0	4.0
1414	6165	71	1	1	1	23.263395	1	11.7
1473	6224	72	1	0	0	23.094319	0	4.1
1501	6252	62	1	3	0	28.632493	0	1.0
1522	6273	77	0	0	1	26.828226	0	8.5
1583	6334	66	0	3	1	38.934002	1	5.7
1802	6553	67	1	0	0	34.274316	0	17.0
1853	6604	79	0	2	1	37.977139	0	18.2
2001	6752	65	0	1	1	30.588889	1	14.0
2072	6823	68	0	0	3	34.244492	1	3.4
2141	6892	72	0	0	2	21.600144	0	19.3

In [20]:

```
1 A['Diagnosis'].value_counts()
```

Out[20]:

```
Diagnosis
0      19
1      10
Name: count, dtype: int64
```



In [21]:

```
1 A1=A.loc[A['Diagnosis']==0]
2 A1
```

Out[21]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
14	4765	64	1	0	2	27.942863	0	2.1
120	4871	70	0	0	1	39.637153	0	3.6
131	4882	60	0	1	1	16.196569	0	4.7
248	4999	66	1	1	0	35.235847	0	17.5
325	5076	88	1	0	1	18.165057	1	18.4
344	5095	72	0	1	2	26.880676	0	4.4
398	5149	68	1	0	2	23.290559	0	5.2
450	5201	61	1	3	3	34.940999	0	10.2
513	5264	84	1	0	1	27.948006	0	0.9
524	5275	62	0	3	2	34.150320	0	19.7
807	5558	79	1	2	1	25.091602	0	4.5
951	5702	90	1	0	1	27.276350	0	3.2
1096	5847	74	0	0	2	30.536551	1	10.8
1414	6165	71	1	1	1	23.263395	1	11.7
1501	6252	62	1	3	0	28.632493	0	1.0
1583	6334	66	0	3	1	38.934002	1	5.7
1802	6553	67	1	0	0	34.274316	0	17.0
2072	6823	68	0	0	3	34.244492	1	3.4
2141	6892	72	0	0	2	21.600144	0	19.3

In [22]:

```
1 #with high Cholesterol Levels many people are not diagnosed with Alzheimer
```

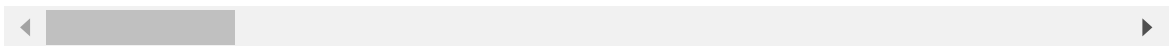
In [23]:

```
1 A2=X.loc[(X['CholesterolTotal']<=200)&(X['CholesterolLDL']<100)&(X['CholesterolHDL']>100)]
2 A2
```

Out[23]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
27	4778	71	0	0	2	18.434789	0	15.5
37	4788	60	1	0	2	31.568689	0	3.4
87	4838	75	0	0	2	31.820253	0	13.5
109	4860	60	1	0	2	24.974286	0	18.4
158	4909	68	1	3	3	15.794386	0	9.5
...	...	...	...	...	...	...	...	...
2000	6751	90	0	2	1	22.161590	0	11.4
2007	6758	60	1	0	1	38.214532	1	8.7
2023	6774	71	0	2	3	27.332495	0	19.6
2094	6845	85	0	0	0	24.385193	0	2.8
2130	6881	81	1	2	0	22.630945	1	2.5

83 rows × 35 columns

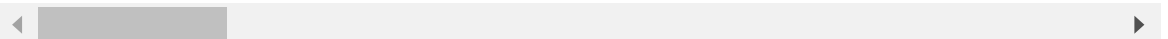


In [24]:

```
1 A3=A2.loc[(A2['Gender']==0)&(A2['Diagnosis']==0)]
2 A3#with optimal level of cholestrol women are less likely to diagnosed
```

Out[24]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
27	4778	71	0	0	2	18.434789	0	15.9
87	4838	75	0	0	2	31.820253	0	13.3
220	4971	70	0	1	1	21.780690	0	11.6
252	5003	79	0	2	1	26.798031	0	6.0
259	5010	76	0	1	1	23.950445	0	13.7
281	5032	68	0	0	3	33.789883	0	7.5
336	5087	79	0	0	1	20.546211	0	19.7
374	5125	80	0	1	3	17.095404	1	14.9
443	5194	65	0	2	2	29.584935	0	5.3
446	5197	80	0	0	1	33.398410	1	7.5
599	5350	79	0	0	1	31.261029	0	10.8
650	5401	87	0	3	1	21.631578	0	14.7
667	5418	64	0	0	0	32.362132	0	10.2
761	5512	86	0	0	1	21.900205	1	0.8
798	5549	82	0	1	2	22.602948	0	1.8
853	5604	75	0	1	0	33.326818	0	11.2
860	5611	71	0	2	2	16.080044	1	19.8
967	5718	80	0	0	1	22.031611	0	19.5
1160	5911	72	0	1	0	38.646316	1	15.4
1385	6136	68	0	0	3	33.603383	0	7.7
1589	6340	73	0	1	3	19.506076	0	12.5
1591	6342	81	0	1	0	38.186388	1	13.4
1618	6369	64	0	0	0	22.413218	0	19.1
1626	6377	69	0	3	1	36.555455	0	7.3
1698	6449	82	0	0	1	26.223176	1	11.9
1823	6574	88	0	1	1	25.260763	1	8.7
1925	6676	60	0	1	0	33.361610	0	8.7
1928	6679	69	0	0	2	20.944052	1	4.5
1946	6697	66	0	3	2	23.987902	0	16.3
2094	6845	85	0	0	0	24.385193	0	2.8



In [25]:

```
1 A3['Diagnosis'].value_counts()
```

Out[25]: Diagnosis

0 30

Name: count, dtype: int64

```
In [26]: 1 X['HeadInjury'].unique()
```

```
Out[26]: array([0, 1], dtype=int64)
```

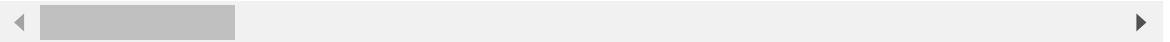
```
In [27]: 1 X.drop(columns='DoctorInCharge',inplace=True)
```

```
In [28]: 1 X
```

```
Out[28]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
0	4751	73	0	0	2	22.927749	0	13.2
1	4752	89	0	0	0	26.827681	0	4.5
2	4753	73	0	3	1	17.795882	0	19.5
3	4754	74	1	0	1	33.800817	1	12.2
4	4755	89	0	0	0	20.716974	0	18.4
...	...	...	...	...	...	...	...	...
2144	6895	61	0	0	1	39.121757	0	1.5
2145	6896	75	0	0	2	17.857903	0	18.7
2146	6897	77	0	0	1	15.476479	0	4.5
2147	6898	78	1	3	1	15.299911	0	8.6
2148	6899	72	0	0	2	33.289738	0	7.8

2149 rows × 34 columns



```
In [29]: 1 X4=X.loc[X['MMSE']<=15]
2 X4
```

```
Out[29]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
2	4753	73	0	3	1	17.795882	0	19.5
3	4754	74	1	0	1	33.800817	1	12.2
4	4755	89	0	0	0	20.716974	0	18.4
6	4757	68	0	3	2	38.387622	1	0.6
7	4758	75	0	0	1	18.776009	0	13.7
...	...	...	...	...	...	...	...	...
2143	6894	66	1	2	1	32.013806	1	9.3
2144	6895	61	0	0	1	39.121757	0	1.5
2145	6896	75	0	0	2	17.857903	0	18.7
2147	6898	78	1	3	1	15.299911	0	8.6
2148	6899	72	0	0	2	33.289738	0	7.8

1112 rows × 34 columns



In [30]:

```
1 x2=X.loc[(X['Forgetfulness']==1)&(X['DifficultyCompletingTasks']==1)&(
2 x2
```

Out[30]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption
161	4912	63	1	0	2	39.793970	0	6.4
178	4929	74	1	1	1	32.148698	1	14.8
457	5208	68	0	0	3	26.634779	0	1.5
749	5500	74	1	1	3	15.014659	1	11.6
1147	5898	90	1	3	0	24.332593	1	12.0
1245	5996	86	1	0	0	16.656064	0	1.9
1476	6227	64	1	0	1	29.714024	0	4.0
1514	6265	67	0	2	2	28.493977	0	14.6
1675	6426	83	1	0	1	36.651524	1	0.4
1699	6450	75	0	0	0	19.626719	1	10.5
1707	6458	71	0	0	2	17.545005	1	3.7
1781	6532	87	0	0	3	25.173319	0	13.1
2008	6759	74	1	0	1	32.651525	0	8.6

In [31]:

```
1 x2['Age'].value_counts().reset_index() #patients above 70 having sympto
```

Out[31]:

	Age	count
0	74	3
1	63	1
2	68	1
3	90	1
4	86	1
5	64	1
6	67	1
7	83	1
8	75	1
9	71	1
10	87	1

In [32]:

```
1 X4['Diagnosis'].value_counts() #MMSE score less than 15 are more likely
```

Out[32]:

```
Diagnosis
0    618
1    494
Name: count, dtype: int64
```

In [33]: 1 x1=X.loc[:,['SystolicBP','DiastolicBP','CholesterolTotal','CholesterolLDL','CholesterolHDL','Cholesterol']]

In [34]: 1 x1

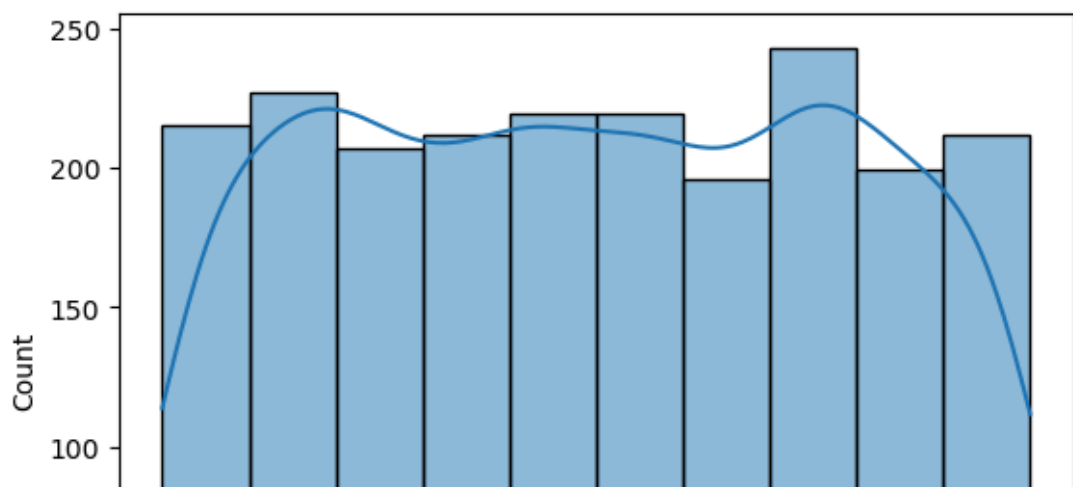
Out[34]:

	SystolicBP	DiastolicBP	CholesterolTotal	CholesterolLDL	CholesterolHDL	Cholesterol'
0	142	72	242.366840	56.150897	33.682563	
1	115	64	231.162595	193.407996	79.028477	
2	99	116	284.181858	153.322762	69.772292	
3	118	115	159.582240	65.366637	68.457491	
4	94	117	237.602184	92.869700	56.874305	
...	...	...	...	...	...	...
2144	122	101	280.476824	94.870490	60.943092	
2145	152	106	186.384436	95.410700	93.649735	
2146	115	118	237.024558	156.267294	99.678209	
2147	103	96	242.197192	52.482961	81.281111	
2148	166	78	283.396797	92.200064	81.920043	

2149 rows × 7 columns

In [35]: 1 import matplotlib.pyplot as plt  
2 import seaborn as sns  
3 for i in x1.columns:  
4 sns.histplot(x1[i],bins=10,kde=True)  
5 plt.show()

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning: use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.  
with pd.option\_context('mode.use\_inf\_as\_na', True):



In [36]: 1 X['CholesterolHDL'].mean()

Out[36]: 59.46353314116864

```
In [37]: 1 X['CholesterolHDL'].median()
```

```
Out[37]: 59.76823749767153
```

```
In [38]: 1 X['CholesterolHDL'].mode()[0]
```

```
Out[38]: 20.00343401498445
```

```
In [39]: 1 X['MMSE'].mean()
```

```
Out[39]: 14.7551319782826
```

```
In [40]: 1 X['MMSE'].median()
```

```
Out[40]: 14.441659908144548
```

```
In [41]: 1 X['MMSE'].mode()[0]
```

```
Out[41]: 0.0053121464417005
```

```
In [42]: 1 F=X.drop(columns='Diagnosis',axis=1)
2 T=X['Diagnosis']
```

```
In [43]: 1 from sklearn.model_selection import train_test_split
2 X_train,X_test,y_train,y_test=train_test_split(F,T,train_size=0.90,rand
```

```
In [44]: 1 from sklearn.preprocessing import MinMaxScaler
2 M=MinMaxScaler()
```

```
In [45]: 1 X_train[['PatientID','Age','BMI','SystolicBP','DiastolicBP','Cholestero
2 X_train
```

```
Out[45]:
```

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholCor
--	-----------	-----	--------	-----------	----------------	-----	---------	------------

1611	0.750000	0.600000	1	0	1	0.278486	0	
1154	0.537244	0.066667	1	0	1	0.426405	0	
820	0.381750	0.500000	0	0	0	0.415574	0	
465	0.216480	0.533333	1	0	2	0.559979	0	
1675	0.779795	0.766667	1	0	1	0.866264	1	
...	...	...	...	...	...	...	...	...
1208	0.562384	0.033333	1	0	1	0.522248	0	
172	0.080074	0.933333	1	1	2	0.652971	0	
983	0.457635	0.266667	0	0	0	0.757322	1	
1251	0.582402	0.233333	1	0	1	0.362522	1	
178	0.082868	0.466667	1	1	1	0.686035	1	

1934 rows × 33 columns

In [46]:

```

1 X_test[['PatientID', 'Age', 'BMI', 'SystolicBP', 'DiastolicBP', 'Cholesterol']]
2 X_test

```

Out[46]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholCor
1953	0.918983	0.333333	0	1	0	0.159542	0	
65	0.029675	1.000000	1	1	1	0.531342	0	
475	0.222798	0.233333	0	0	2	0.564601	1	
1719	0.808761	0.200000	1	0	1	0.066571	0	
527	0.247292	0.533333	1	2	3	0.315526	0	
...	...	...	...	...	...	...	...	...
1120	0.526613	0.633333	0	0	1	0.496167	0	
1519	0.714555	0.166667	0	0	1	0.894384	0	
590	0.276967	0.366667	0	0	1	0.251246	0	
2121	0.998116	0.033333	0	0	3	0.424122	0	
1432	0.673575	0.366667	1	0	3	0.536823	0	

215 rows × 33 columns

In [47]:

```

1 from sklearn.model_selection import GridSearchCV
2 from sklearn.linear_model import LogisticRegression
3 Log=LogisticRegression()
4 params={'C':[0.1,0.01,0.02,0.3],'penalty':['l1','l2']}
5 G=GridSearchCV(Log,param_grid=params,scoring="accuracy",cv=7)

```

In [48]:

```

1 G.fit(X_train,y_train)

```

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\linear\_model\\_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):  
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)  
Please also refer to the documentation for alternative solver options:  
[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression) ([https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression))

```

n_iter_i = _check_optimize_result(
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)



In [49]: 1 G.best\_params\_

Out[49]: {'C': 0.3, 'penalty': 'l2'}

In [50]: 1 O=G.best\_estimator\_  
2 O

Out[50]: LogisticRegression(C=0.3)

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In [51]: 1 Pr=O.predict(X\_test)  
2 Pr

Out[51]: array([1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,  
1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0,  
0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0,  
0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,  
0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,  
1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,  
0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0,  
0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1,  
0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1,  
0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1])

In [52]: 1 O.score(X\_train,y\_train)

Out[52]: 0.8500517063081696

In [53]: 1 O.score(X\_test,y\_test)

Out[53]: 0.8372093023255814

In [54]: 1 from sklearn.metrics import accuracy\_score,classification\_report,confus

In [55]: 1 accuracy\_score(y\_test,Pr)

Out[55]: 0.8372093023255814

In [56]: 1 print(classification\_report(y\_test,Pr))

	precision	recall	f1-score	support
0	0.86	0.88	0.87	136
1	0.79	0.76	0.77	79
accuracy			0.84	215
macro avg	0.83	0.82	0.82	215
weighted avg	0.84	0.84	0.84	215

```
In [57]: 1 confusion_matrix(y_test,Pr)
```

```
Out[57]: array([[120, 16],
                [ 19, 60]], dtype=int64)
```

```
In [58]: 1 from sklearn.model_selection import GridSearchCV
2 from sklearn.neighbors import KNeighborsClassifier
3 KN=KNeighborsClassifier()
4 params={'n_neighbors':[4,3,8,10]}
5 V=GridSearchCV(KN,param_grid=params,scoring="accuracy",cv=7)
```

```
In [59]: 1 V.fit(X_train,y_train)
```

```
Out[59]: GridSearchCV(cv=7, estimator=KNeighborsClassifier(),
                    param_grid={'n_neighbors': [4, 3, 8, 10]}, scoring='accuracy')
```

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```
In [60]: 1 V.best_params_
```

```
Out[60]: {'n_neighbors': 8}
```

```
In [61]: 1 T=V.best_estimator_
2 T
```

```
Out[61]: KNeighborsClassifier(n_neighbors=8)
```

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```
In [62]: 1 T.score(X_train,y_train)
```

```
Out[62]: 0.8252326783867632
```

```
In [63]: 1 T.score(X_test,y_test)
```

```
Out[63]: 0.7813953488372093
```

```
In [64]: 1 PDT=T.predict(X_test)
          2 PDT
```

```
Out[64]: array([1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
                1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0,
                0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
                1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0])
```

```
In [65]: 1 from sklearn.model_selection import GridSearchCV
          2 from sklearn.svm import SVC
          3 s=SVC()
          4 para={"gamma":[0.03,0.5,0.8,0.1],"kernel":["rbf"]}
          5 g=GridSearchCV(s,param_grid=para,scoring="accuracy",cv=8)
```

```
In [66]: 1 g.fit(X_train,y_train)
```

```
Out[66]: GridSearchCV(cv=8, estimator=SVC(),
                      param_grid={'gamma': [0.03, 0.5, 0.8, 0.1], 'kernel': ['rbf']},
                      scoring='accuracy')
```

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```
In [67]: 1 g.best_params_
```

```
Out[67]: {'gamma': 0.03, 'kernel': 'rbf'}
```

```
In [68]: 1 Model=g.best_estimator_
          2 Model
```

```
Out[68]: SVC(gamma=0.03)
```

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```
In [69]: 1 pre=Model.predict(X_test)
          2 pre
```

```
Out[69]: array([1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0,
                1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0,
                0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
                0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1,
                0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0])
```

```
In [70]: 1 Model.score(X_train,y_train)
```

```
Out[70]: 0.9146845915201655
```

```
In [71]: 1 Model.score(X_test,y_test)
```

```
Out[71]: 0.8093023255813954
```

```
In [72]: 1 from sklearn.naive_bayes import GaussianNB
          2 from sklearn.naive_bayes import BernoulliNB
          3 from sklearn.naive_bayes import ComplementNB
          4 from sklearn.naive_bayes import CategoricalNB
          5 N=GaussianNB()
          6 B=BernoulliNB()
          7 C=ComplementNB()
          8 c=CategoricalNB()
```

```
In [73]: 1 N.fit(X_train,y_train)
```

```
Out[73]: GaussianNB()
```

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```
In [74]: 1 N.score(X_train,y_train)
```

```
Out[74]: 0.8107549120992761
```

```
In [75]: 1 N.score(X_test,y_test)
```

```
Out[75]: 0.8418604651162791
```

In [76]: 1 B.fit(X\_train,y\_train)

Out[76]: BernoulliNB()

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**  
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In [77]: 1 B.score(X\_train,y\_train)

Out[77]: 0.7145811789038262

In [78]: 1 B.score(X\_test,y\_test)

Out[78]: 0.7209302325581395

In [79]: 1 p=B.predict(X\_test)  
2 p

Out[79]: array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,  
0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0,  
0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,  
0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,  
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,  
1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,  
0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0,  
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0,  
0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,  
0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1])

In [80]: 1 C.fit(X\_train,y\_train)

Out[80]: ComplementNB()

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**  
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In [81]: 1 C.score(X\_train,y\_train)

Out[81]: 0.7533609100310238

In [82]: 1 C.score(X\_test,y\_test)

Out[82]: 0.7255813953488373

In [83]: 1 c.fit(X\_train,y\_train)

Out[83]: CategoricalNB()

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**  
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In [84]: 1 c.score(X\_train,y\_train)

Out[84]: 0.921923474663909

In [85]: 1 c.score(X\_test,y\_test)

Out[85]: 0.9069767441860465

In [86]: 1 cprd=c.predict(X\_test)  
2 cprd

Out[86]: array([1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,  
1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0,  
0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,  
0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1,  
0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,  
1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,  
0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0,  
0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1,  
0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1,  
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1], dtype=int64)

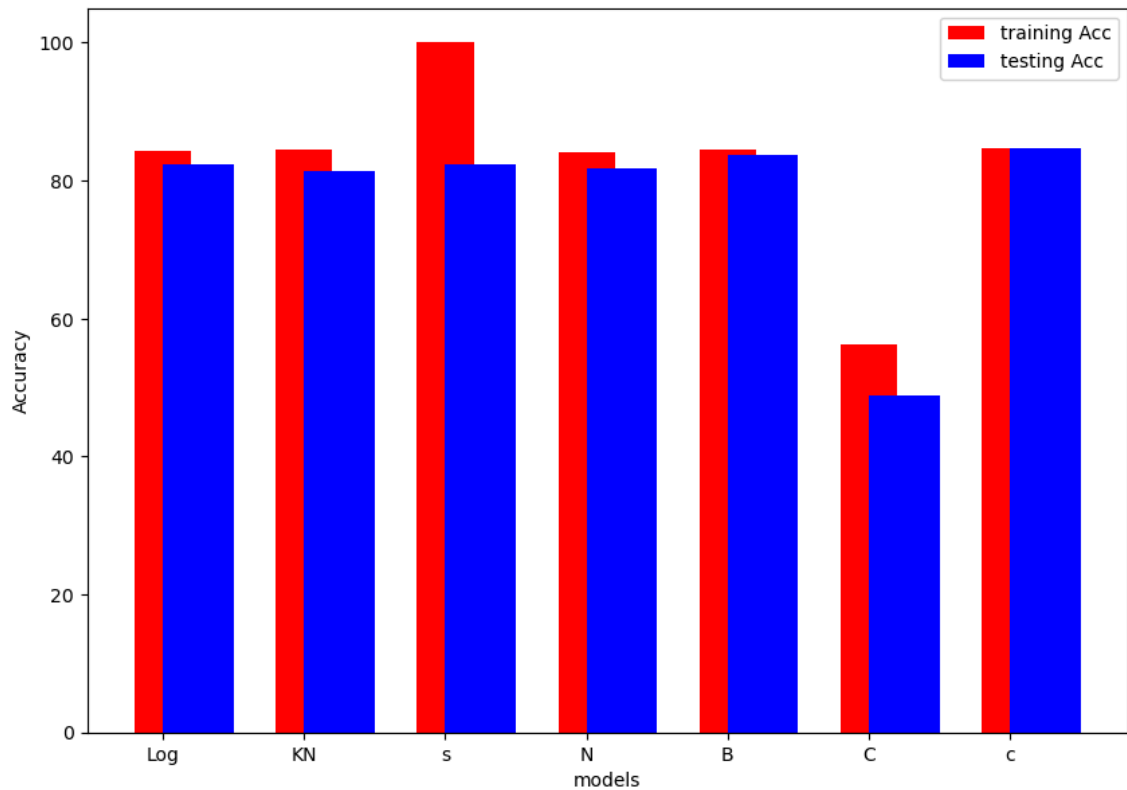
In [87]: 1 Y={"models":["Log","KN","s","N","B","C","c"],"train":[84.33,84.53,100,8

In [88]: 1 Y=pd.DataFrame(Y)  
2 Y

Out[88]:

	models	train	test
0	Log	84.33	82.32
1	KN	84.53	81.39
2	s	100.00	82.32
3	N	84.02	81.86
4	B	84.48	83.72
5	C	56.25	48.83
6	c	84.69	84.69

```
In [89]: 1 plt.figure(figsize=(10,7))
2 plt.bar(Y['models'],Y['train'],color="red",width=0.4,align='center',label='training Acc')
3 plt.bar(Y['models'],Y['test'],color="blue",width=0.5,align='edge',label='testing Acc')
4 plt.legend()
5 plt.xlabel('models')
6 plt.ylabel('Accuracy')
7 plt.show()
```



```
In [90]: 1 #here CategoricalNB is working fine in comparision to others
```

#ANN

```
In [91]: 1 import tensorflow as tf
2 from tensorflow import keras
3 from tensorflow.keras.models import Sequential
4 from tensorflow.keras.layers import Dense,Dropout
```

```
In [92]: 1 P=Sequential([
2         Dense(140,input_shape=(X_train.shape[1],),activation="relu"),
3         Dense(120,activation="relu"),
4         Dense(100,activation="relu"),
5         Dense(90,activation="relu"),
6         Dense(60,activation="relu"),
7         Dropout(0.2),
8         Dense(60,activation="relu"),
9         Dense(1,activation="sigmoid"),
10      ])
```

C:\Users\Admin\AppData\Roaming\Python\Python311\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
In [93]: 1 P.compile(
2         loss="categorical_crossentropy",
3         optimizer="adam",
4         metrics=["accuracy"]
5     )
```

```
In [94]: 1 P.fit(X_train,y_train,epochs=60)
```

Epoch 1/60

C:\Users\Admin\AppData\Roaming\Python\Python311\site-packages\keras\src\losses\losses.py:27: SyntaxWarning: In loss categorical\_crossentropy, expected y\_pred.shape to be (batch\_size, num\_classes) with num\_classes > 1. Received: y\_pred.shape=(None, 1). Consider using 'binary\_crossentropy' if you only have 2 classes.

```
return self.fn(y_true, y_pred, **self._fn_kwargs)
```

61/61 ————— 4s 2ms/step - accuracy: 0.6180 - loss: 0.0000e+00

Epoch 2/60

61/61 ————— 0s 2ms/step - accuracy: 0.6396 - loss: 0.0000e+00

Epoch 3/60

61/61 ————— 0s 2ms/step - accuracy: 0.6490 - loss: 0.0000e+00

Epoch 4/60

61/61 ————— 0s 2ms/step - accuracy: 0.6562 - loss: 0.0000e+00



7/7  0s 20ms/step

```
In [98]: 1 from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

In [99]: 1 confusion\_matrix(y\_test,Pred)

Out[99]: array([[136, 0],  
[ 79, 0]], dtype=int64)

In [100]: 1 accuracy\_score(y\_test,Pred)

Out[100]: 0.6325581395348837

In [101]: 1 print(classification\_report(y\_test,Pred))

	precision	recall	f1-score	support
0	0.63	1.00	0.77	136
1	0.00	0.00	0.00	79
accuracy			0.63	215
macro avg	0.32	0.50	0.39	215
weighted avg	0.40	0.63	0.49	215

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

```

1
2
3
4 Goal:
5 The objective of this project is to predict the likelihood of
  Alzheimer's disease in patients based on features such as
  Forgetfulness, DifficultyCompletingTasks, BehavioralProblems,
  FunctionalAssessment, MMSE (Mini-Mental State Examination), age,
  weight, and other relevant factors. This helps in early diagnosis,
  enabling timely intervention and better management of the disease.
6
7 Discussion:
8 Insights:
9
10 #The analysis reveals that MMSE scores and FunctionalAssessment
   ratings are the most critical indicators of Alzheimer's progression.
11 #Features like age and Forgetfulness also significantly contribute to
   the predictive power of the models, especially when combined with
   behavioral and task-completion assessments.
12 #Older patients with low MMSE scores, high difficulty completing
   tasks, and behavioral problems are more likely to exhibit Alzheimer's
   symptoms.
```

```
13
14 Model Comparison:
15
16 Various machine learning models such as Random Forest, Support Vector
    Machines (SVM), and Gradient Boosting were compared to an Artificial
    Neural Network (ANN).
17
18 Conclusion:
19 #This project successfully developed predictive models for
    Alzheimer's disease diagnosis.
20 #Using machine learning techniques and ANN, we demonstrated the
    importance of MMSE scores, behavioral patterns, and functional
    assessments in predicting the disease.
21 #The findings underscore the potential for personalized interventions
    and better patient care through early diagnosis.
```

In [ ]:

1