

Introduction

The Cardiovascular Disease dataset is a collection of health-related information used for analyzing and predicting cardiovascular diseases. It encompasses diverse data such as age, gender, blood pressure, cholesterol levels, and lifestyle factors. This dataset serves as a valuable resource for researchers and healthcare professionals to better understand and mitigate the risks associated with cardiovascular diseases.

1 import Necessary Library

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

2 import Dataset

In [116... df = pd.read_csv("/kaggle/input/cardiovascular-disease-dataset/cardio_train.csv

3 Data Analysis

In [117	df.head()													
Out[117		id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	ac	
	0	0	18393	2	168	62.0	110	80	1	1	0	0		
	1	1	20228	1	156	85.0	140	90	3	1	0	0		
	2	2	18857	1	165	64.0	130	70	3	1	0	0		
	3	3	17623	2	169	82.0	150	100	1	1	0	0		
	4	4	17474	1	156	56.0	100	60	1	1	0	0		
	4												•	
In [118	d-	f.ta	il()											

Out[118		id	age	gender	heigh	t weight	ap_hi	ap_lo	cholesterol	gluc	smoke
	69995	99993	19240	2	168	3 76.0	120	80	1	1	1
	69996	99995	22601	1	158	3 126.0	140	90	2	2	0
	69997	99996	19066	2	183	3 105.0	180	90	3	1	0
	69998	99998	22431	1	163	3 72.0	135	80	1	2	0
	69999	99999	20540	1	170	72.0	120	80	2	1	0
	4										+
In [119	df.in	fo()									
F C	RangeInd Data col # Col 0 id 1 age 2 gen 3 hei 4 wei 5 ap_ 6 ap_	ex: 700 umns (t umn der ght ght hi lo lestero	000 ent cotal 1 Non 700 700 700 700 700 700 700 700	rame.Data ries, 0 t 3 columns -Null Cou 00 non-nu 00 non-nu 00 non-nu 00 non-nu 00 non-nu 00 non-nu	:0 6999 :): int Di :int Di :ill ii	type nt64 nt64 nt64 nt64 loat64 nt64 nt64					
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n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes:	ke o ive dio float64 sage: 6	700 700 700 700 1(1), i	00 non-nu 00 non-nu 00 non-nu 00 non-nu nt64(12)	ıll i: ıll i: ıll i:	nt64 nt64 nt64	er	heigh	nt w	eight	a
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes:	ke o ive dio float64 sage: 6	700 700 700 700 700 (1), i 5.9 MB	00 non-nu 00 non-nu 00 non-nu 00 non-nu nt64(12)	all in a second	nt64 nt64 nt64 nt64		heigh			a 70000.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u	ke o ive dio float64 sage: 6	700 700 700 700 1(1), i 5.9 MB	00 non-nu 00 non-nu 00 non-nu 00 non-nu nt64(12)	all in	nt64 nt64 nt64 nt64	00 700		70000.00		70000.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.de:	oke o ive dio float64 sage: 6 scribe(700 700 700 700 1(1), i 5.9 MB) id	00 non-nu 00 non-nu 00 non-nu 00 non-nu nt64(12)	all in	gend	700 700 71 1	00.00000	70000.00	00000	
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des	70000.0 49972.4	700 700 700 700 1(1), i 5.9 MB) id	00 non-nu 00 non-nu 00 non-nu 00 non-nu 00 non-nu 01 nt64(12) 70000.000	age	gend (70000.0000	700 700 71 1	00.00000 64.35922	70000.00 74.20 74.39	00000	70000.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std	70000.0 49972.4	700 700 700 700 (1), i i.9 MB) id 000000 .19900 .02323	00 non-nu 00 non-nu 00 non-nu 00 non-nu 00 non-nu 70000.000 19468.865	age 1000 7 814 667	gend 70000.0000 1.3495	700 700 71 1 38	00.00000 64.35922 8.21012	70000.00 74.20 74.39 10 10.00	00000 05690 05757	70000.000 128.817 154.011
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min	70000.0 49972.4 28851.3	700 700 700 700 1(1), i 5.9 MB) id 000000 .19900 .02323 .000000	70000.000 19468.865 2467.251	age 1000 7 814 667 000 000	gend 70000.00000 1.3495 0.47683	700 700 71 1 38 00 1	00.00000 64.35922 8.21012 55.00000	70000.00 74.20 74.39 10 10.00 10 65.00	00000 05690 05757 00000	70000.000 128.817 154.011 -150.000
n	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min 25%	70000.0 49972.4 25006.7	700 700 700 700 1(1), i 5.9 MB) id 100000 .19900 .02323 .00000 .00000	70000.000 19468.865 2467.251 10798.000	age 0000 7 814 6667 0000 0000	gend (0000.00000 1.3495 0.4768: 1.00000	700 700 71 1 388 000 1 000 1	00.00000 64.35922 8.21012 55.00000	70000.00 74.20 74.39 10 10.00 10 65.00 10 72.00	00000 05690 05757 00000	70000.000 128.817 154.013 -150.000 120.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min 25% 50%	70000.0 49972.4 25006.7 50001.5	700 700 700 700 1(1), i 5.9 MB) id 000000 02323 000000 050000 000000	70000.000 19468.865 2467.251 10798.000 19703.000	age 0000 7 814 6667 0000 0000	gend 70000.00000 1.3495 0.4768 1.00000 1.00000	700 700 71 1 388 000 1 000 1	00.00000 64.35922 8.21012 55.00000 59.00000	70000.00 74.20 74.20 16 14.39 10 10.00 10 65.00 10 72.00 10 82.00	00000 05690 05757 00000 00000	70000.000 128.817 154.013 -150.000 120.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min 25% 50% 75%	70000.0 49972.4 28851.3 0.0 25006.7 74889.2	700 700 700 700 1(1), i 5.9 MB) id 000000 02323 000000 050000 000000	70000.000 19468.865 2467.251 10798.000 17664.000 19703.000	age 0000 7 814 6667 0000 0000	gend (0000.0000) 1.3495 0.4768 1.00000 1.00000 2.00000	700 700 71 1 388 000 1 000 1	00.00000 64.35922 8.21012 55.00000 59.00000 65.00000	70000.00 74.20 74.20 16 14.39 10 10.00 10 65.00 10 72.00 10 82.00	00000 05690 05757 00000 00000	70000.000 128.817 154.011 -150.000 120.000 140.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min 25% 50% 75%	70000.0 49972.4 28851.3 0.0 25006.7 50001.5 74889.2	700 700 700 700 1(1), i 5.9 MB) id 000000 02323 000000 050000 000000	70000.000 19468.865 2467.251 10798.000 17664.000 19703.000	age 0000 7 814 6667 0000 0000	gend (0000.0000) 1.3495 0.4768 1.00000 1.00000 2.00000	700 700 71 1 388 000 1 000 1	00.00000 64.35922 8.21012 55.00000 59.00000 65.00000	70000.00 74.20 74.20 16 14.39 10 10.00 10 65.00 10 72.00 10 82.00	00000 05690 05757 00000 00000	70000.000 128.817 154.011 -150.000 120.000 140.000 16020.000
n In [120	8 glu 9 smo 10 alc 11 act 12 car dtypes: memory u df.des count mean std min 25% 50% 75% max	70000.0 49972.4 28851.3 0.0 25006.7 50001.5 74889.2	700 700 700 700 1(1), i 5.9 MB) id 000000 02323 000000 050000 000000	70000.000 19468.865 2467.251 10798.000 19703.000 23713.000	age 0000 7 814 6667 0000 0000 0000	gend (0000.0000) 1.3495 0.4768 1.00000 1.00000 2.00000	700 700 71 1 388 000 1 000 1	00.00000 64.35922 8.21012 55.00000 59.00000 70.00000	70000.00 74.20 74.20 16 14.39 10 10.00 10 65.00 10 72.00 10 82.00 10 200.00	00000 05690 05757 00000 00000	70000.000 128.817 154.011 -150.000 120.000 140.000 16020.000

```
gender
                        0.003502
                                  -0.022811
                                            1.000000
                                                       0.499033
                                                                 0.155406
                                                                            0.006005
                                                                                      0.015254
                       -0.003038
                                  -0.081515
                                            0.499033
                                                       1.000000
                                                                 0.290968
                                                                            0.005488
                                                                                      0.006150
               height
                       -0.001830
                                                                            0.030702
               weight
                                  0.053684
                                            0.155406
                                                       0.290968
                                                                 1.000000
                                                                                      0.043710
                ap_hi
                        0.003356
                                  0.020764
                                            0.006005
                                                       0.005488
                                                                 0.030702
                                                                            1.000000
                                                                                      0.016086
                       -0.002529
                                  0.017647
                                            0.015254
                                                       0.006150
                                                                 0.043710
                                                                            0.016086
                                                                                      1.000000
                ap_lo
           cholesterol
                        0.006106
                                  0.154424
                                            -0.035821
                                                      -0.050226
                                                                 0.141768
                                                                            0.023778
                                                                                      0.024019
                        0.002467
                                  0.098703
                                            -0.020491
                                                      -0.018595
                                                                 0.106857
                                                                            0.011841
                                                                                      0.010806
               smoke
                       -0.003699
                                  -0.047633
                                                       0.187989
                                                                 0.067780
                                                                           -0.000922
                                                                                      0.005186
                                            0.338135
                 alco
                        0.001210
                                  -0.029723
                                            0.170966
                                                       0.094419
                                                                 0.067113
                                                                            0.001408
                                                                                      0.010601
                active
                        0.003755
                                  -0.009927
                                             0.005866
                                                      -0.006570
                                                                 -0.016867
                                                                           -0.000033
                                                                                      0.004780
               cardio
                        0.003799
                                  0.238159
                                            0.008109
                                                      -0.010821
                                                                 0.181660
                                                                            0.054475
                                                                                      0.065719
In [122...
            df.columns
           Out[122...
                 dtype='object')
In [123...
            df["cardio"].value_counts()
           cardio
Out[123...
                35021
           1
                34979
           Name: count, dtype: int64
```

4 Data cleaning and Preprocessing:

In [124	df.head()													
Out[124	id age gender height weight ap_hi ap_lo cholesterol gluc smoke alco a													
	0	0	18393	2	168	62.0	110	80	1	1	0	0		
	1	1	20228	1	156	85.0	140	90	3	1	0	0		
	2	2	18857	1	165	64.0	130	70	3	1	0	0		
	3	3	17623	2	169	82.0	150	100	1	1	0	0		
	4	4	17474	1	156	56.0	100	60	1	1	0	0		
	←													
In [125	<pre>df['age']=(df['age']/365).round(0)</pre>													
In [126	df	f.he	ead()											
Out[126		id	age g	gender l	neight v	veight a	np_hi a	ip_lo d	cholesterol g	gluc s	smoke a	alco a	activ	

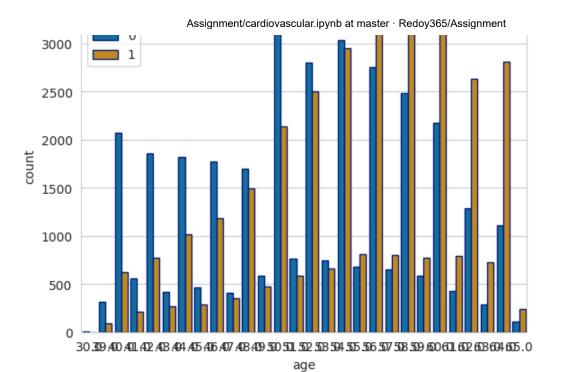
```
0 50.0
                              2
                                    168
                                            62.0
                                                   110
                                                           80
                                                                         1
                                                                               1
                                                                                       0
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               1
                  55.0
                              1
                                    156
                                            85.0
                                                   140
                                                           90
                                                                         3
                                                                               1
                                                                                       0
                                                                                             0
                                                                         3
            2
               2
                  52.0
                              1
                                    165
                                            64.0
                                                   130
                                                           70
                                                                                       0
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                                                                               1
            3
               3
                              2
                                    169
                                            82.0
                                                   150
                                                          100
                                                                         1
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                  48.0
                                                                               1
                 48.0
                              1
                                    156
                                            56.0
                                                   100
                                                           60
                                                                         1
                                                                               1
                                                                                       0
                                                                                             0
In [127...
            df = df.drop(['id'], axis=1)
In [128...
            df.head()
Out[128...
                    gender height weight ap_hi ap_lo
                                                            cholesterol gluc smoke
                                                                                           active
                                                                                      alco
               age
           0 50.0
                          2
                                168
                                        62.0
                                               110
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            1 55.0
                          1
                                156
                                        85.0
                                               140
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                                                                     3
                                                                                   0
                                                                                                 0
            2 52.0
                          1
                                165
                                        64.0
                                               130
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                                                                           1
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            3 48.0
                          2
                                169
                                        82.0
                                               150
                                                       100
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            4 48.0
                          1
                                156
                                        56.0
                                               100
                                                        60
                                                                     1
                                                                           1
                                                                                   0
                                                                                         0
                                                                                                 0
In [129...
            df.isnull().sum()
                            0
Out[129...
           age
           gender
                            0
           height
                            0
           weight
                            0
           ap_hi
                            0
           ap_lo
                            0
           cholesterol
                            0
           gluc
                            0
           smoke
                            0
           alco
                            0
           active
                            0
                            0
           cardio
           dtype: int64
In [130...
            df.isnull().values.any()
           False
Out[130...
In [131...
            df.isna().sum()
                            0
Out[131...
           age
                            0
           gender
           height
                            0
           weight
                            0
           ap_hi
                            0
                            0
           ap_lo
           cholesterol
                            0
           gluc
                            0
           smoke
                            0
```

alco 0
active 0
cardio 0
dtype: int64

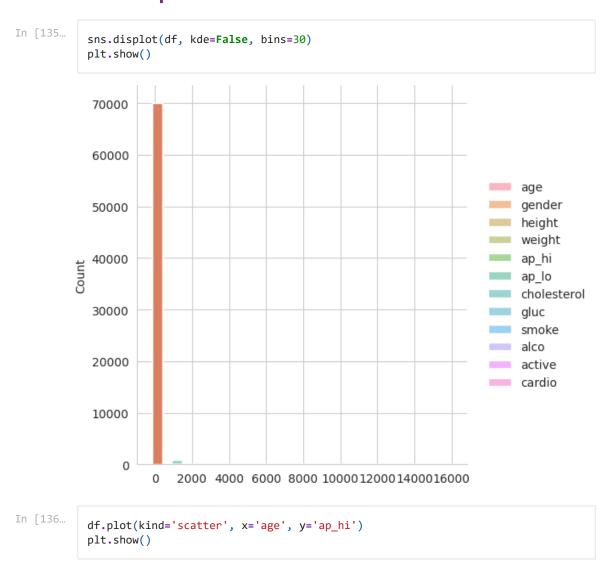
5 | Data visualisation 📊 📉

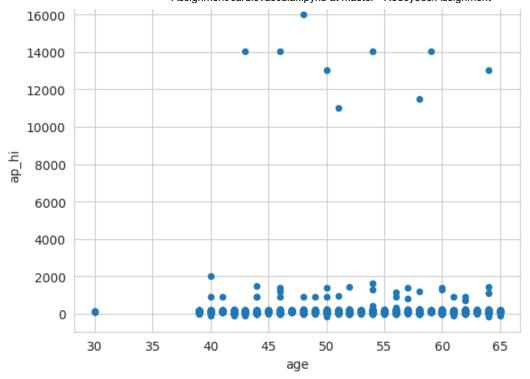
EDA(Exploratory Data Analysis)

5.1 Countplot

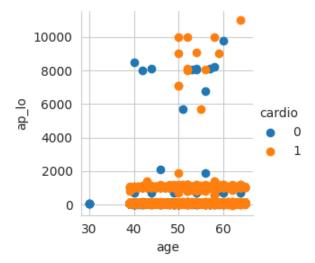


5.2 displot





```
In [137...
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="cardio").map(plt.scatter, "age", "ap_lo").add_legend();
plt.show();
```

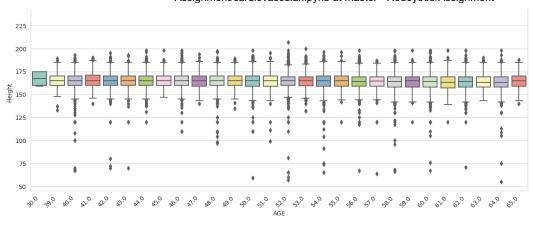


5.3 boxplot

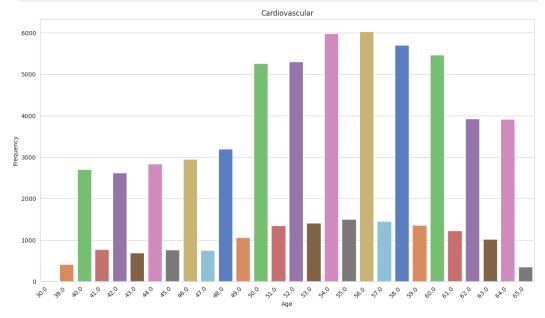
```
In [138...
# sepal_length vs sepal_width boxplot

plt.figure(figsize=(15, 6))
sns.boxplot(x='age', y='height', data=df, palette='Set3')
plt.title('Age vs Height')
plt.xlabel('AGE')
plt.ylabel('Height')
plt.xticks(rotation=45, ha='right')
plt.show()

Age vs Height
```



```
# sepat_length
plt.figure(figsize=(15, 8))
sns.countplot(x='age', data=df, palette='muted')
plt.title('Cardiovascular')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```



```
# sepal_length
plt.figure(figsize=(15, 8))
sns.countplot(x='cholesterol', data=df, palette='muted')
plt.title('Cardiovascular')
plt.xlabel('cholesterol')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```

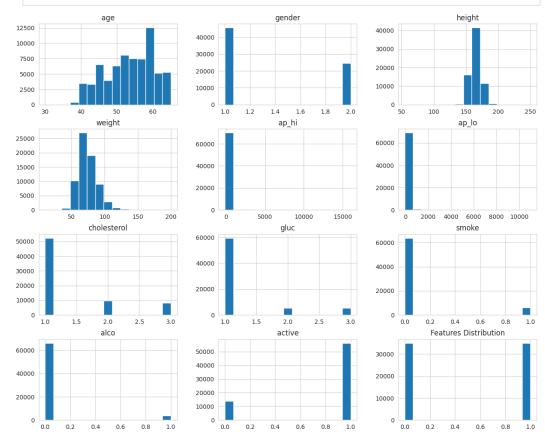




5.4 hist plot

```
In [141...
```

```
df.hist(figsize=(15,12),bins = 15)
plt.title("Features Distribution")
plt.show()
```



5.5 dens_plot

```
In [142...

def dens_plot(features,class_var):
    #adding the white grid style
    sns.set_style(style="whitegrid")
    #adding datapoint colour and size
    sns.FacetGrid(data=df, hue=class_var)\
        .map(sns.distplot,features)\
        .add_legend()

dens_plot("age","cholesterol")
    plt.show()
```

/opt/conda/lib/pytnon3.lu/site-packages/seaborn/axisgrid.py:848: Userwarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

func(*plot_args, **plot_kwargs)
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:848: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

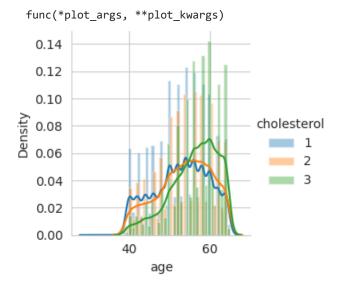
For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

func(*plot_args, **plot_kwargs)
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:848: UserWarning:

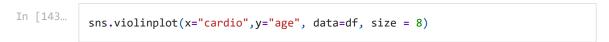
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

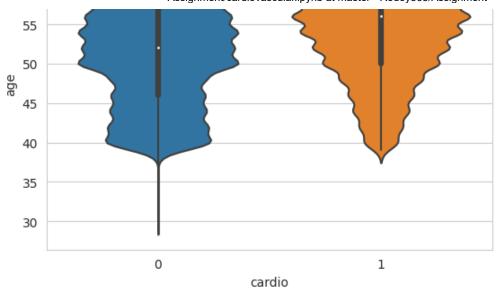


5.6 violinplot

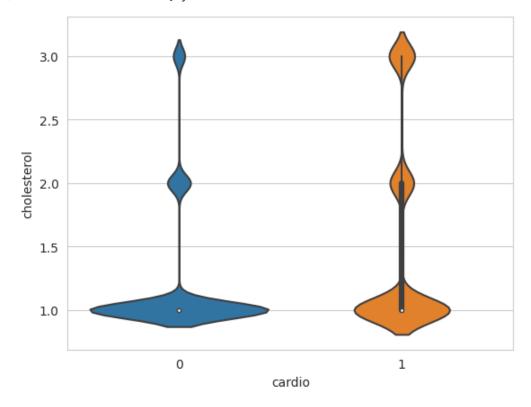


Out[143... <Axes: xlabel='cardio', ylabel='age'>





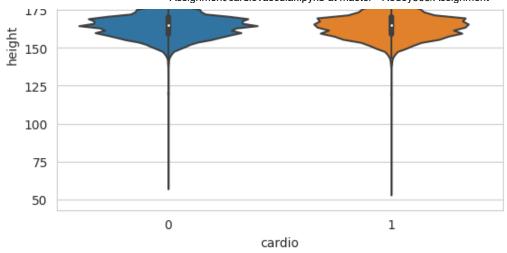
Out[144... <Axes: xlabel='cardio', ylabel='cholesterol'>



In [145...
sns.violinplot(x="cardio",y="height", data=df, size = 8)

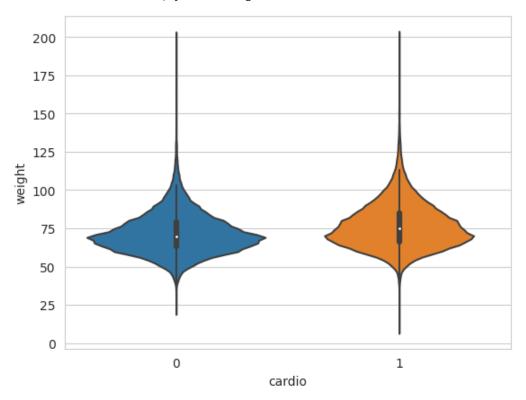
Out[145... <Axes: xlabel='cardio', ylabel='height'>





In [146... sns.violinplot(x="cardio",y="weight", data=df, size = 8)

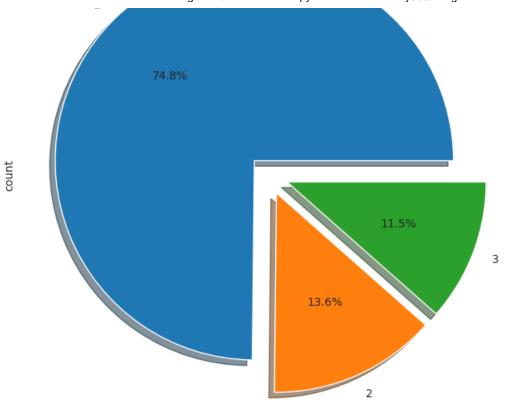
Out[146... <Axes: xlabel='cardio', ylabel='weight'>



5.7 Pie Plot

```
ax=plt.subplots(1,1,figsize=(10,8))
    df['cholesterol'].value_counts().plot.pie(explode=[0.1,0.1,0.1],autopct='%1.1f%
    plt.title("Cardiovascular cholesterol %")
    plt.show()
```

Cardiovascular cholesterol %



In [148	df.head()												
Out[148		age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	
	0	50.0	2	168	62.0	110	80	1	1	0	0	1	
	1	55.0	1	156	85.0	140	90	3	1	0	0	1	
	2	52.0	1	165	64.0	130	70	3	1	0	0	0	
	3	48.0	2	169	82.0	150	100	1	1	0	0	1	
	4	48.0	1	156	56.0	100	60	1	1	0	0	0	
	4												

6 | Split the Dataset

```
In [149... df = df[:10000]
In [150... from sklearn.model_selection import train_test_split
In [151... x = df.iloc[:,:-1]
In [152... x.head()
Out[152... age gender height weight ap_hi ap_lo cholesterol gluc smoke alco active
```

Machine Learning Algorithm

In []:

(1). KNN

```
In [162... from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

In [163... knn_classifier = KNeighborsClassifier(n_neighbors=3)

In [164... knn_classifier.fit(x_train, y_train)

Out[164... KNeighborsClassifier(n_neighbors=3)
In a Jupyter environment, please rerun this cell to show the HTML representation
```

or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this

• **(b)** Test accuracy KNN

page with nbviewer.org.

• 6 Training accuracy KNN

```
In [168... y_pred_train = knn_classifier.predict(x_train)
In [169... accuracy = accuracy_score(y_pred_train, y_train)
In [170... accuracy
Out[170... 0.80775
```

(2). Naive Bayes classifier

```
In [171... from sklearn.naive_bayes import GaussianNB from sklearn.naive_bayes import BernoulliNB from sklearn.naive_bayes import MultinomialNB from sklearn import metrics

In [172... # GaussianNB
```

```
In [173... G_classifier = GaussianNB()

In [174... G_classifier.fit(x_train, y_train)

Out[174... GaussianNB()

In a Jupyter environment, please rerun this cell to show the HTML representation
```

or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

• 🖰 Test accuracy (Naive Bayes) GaussianNB

```
In [175... predictions_G = G_classifier.predict(x_test)
In [176... accuracy = metrics.accuracy_score(y_test, predictions_G)
In [177... accuracy
Out[177... 0.5965
```

• 🖰 Training accuracy (Naive Bayes) GaussianNB

```
In [178...
            predictions G = G classifier.predict(x train)
In [179...
            accuracy = metrics.accuracy_score(y_train, predictions_G)
In [180...
            accuracy
Out[180...
In [181...
            # BernoulliNB
In [182...
            B classifier = BernoulliNB()
In [183...
            B_classifier.fit(x_train, y_train)
          BernoulliNB()
Out[183...
          In a Jupyter environment, please rerun this cell to show the HTML representation
          or trust the notebook.
```

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

🖟 🦰 Test accuracy (Naive Bayes) BernoulliNB

Tn Γ194

```
In [185... predictions_B = B_classifier.predict(x_test)

In [186... accuracy_B = metrics.accuracy_score(y_test, predictions_B)

In [186... accuracy_B

Out[186... 0.5185
```



```
In [187... predictions_B = B_classifier.predict(x_train)

In [188... accuracy_B = metrics.accuracy_score(y_train, predictions_B)

In [189... accuracy_B

Out[189... 0.51275
```

(3) Decision Tree

```
In [190... from sklearn.tree import DecisionTreeClassifier

In [191... clf = DecisionTreeClassifier()

In [192... clf.fit(x_train, y_train)

Out[192... DecisionTreeClassifier()

In a lumptor environment, places resum this cell to show the HTML representation
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

(4). Kandom Forest

```
In [196... from sklearn.ensemble import RandomForestClassifier

In [197... rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

In [198... rf_classifier.fit(x_train, y_train)

Out[198... RandomForestClassifier(random_state=42)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this
```

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

(5). Boosting Algorithm

Testing Accuracy: 0.7125

```
In [202... from sklearn.ensemble import AdaBoostClassifier
In [203... base_classifier = DecisionTreeClassifier(max_depth=3)
In [204... adaboost_classifier = AdaBoostClassifier(base_classifier, n_estimators=50, rar
In [205... adaboost_classifier.fit(x_train, y_train)
Out[205... AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth=3), random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Training Accuracy: 0.759125 Testing Accuracy: 0.724

(6).SVM

```
In [209... from sklearn.preprocessing import StandardScaler from sklearn.svm import SVC

In [210... scaler = StandardScaler()
    X_train = scaler.fit_transform(x_train)
    X_test = scaler.transform(x_test)

In [211... svm_classifier = SVC(kernel='linear', C=1.0)

In [212... svm_classifier.fit(x_train, y_train)

Out[212... SVC(kernel='linear')
    In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
```

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

(7). Logistic Regression

Testing Accuracy: 0.7255

```
^{\text{lil}} ^{\text{LZLU...}} | from sklearn import linear_model
In [217...
           lrg = linear model.LogisticRegression()
In [218...
           lrg.fit(x_train, y_train)
         /opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: C
         onvergenceWarning: 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
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressio
           n_iter_i = _check_optimize_result(
         LogisticRegression()
Out[218...
         In a Jupyter environment, please rerun this cell to show the HTML representation
          or trust the notebook.
          On GitHub, the HTML representation is unable to render, please try loading this
          page with nbviewer.org.
In [219...
           train_predictions = lrg.predict(X_train)
           train_accuracy7 = accuracy_score(y_train, train_predictions)
         /opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does
         not have valid feature names, but LogisticRegression was fitted with feature nam
           warnings.warn(
In [220...
           test_predictions = lrg.predict(X_test)
           test_accuracy7 = accuracy_score(y_test, test_predictions)
         /opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does
         not have valid feature names, but LogisticRegression was fitted with feature nam
           warnings.warn(
In [221...
           print(f"Training Accuracy: {train_accuracy7}")
           print(f"Testing Accuracy: {test accuracy7}")
         Training Accuracy: 0.578
         Testing Accuracy: 0.5815
          (9). Gradient Boosting Machines (GBM)
```

```
In [223... from sklearn.ensemble import GradientBoostingClassifier

In [223... model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_de

In [224... model.fit(X_train, y_train)
```

Out[224...

GradientBoostingClassifier(random_state=42)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Training Accuracy: 0.74425 Testing Accuracy: 0.737

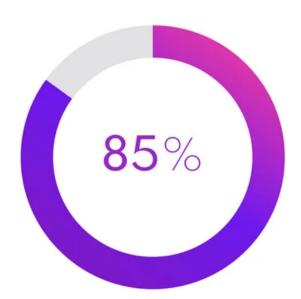
Random Forest Algorithm is the best accuracy

(Random Forest)

Training Accuracy: 0.994125

Testing Accuracy: 0.7125

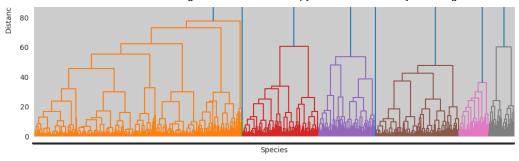
** mean Accuracy: 0.85





10 | Hierarchical Clustering

```
In [228...
            from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
            from sklearn.preprocessing import StandardScaler
In [229...
            scaler = StandardScaler()
            X_scaled = scaler.fit_transform(x)
In [230...
            linkage_matrix = linkage(X_scaled, method='ward')
In [233...
            df.head()
Out[233...
               age gender height weight ap_hi ap_lo cholesterol gluc smoke alco active
                                                                                       0
           0
              50.0
                         2
                               168
                                       62.0
                                              110
                                                      80
                                                                   1
                                                                         1
                                                                                 0
                                                                                              1
           1 55.0
                         1
                               156
                                       85.0
                                              140
                                                      90
                                                                   3
                                                                         1
                                                                                       0
                                                                                 0
                                                                                              1
              52.0
                         1
                               165
                                       64.0
                                              130
                                                      70
                                                                         1
                                                                                              0
                         2
                                       82.0
                                                                   1
                                                                         1
                                                                                       0
              48.0
                               169
                                              150
                                                     100
                                                                                              1
                         1
                               156
                                       56.0
                                              100
                                                                   1
                                                                         1
                                                                                 0
                                                                                       0
                                                                                              0
              48.0
                                                      60
In [234...
            plt.figure(figsize=(12, 6))
            dendrogram(linkage_matrix, labels=df['cardio'].values, orientation='top', dist
            plt.title('Hierarchical Clustering Dendrogram')
            plt.xlabel('cardio')
            plt.ylabel('Distance')
            plt.show()
                                         Hierarchical Clustering Dendrogram
           160
           140
           120
           100
```



In []: