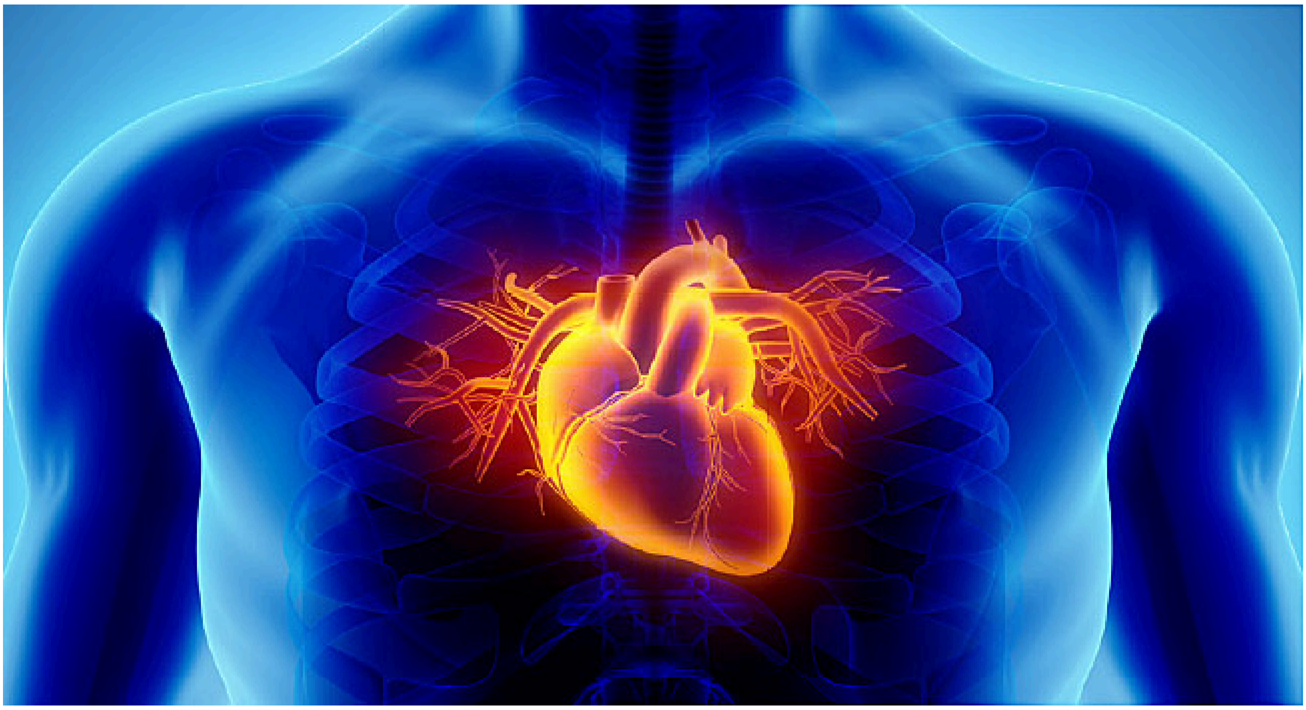
Heart Disease Diagnosis



Business Problem

Data

This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date. The "goal" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4.

Problem Statemtent

By using these data we have to Predict wheather a patient is suffering from heart disease or not based on different parameters

Data Description

```
age - age in years
sex - (1 = male; 0 = female)
```

```
cp - chest pain type
    0: Typical angina: chest pain related decrease blood supply to the heart
    1: Atypical angina: chest pain not related to heart
    2: Non-anginal pain: typically esophageal spasms (non heart related)
    3: Asymptomatic: chest pain not showing signs of disease
trestbps - resting blood pressure (in mm Hg on admission to the hospital) anything above 130-140 i
chol - serum cholestoral in mg/dl
    serum = LDL + HDL + .2 * triglycerides
    above 200 is cause for concern
fbs - (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
    '>126' mg/dL signals diabetes
restecg - resting electrocardiographic results
    0: Nothing to note
    1: ST-T Wave abnormality
        can range from mild symptoms to severe problems
        signals non-normal heart beat
    2: Possible or definite left ventricular hypertrophy
        Enlarged heart's main pumping chamber
thalach - maximum heart rate achieved
exang - exercise induced angina (1 = yes; 0 = no)
oldpeak - ST depression induced by exercise relative to rest looks at stress of heart during excer
slope - the slope of the peak exercise ST segment
    0: Upsloping: better heart rate with excercise (uncommon)
    1: Flatsloping: minimal change (typical healthy heart)
    2: Downslopins: signs of unhealthy heart
ca - number of major vessels (0-3) colored by flourosopy
    colored vessel means the doctor can see the blood passing through
    the more blood movement the better (no clots)
thal - thalium stress result
    1,3: normal
    6: fixed defect: used to be defect but ok now
    7: reversable defect: no proper blood movement when excercising
target - have disease or not (1=yes, 0=no) (= the predicted attribute)
```

Business objectives and constraints

1. The cost of a mis-classification can be very high.
2. There is some latency concerns.

Importing Necessary Libraries

```
# Plotting Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#import cufflinks as cf
%matplotlib inline

# Metrics for Classification technique
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

# Scaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import  RandomizedSearchCV, train_test_split

from xgboost import XGBClassifier
!pip install catboost
from catboost import CatBoostClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
```

```
Collecting catboost
  Downloading catboost-1.2.5-cp310-cp310-manylinux2014_x86_64.whl.metadata (1.2 kB)
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (frc
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from c
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/di
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-pack
Downloading catboost-1.2.5-cp310-cp310-manylinux2014_x86_64.whl (98.2 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 98.2/98.2 MB 5.2 MB/s eta 0:00:00
Installing collected packages: catboost
Successfully installed catboost-1.2.5
```

Mounting the GDrive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Data Loading

Our first step is to extract train and test data. We will be extracting data using pandas function read_csv. Specify the location to the dataset and import them.

```
# Importing Data

data = pd.read_csv("/content/heart.csv")
data.head(6) # Mention no of rows to be displayed from the top in the argument
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	tha
0	63	1	3	145	233	1	0	150	0	2.3	0	0	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	
5	57	1	0	140	192	0	1	148	0	0.4	1	0	

Exploratory Data Analysis

```
#Size of the dataset
data.shape
```

```
(303, 14)
```

We have a dataset with 303 rows which indicates a smaller set of data.

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
```

```
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

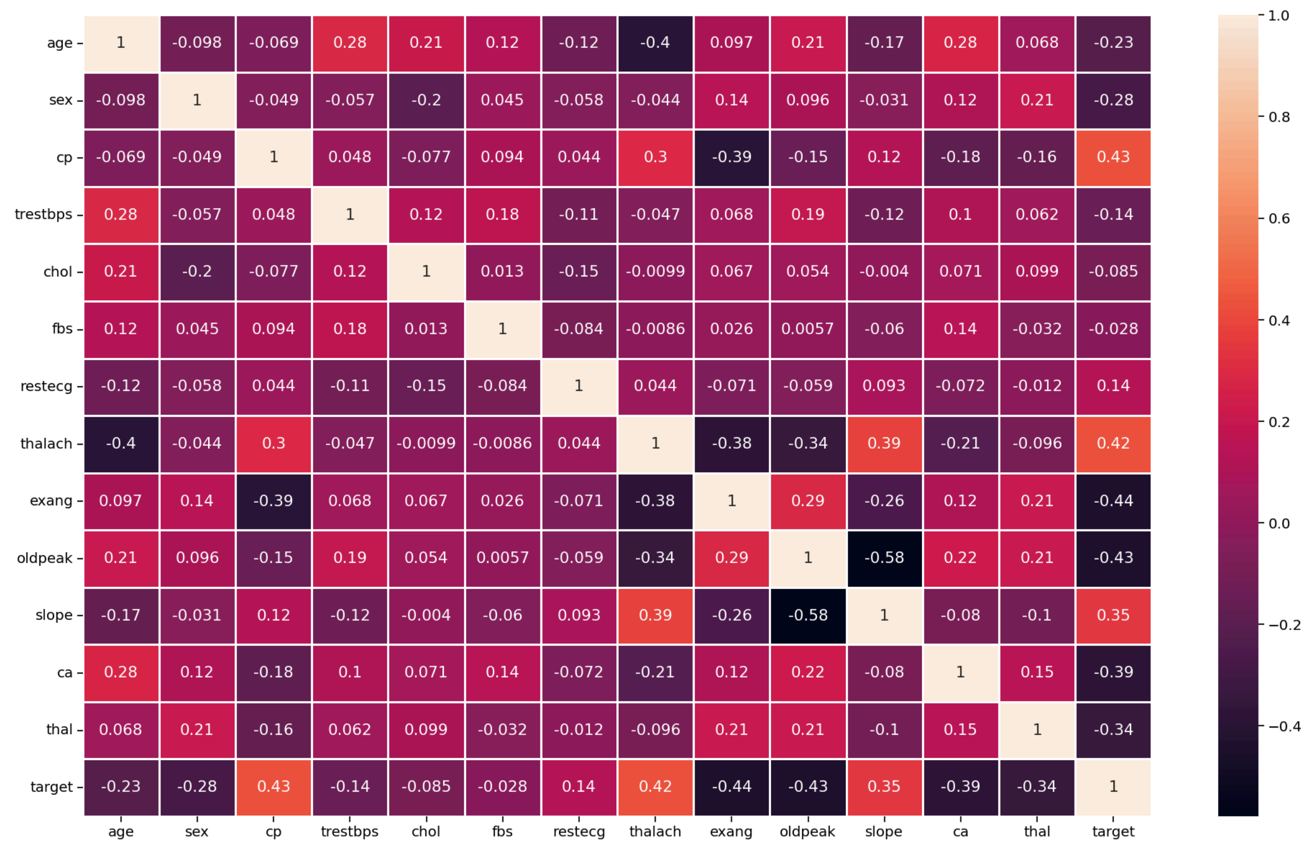
- Out of 14 features, we have 13 int type and only one with float data type.
- Woah! We have no missing values in our dataset.

```
data.describe()
```

	age	sex	cp	trestbps	chol	fbs	restec
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.00000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.52805
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.52586
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.00000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.00000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.00000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.00000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.00000

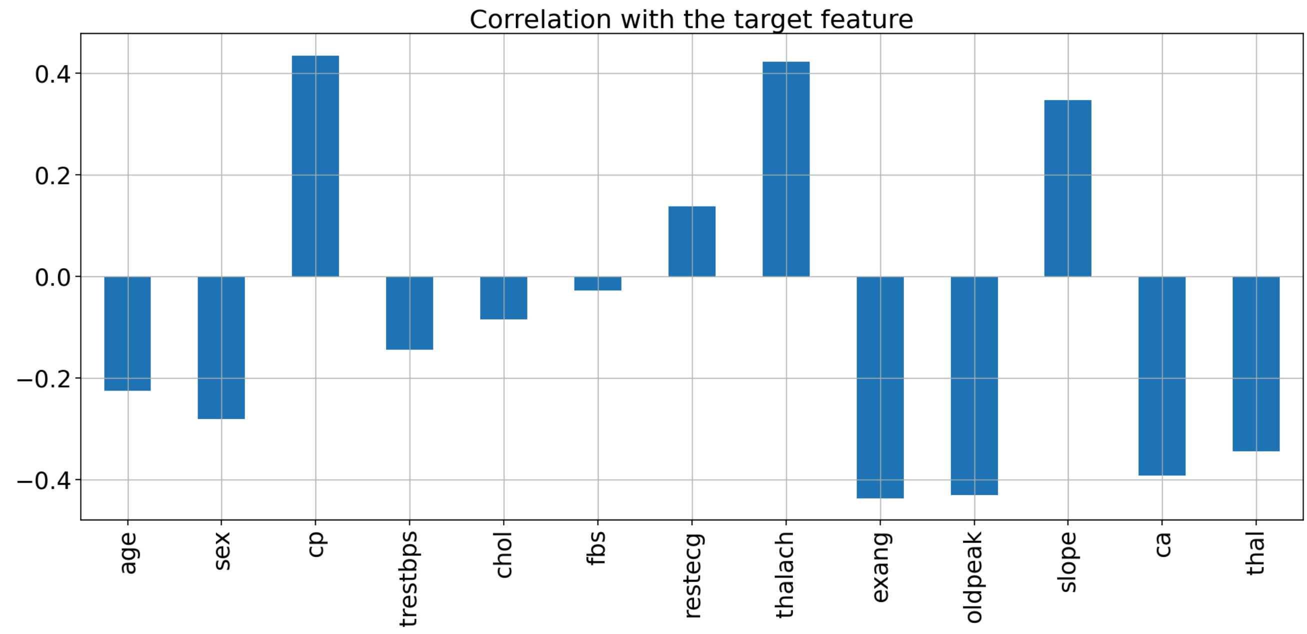
Let's check correleation between various features.

```
plt.figure(figsize=(20,12))
sns.set_context('notebook',font_scale = 1.3)
sns.heatmap(data.corr(),annot=True,linewidth =2)
plt.tight_layout()
```



Let's check the correlation of various features with the target feature.

```
# plt.figure(figsize=(20,12))
sns.set_context('notebook',font_scale = 2.3)
data.drop('target', axis=1).corrwith(data.target).plot(kind='bar', grid=True, figsize=(20
                                                                    title="Correlation with the target fea
plt.tight_layout()
```

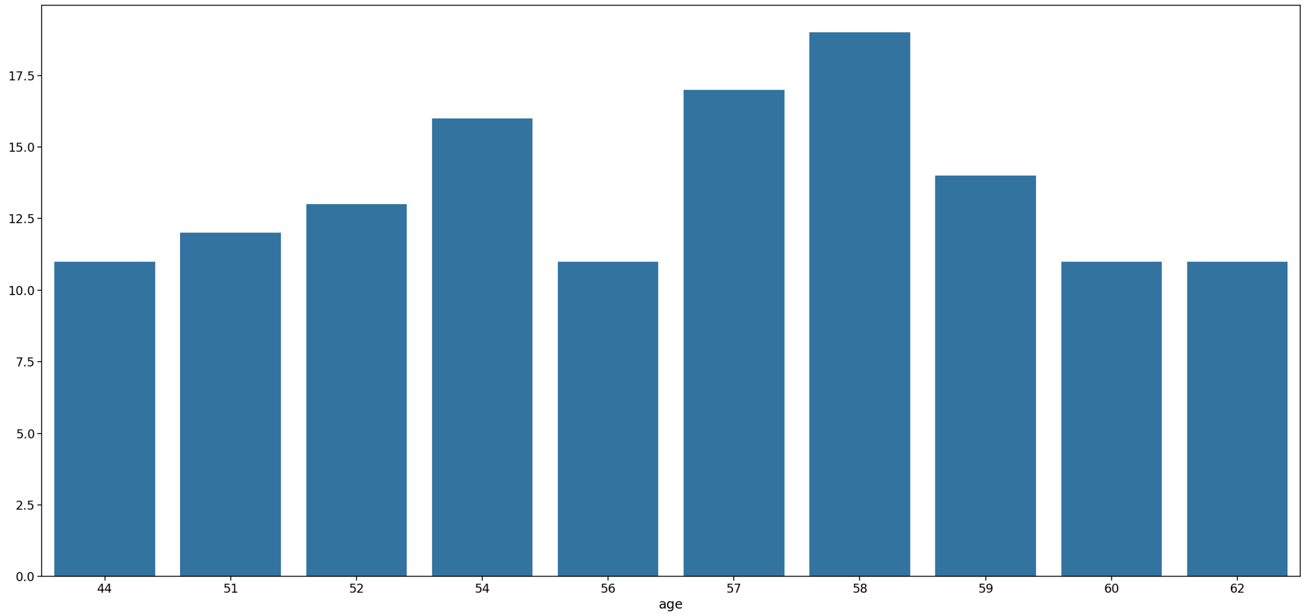


- Four feature("cp", "restecg", "thalach", "slope") are positively correlated with the target feature.
- Other features are negatively correlated with the target feature.

Individual Feature Analysis

Age("age") Analysis

```
# Let's check 10 ages and their count

plt.figure(figsize=(25,12))
sns.set_context('notebook',font_scale = 1.5)
sns.barplot(x=data.age.value_counts()[:10].index,y=data.age.value_counts()[:10].values)
plt.tight_layout()
```



Let's check the range of age in the dataset.

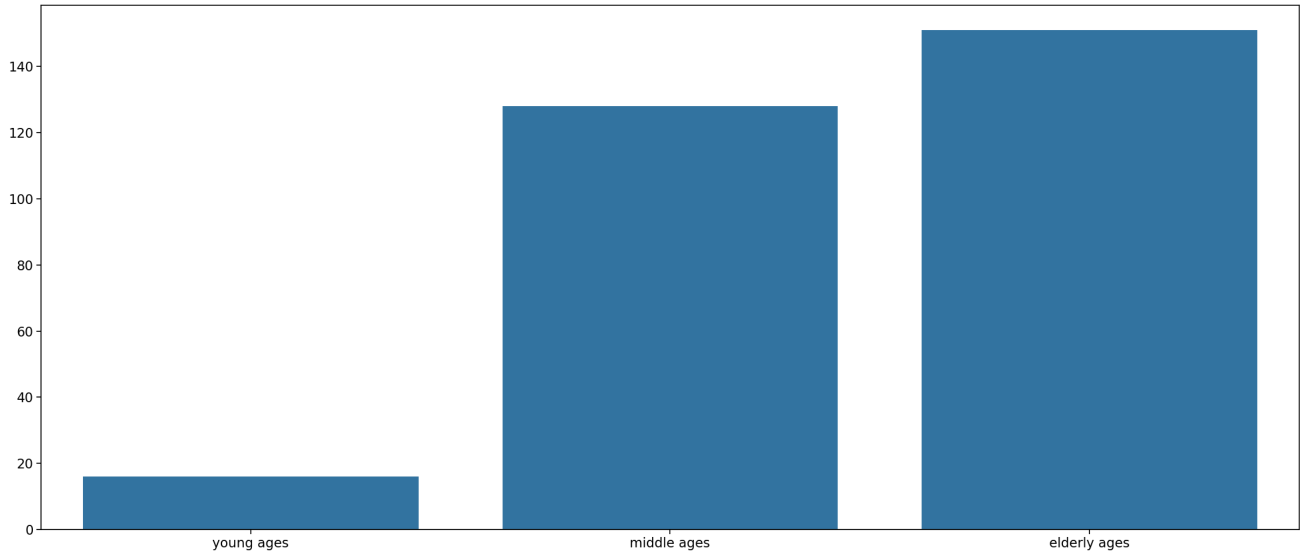
```
minAge=min(data.age)
maxAge=max(data.age)
meanAge=data.age.mean()
print('Min Age :',minAge)
print('Max Age :',maxAge)
print('Mean Age :',meanAge)
```

```
Min Age : 29
Max Age : 77
Mean Age : 54.366336633663366
```

We should divide the Age feature into three parts - "Young", "Middle" and "Elder"

```
Young = data[(data.age>=29)&(data.age<40)]
Middle = data[(data.age>=40)&(data.age<55)]
Elder = data[(data.age>55)]
```

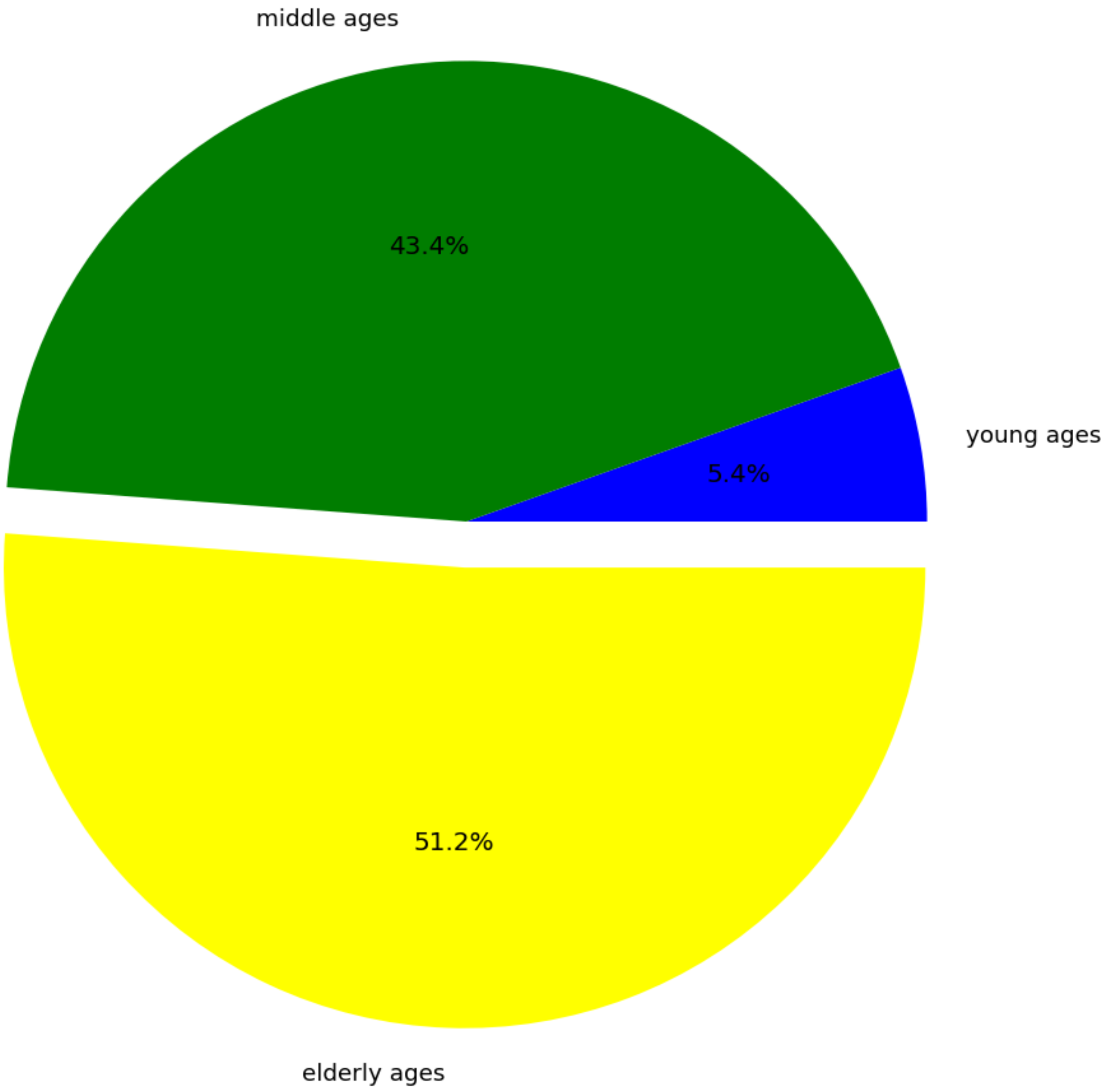
```
plt.figure(figsize=(23,10))
sns.set_context('notebook',font_scale = 1.5)
sns.barplot(x=['young ages','middle ages','elderly ages'],y=[len(Young),len(Middle),len(E
plt.tight_layout()
```



A large proportion of dataset contains Elder people.

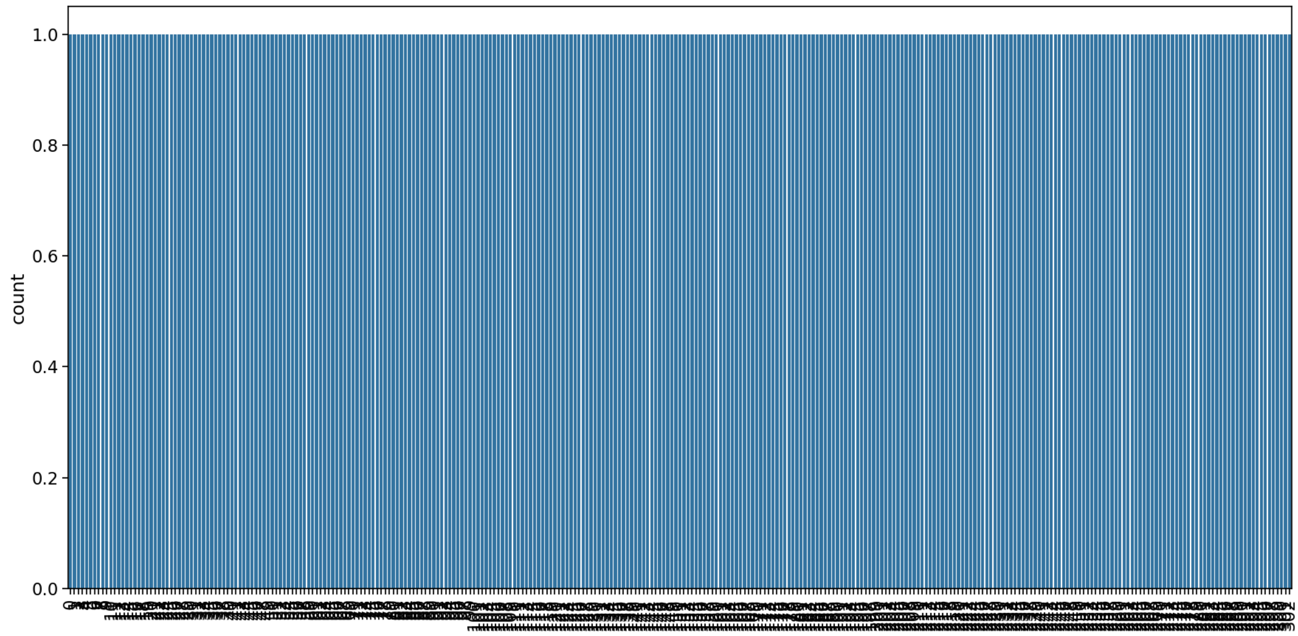
Elderly people are more likely to suffer from heart disease.

```
colors = ['blue','green','yellow']
explode = [0,0,0.1]
plt.figure(figsize=(10,10))
sns.set_context('notebook',font_scale = 1.2)
plt.pie([len(Young),len(Middle),len(Elder)],labels=['young ages','middle ages','elderly a
plt.tight_layout()
```



Sex("sex") Feature Analysis

```
plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.5)
sns.countplot(data['sex'])
plt.xticks(rotation=90)  # Rotate the x-axis labels
plt.tight_layout()
plt.show()
```



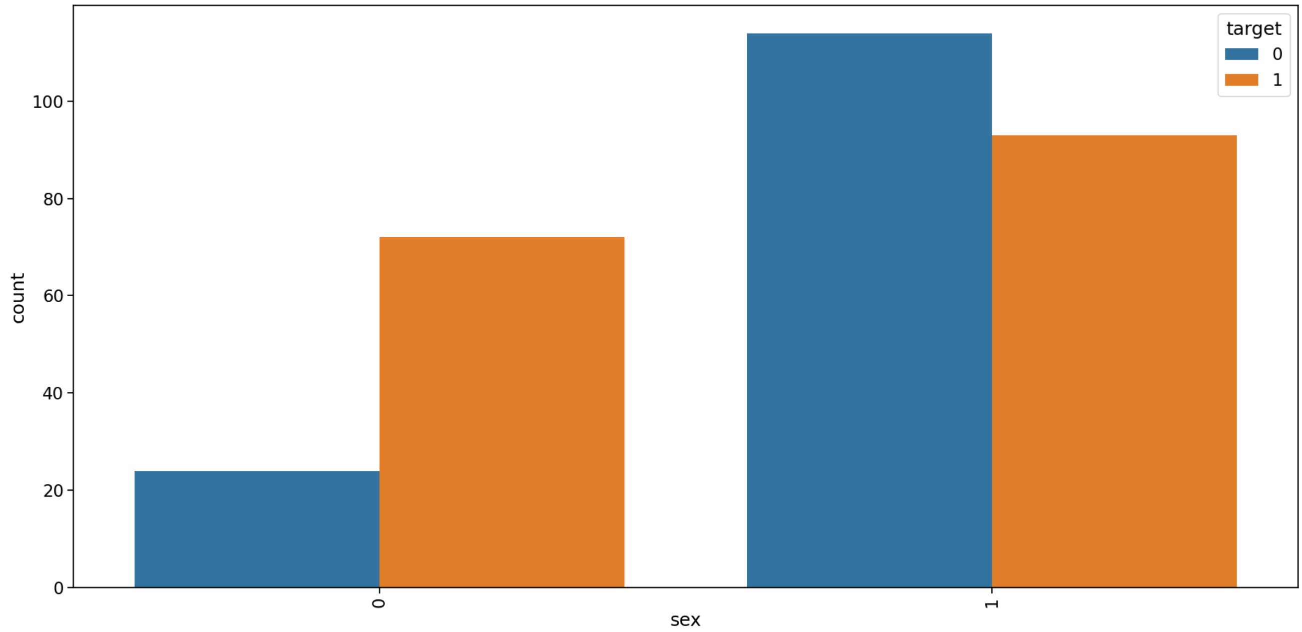

```
data
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	t
0	63	1	3	145	233	1	0	150	0	2.3	0	0	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
298	57	0	0	140	241	0	1	123	1	0.2	1	0	
299	45	1	3	110	264	0	1	132	0	1.2	1	0	
300	68	1	0	144	193	1	1	141	0	3.4	1	2	
301	57	1	0	130	131	0	1	115	1	1.2	1	1	
302	57	0	1	130	236	0	0	174	0	0.0	1	1	

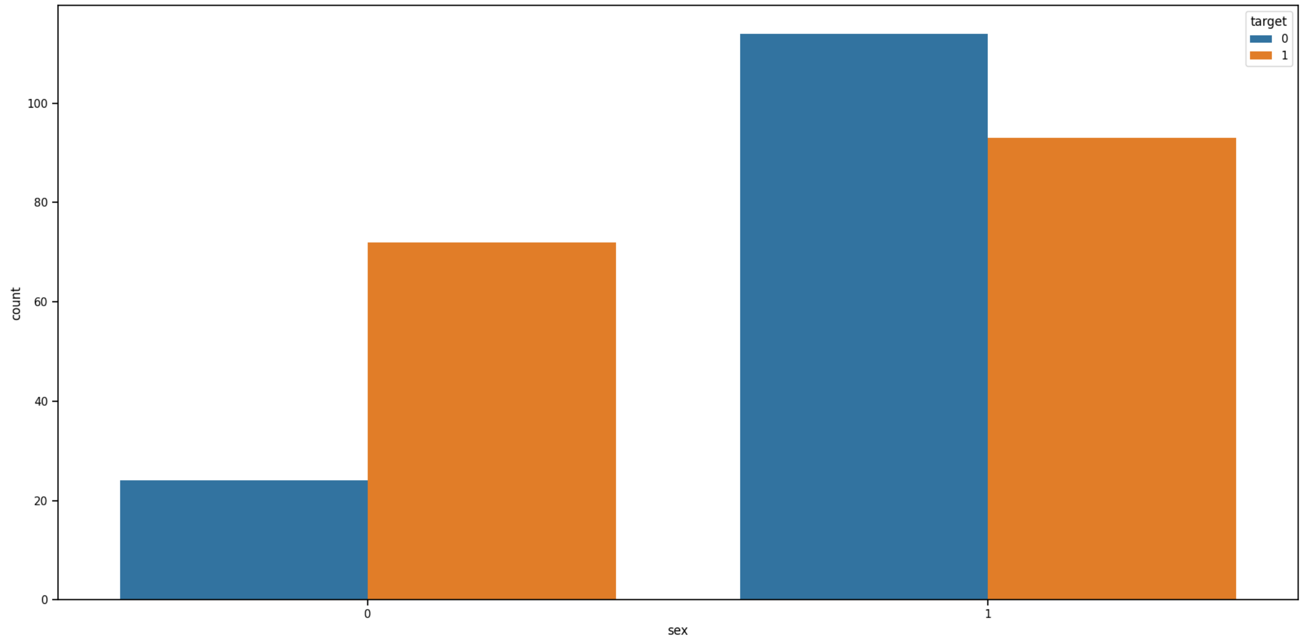
303 rows × 14 columns

Ratio of Male to Female is approx 2:1

```
plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.5)
sns.countplot(x='sex', hue='target', data=data)  # Add 'hue' as needed
plt.xticks(rotation=90)  # Rotate the x-axis labels
plt.tight_layout()
plt.show()
```



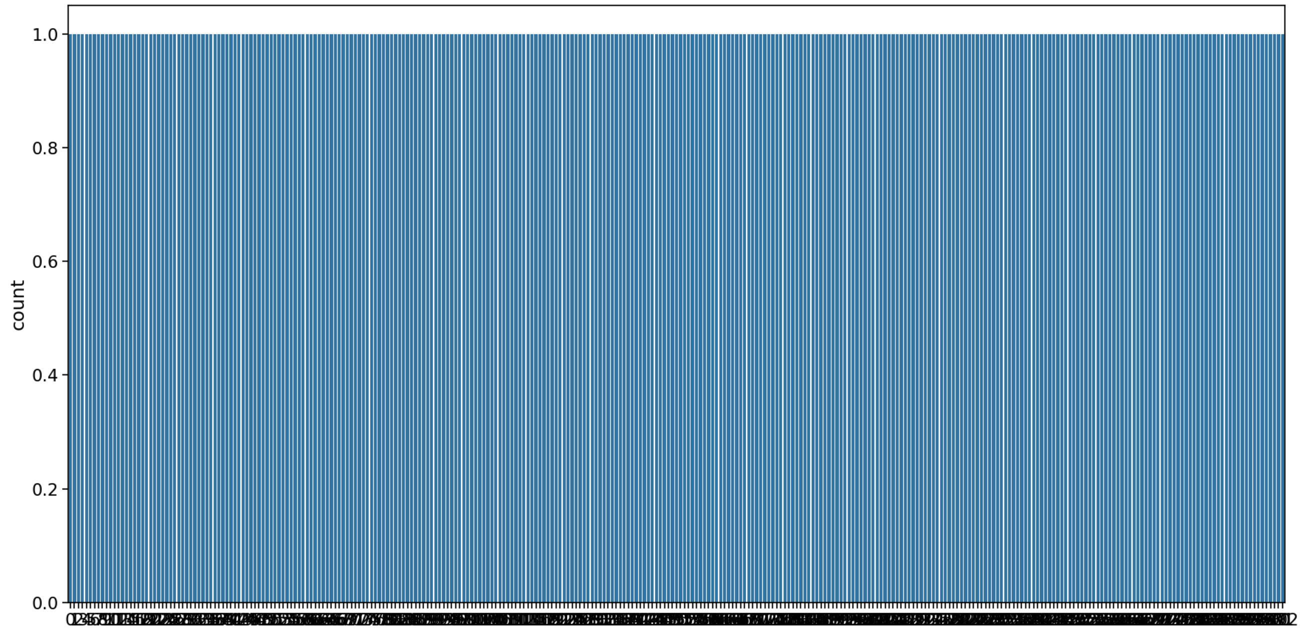

```
# Let's plot the relation between sex and target.

plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.0)
sns.countplot(x='sex', hue='target', data=data)  # Specify 'x' and 'hue'
plt.xticks(rotation=0)  # Keep labels horizontal since there are only two categories
plt.tight_layout()
plt.show()
```



Males are more likely to have heart disease than Female.

Chest Pain Type("cp") Analysis

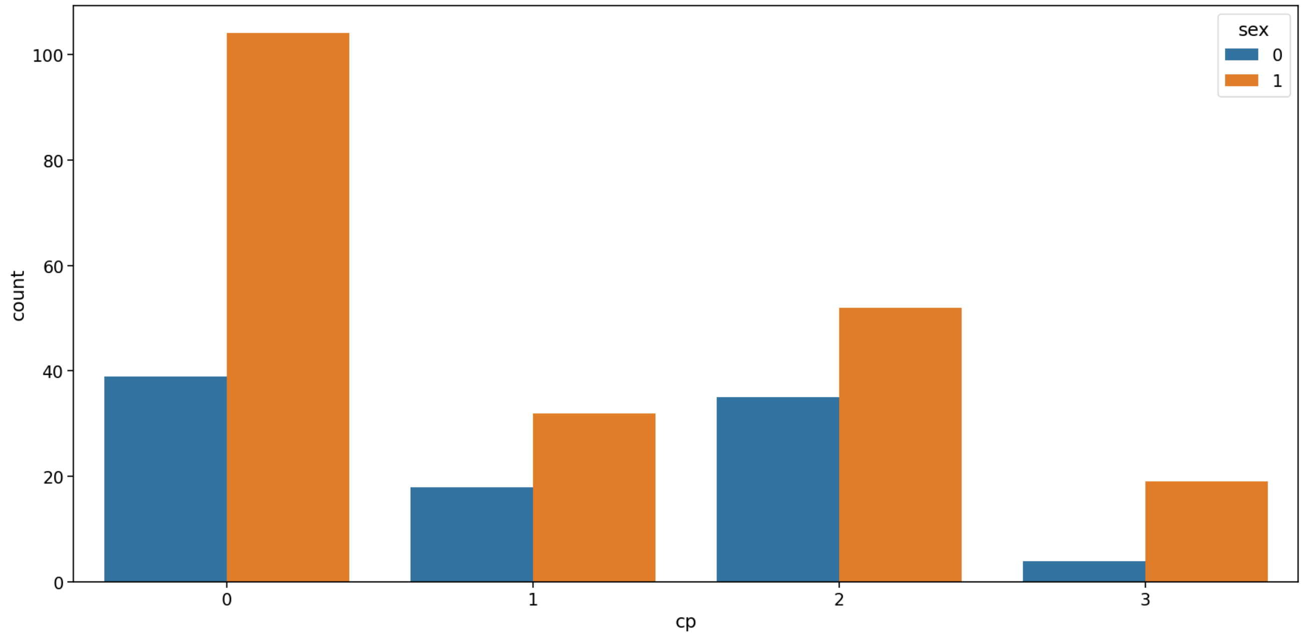
```
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(data['cp'])
plt.tight_layout()
```



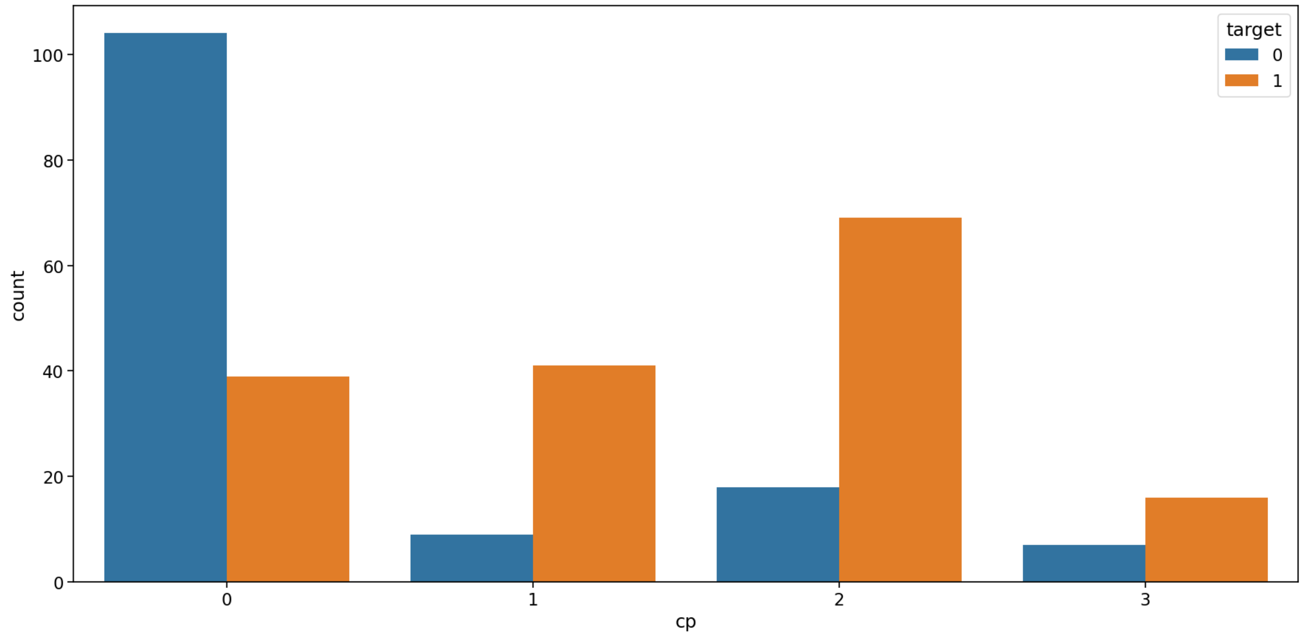
As seen, there are 4 types of chest pain

1. status at least
2. condition slightly distressed
3. condition medium problem
4. condition too bad

```
plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.5)
sns.countplot(x='cp', hue='sex', data=data)  # Correctly specify 'x' and 'hue'
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.5)
sns.countplot(x='cp', hue='target', data=data)  # Correctly specify 'x' and 'hue'
plt.tight_layout()
plt.show()
```

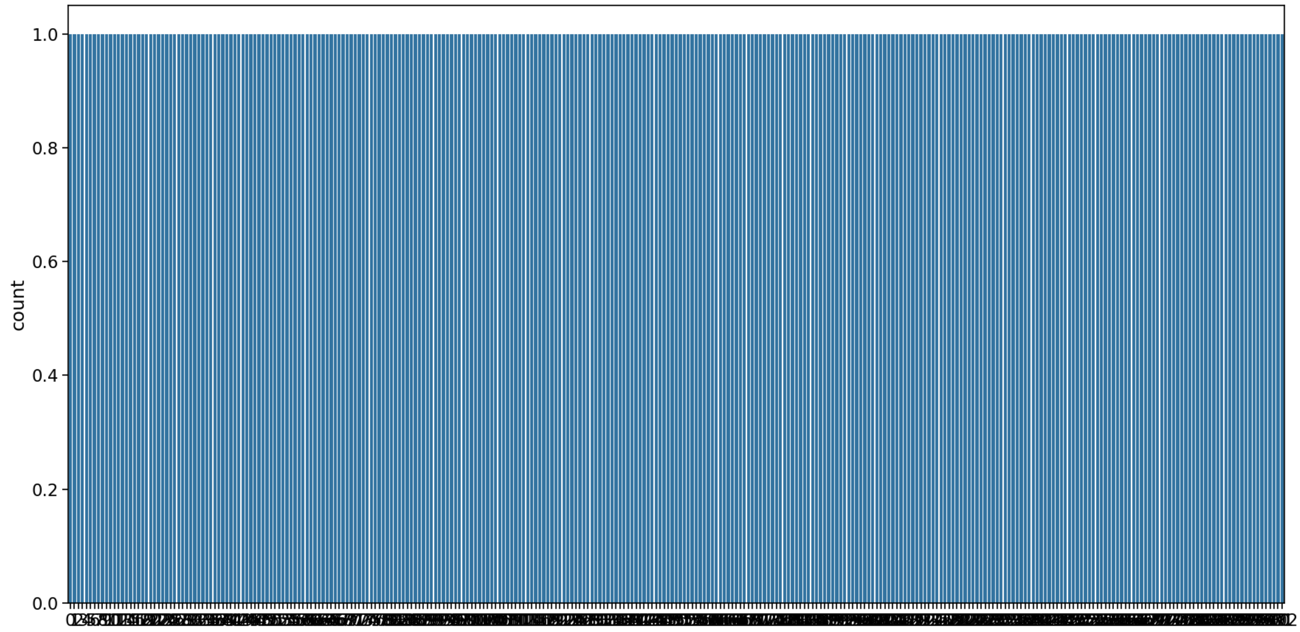


- People having least chest pain are not likely to heart disease.
- People having severe chest pain are likely to heart disease.

Elderly people are more likely to have chest pain.

Thal Analysis

```
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(data['thal'])
plt.tight_layout()
```

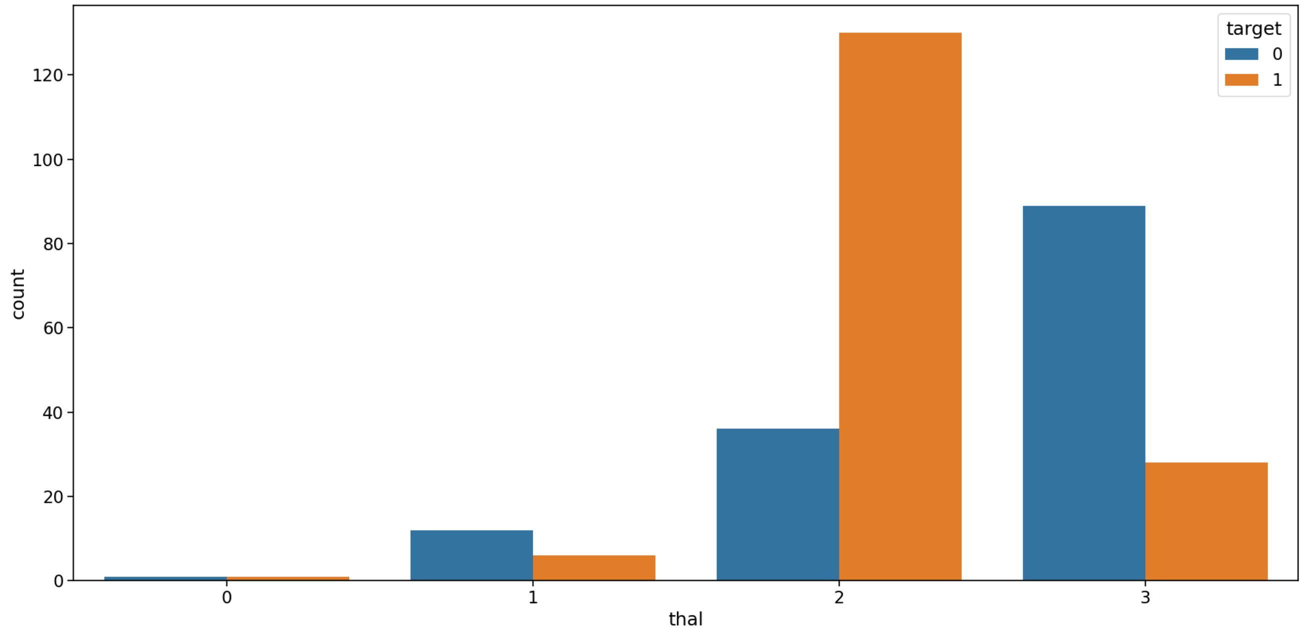



```
data.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	tha
0	63	1	3	145	233	1	0	150	0	2.3	0	0	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	

1. 3 = normal
2. 6 = fixed defect
3. 7 = reversable defect

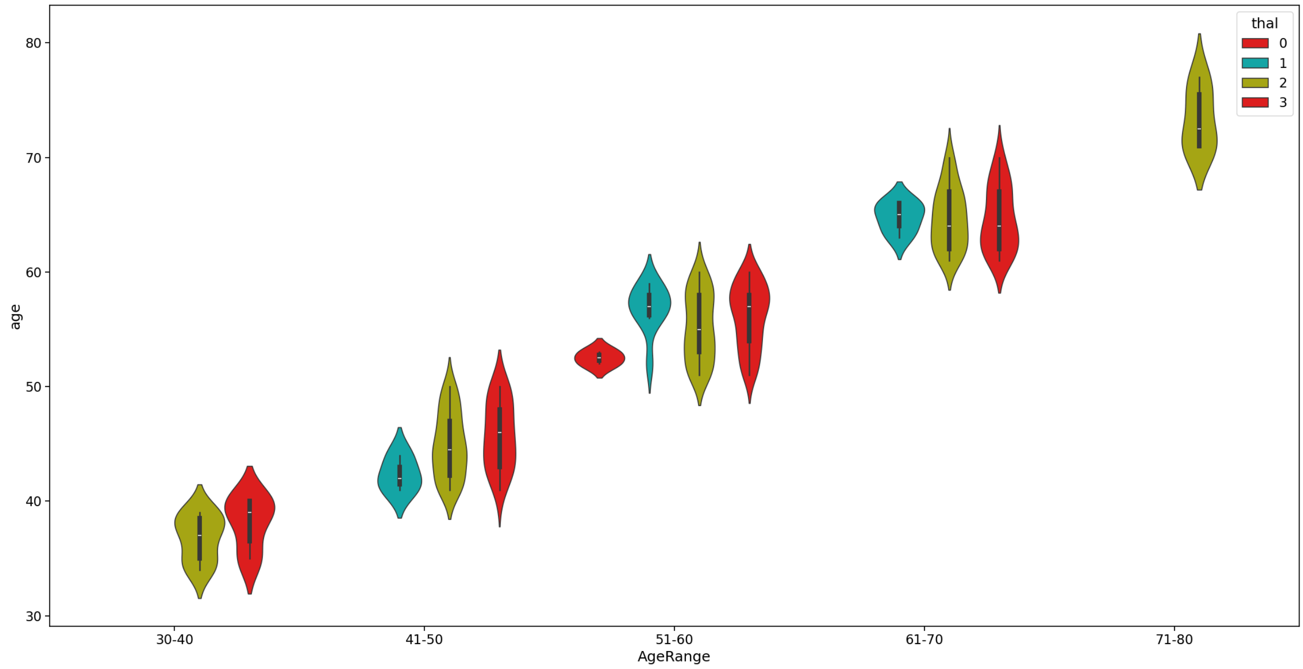
```
plt.figure(figsize=(18, 9))
sns.set_context('notebook', font_scale=1.5)
sns.countplot(x='thal', hue='target', data=data)  # Correctly specify 'x' and 'hue'
plt.tight_layout()
plt.show()
```



People with fixed defect are more likely to have heart disease.

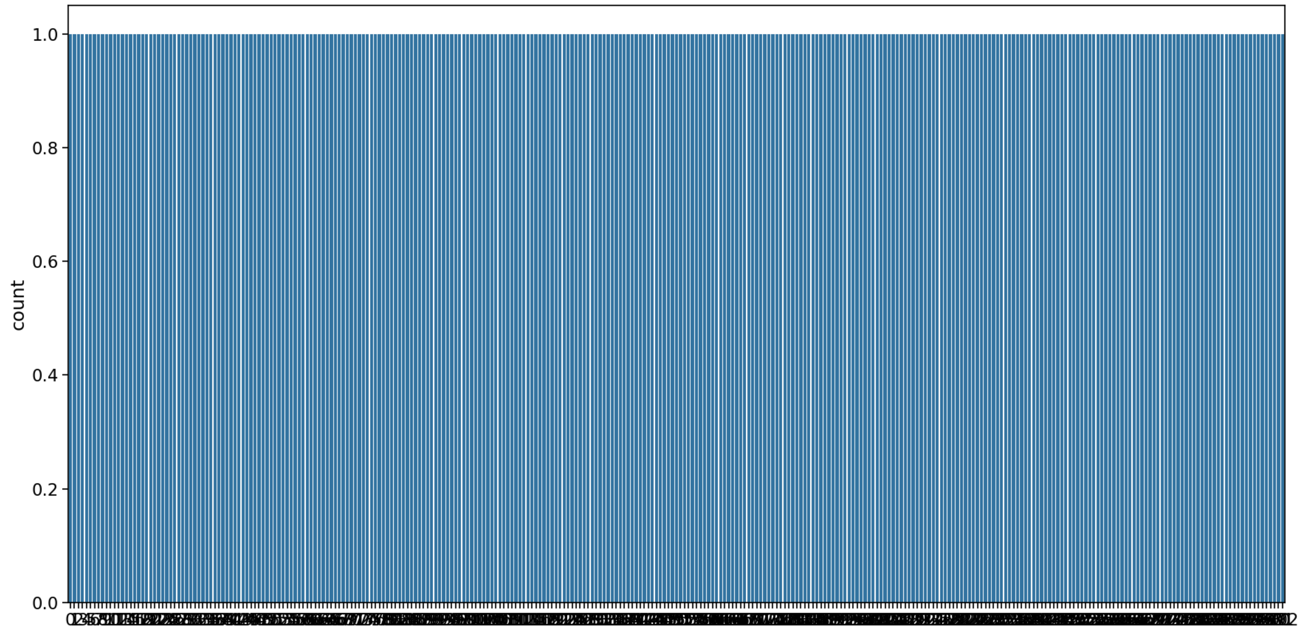
```
# Define age ranges (bins)
bins = [29, 40, 50, 60, 70, 80]
labels = ['30-40', '41-50', '51-60', '61-70', '71-80']

# Create a new AgeRange column based on the bins
data['AgeRange'] = pd.cut(data['age'], bins=bins, labels=labels)


plt.figure(figsize=(23, 12))
sns.set_context('notebook', font_scale=1.5)
sns.violinplot(x="AgeRange", y="age", data=data, palette=["r", "c", "y"], hue="thal")
plt.tight_layout()
plt.show()
```

```
<ipython-input-34-db5a88e9e86e>:3: UserWarning:
The palette list has fewer values (3) than needed (4) and will cycle, which may produ
  sns.violinplot(x="AgeRange", y="age", data=data, palette=["r", "c", "y"], hue="thal
```



Target

```
plt.figure(figsize=(18,9))
sns.set_context('notebook',font_scale = 1.5)
sns.countplot(data['target'])
plt.tight_layout()
```



The ratio between 1 and 0 is much less than 1.5 which indicates that target feature is not imbalanced. So for a balanced dataset, we can use accuracy_score as evaluation metrics for our model.

```
data.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	tha
0	63	1	3	145	233	1	0	150	0	2.3	0	0	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	
3	56	1	1	120	236	0	1	178	0	0.8	2	0	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	

Feature Enginnering

```
categorical_val = []
continous_val = []
for column in data.columns:
    print("--------------------")
    print(f"{column} : {data[column].unique()}")
    if len(data[column].unique()) <= 10:
        categorical_val.append(column)
    else:
        continous_val.append(column)
```

```
--------------------
age : [63 37 41 56 57 44 52 54 48 49 64 58 50 66 43 69 59 42 61 40 71 51 65 53
 46 45 39 47 62 34 35 29 55 60 67 68 74 76 70 38 77]
--------------------
sex : [1 0]
--------------------
cp : [3 2 1 0]
--------------------
trestbps : [145 130 120 140 172 150 110 135 160 105 125 142 155 104 138 128 108 134
 122 115 118 100 124  94 112 102 152 101 132 148 178 129 180 136 126 106
 156 170 146 117 200 165 174 192 144 123 154 114 164]
--------------------
chol : [233 250 204 236 354 192 294 263 199 168 239 275 266 211 283 219 340 226
 247 234 243 302 212 175 417 197 198 177 273 213 304 232 269 360 308 245
 208 264 321 325 235 257 216 256 231 141 252 201 222 260 182 303 265 309
 186 203 183 220 209 258 227 261 221 205 240 318 298 564 277 214 248 255
 207 223 288 160 394 315 246 244 270 195 196 254 126 313 262 215 193 271
 268 267 210 295 306 178 242 180 228 149 278 253 342 157 286 229 284 224
 206 167 230 335 276 353 225 330 290 172 305 188 282 185 326 274 164 307
 249 341 407 217 174 281 289 322 299 300 293 184 409 259 200 327 237 218
 319 166 311 169 187 176 241 131]
--------------------
fbs : [1 0]
--------------------
restecg : [0 1 2]
--------------------
thalach : [150 187 172 178 163 148 153 173 162 174 160 139 171 144 158 114 151 161
 179 137 157 123 152 168 140 188 125 170 165 142 180 143 182 156 115 149
 146 175 186 185 159 130 190 132 147 154 202 166 164 184 122 169 138 111
 145 194 131 133 155 167 192 121  96 126 105 181 116 108 129 120 112 128
 109 113  99 177 141 136  97 127 103 124  88 195 106  95 117  71 118 134
  90]
--------------------
exang : [0 1]
--------------------
oldpeak : [2.3 3.5 1.4 0.8 0.6 0.4 1.3 0.  0.5 1.6 1.2 0.2 1.8 1.  2.6 1.5 3.  2.4
 0.1 1.9 4.2 1.1 2.  0.7 0.3 0.9 3.6 3.1 3.2 2.5 2.2 2.8 3.4 6.2 4.  5.6
 2.9 2.1 3.8 4.4]
--------------------
slope : [0 2 1]
--------------------
ca : [0 2 1 3 4]
--------------------
thal : [1 2 3 0]
--------------------
target : [1 0]
--------------------
AgeRange : ['61-70', '30-40', '41-50', '51-60', '71-80', NaN]
Categories (5, object): ['30-40' < '41-50' < '51-60' < '61-70' < '71-80']
```

```
categorical_val.remove('target')
dfs = pd.get_dummies(data, columns = categorical_val)
```

```
dfs.head(6)
```

	age	trestbps	chol	thalach	oldpeak	target	sex_0	sex_1	cp_0	cp_1	...	ca_4
0	63	145	233	150	2.3	1	False	True	False	False	...	False
1	37	130	250	187	3.5	1	False	True	False	False	...	False
2	41	130	204	172	1.4	1	True	False	False	True	...	False
3	56	120	236	178	0.8	1	False	True	False	True	...	False
4	57	120	354	163	0.6	1	True	False	True	False	...	False
5	57	140	192	148	0.4	1	False	True	True	False	...	False

6 rows × 36 columns

```
sc = StandardScaler()
col_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
dfs[col_to_scale] = sc.fit_transform(dfs[col_to_scale])
```

```
dfs.head(6)
```

	age	trestbps	chol	thalach	oldpeak	target	sex_0	sex_1	cp_0	cp_
0	0.952197	0.763956	-0.256334	0.015443	1.087338	1	False	True	False	Fals
1	-1.915313	-0.092738	0.072199	1.633471	2.122573	1	False	True	False	Fals
2	-1.474158	-0.092738	-0.816773	0.977514	0.310912	1	True	False	False	Tru
3	0.180175	-0.663867	-0.198357	1.239897	-0.206705	1	False	True	False	Tru
4	0.290464	-0.663867	2.082050	0.583939	-0.379244	1	True	False	True	Fals
5	0.290464	0.478391	-1.048678	-0.072018	-0.551783	1	False	True	True	Fals

6 rows × 36 columns

Modelling

Splitting our dataset

```
X = dfs.drop('target', axis=1)
y = dfs.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
X_train.head()
```

	age	trestbps	chol	thalach	oldpeak	sex_0	sex_1	cp_0	cp_1	cp_
124	-1.694735	-2.148802	-0.913400	1.283627	-0.896862	True	False	False	False	Tru
72	-2.797624	-0.092738	-0.816773	2.289429	-0.896862	False	True	False	True	Fals
15	-0.481558	-0.663867	-0.526890	0.365287	0.483451	True	False	False	False	Tru
10	-0.040403	0.478391	-0.140381	0.452748	0.138373	False	True	True	False	Fals
163	-1.805024	0.364165	-1.377212	1.021244	-0.896862	False	True	False	False	Tru

5 rows × 35 columns

We will work on following algo -

- KNN
- Random Forest Classifier
- XGBoost
- CatBoost

KNN

```
knn = KNeighborsClassifier(n_neighbors = 10)
```

```
knn.fit(X_train,y_train)
```

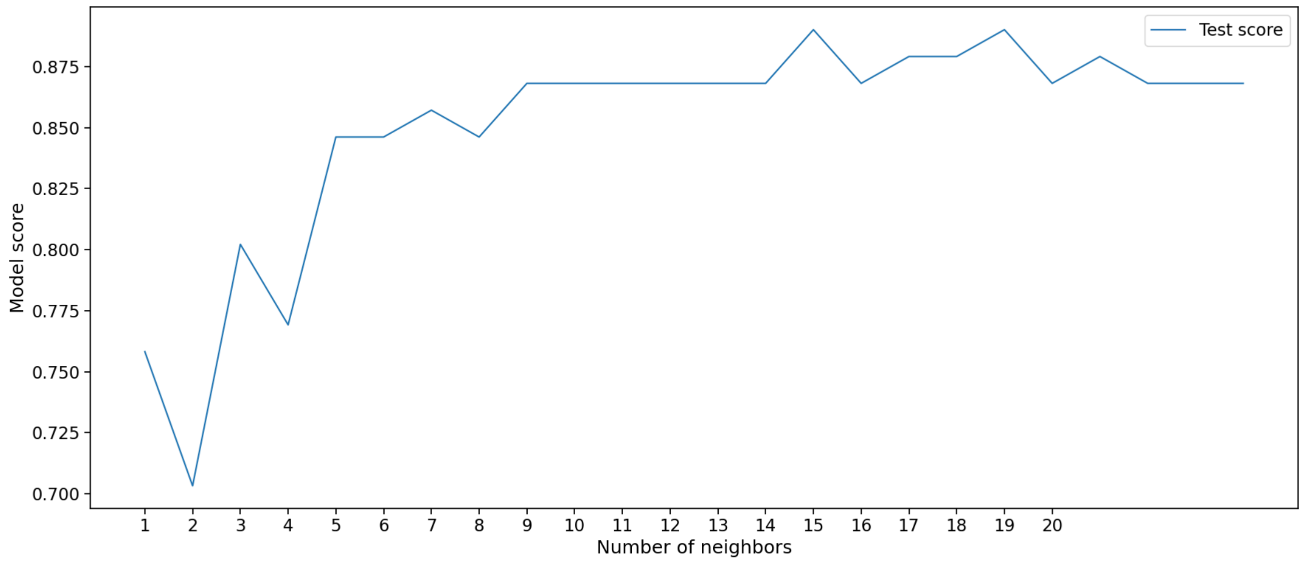
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=10)
```

```
y_pred1 = knn.predict(X_test)
```

```
print(accuracy_score(y_test,y_pred1))
```

```
0.8681318681318682
```

```
# Hyperparameter Optimization

test_score = []
neighbors = range(1, 25)

for k in neighbors:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    test_score.append(accuracy_score(y_test, model.predict(X_test)))


plt.figure(figsize=(18, 8))
plt.plot(neighbors, test_score, label="Test score")
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()
plt.tight_layout()
```



At K=19, we are getting highest test accuracy.

```
knn = KNeighborsClassifier(n_neighbors = 19)
```

```
knn.fit(X_train,y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=19)
```

```
y_pred1 = knn.predict(X_test)
```

```
print(accuracy_score(y_test,y_pred1))
```

```
0.8901098901098901
```

We achieved accuracy 89% with KNN Model after Hyperparameter Optimization.

Random Forest Classifier

```
rfc = RandomForestClassifier()
rfc.fit(X_train,y_train)
y_pred2 = rfc.predict(X_test)
```

```
print(accuracy_score(y_test,y_pred2))
```

```
0.8241758241758241
```

```
## Hyperparameter Optimization

max_depth = [int(x) for x in np.linspace(10, 110, num=11)]
max_depth.append(None)

params2 ={

    'n_estimators': [int(x) for x in np.linspace(start=200, stop=2000, num=10)],
    'max_features': ['auto', 'sqrt'],
    'max_depth': max_depth,
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}
```

```
rfc = RandomForestClassifier(random_state=42)
```

```
rfcs = RandomizedSearchCV(estimator=rfc, param_distributions=params2, n_iter=100, cv=5, v
```

```
rfcs.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:42
205 fits failed out of a total of 500.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_sc

Below are more details about the failures:
--------------------------------------------------------------------------------
110 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validati
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1145, in w
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 638, in _v
    validate_parameter_constraints(
  File "/usr/local/lib/python3.10/dist-packages/sklearn/utils/_param_validation.p
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' paramet

--------------------------------------------------------------------------------
95 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validati
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1145, in w
    estimator._validate_params()
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 638, in _v
    validate_parameter_constraints(
```