The Problem Statement:

To build an application to classify the patients to be healthy or suffering from cardiovascular disease based on the given attributes.

Features:

1. Age | Objective Feature | age | int (days)
2. Height | Objective Feature | height | int (cm) |
3. Weight | Objective Feature | weight | float (kg) |
4. Gender | Objective Feature | gender | categorical code |
5. Systolic blood pressure | Examination Feature | ap_hi | int |
6. Diastolic blood pressure | Examination Feature | ap_lo | int |
7. Cholesterol | Examination Feature | cholesterol | 1: normal, 2: above normal, 3: well above normal |
8. Glucose | Examination Feature | gluc | 1: normal, 2: above normal, 3: well above normal |
9. Smoking | Subjective Feature | smoke | binary |
10. Alcohol intake | Subjective Feature | alco | binary |
11. Physical activity | Subjective Feature | active | binary |
12. Presence or absence of cardiovascular disease | Target Variable | cardio | binary |

All of the dataset values were collected at the moment of medical examination.

In [1]:

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

%matplotlib inline

import warnings
warnings.filterwarnings('ignore')


from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.tree import DecisionTreeClassifier
```

In [2]:
```
# Load the data
cardio = pd.read_csv('cardio_train.csv', delimiter=';')
cardio.head(3)
```

Out[2]:

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	alco	active	cardio
0	988	22469	1	155	69.0	130	80	2	2	0	0	1	0
1	989	14648	1	163	71.0	110	70	1	1	0	0	1	1
2	990	21901	1	165	70.0	120	80	1	1	0	0	1	0

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69301 entries, 0 to 69300
Data columns (total 13 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           69301 non-null  int64  
 1   age          69301 non-null  int64  
 2   gender       69301 non-null  int64  
 3   height       69301 non-null  int64  
 4   weight       69301 non-null  float64
 5   ap_hi        69301 non-null  int64  
 6   ap_lo        69301 non-null  int64  
 7   cholesterol  69301 non-null  int64  
 8   gluc         69301 non-null  int64  
 9   smoke        69301 non-null  int64  
 10  alco         69301 non-null  int64  
 11  active       69301 non-null  int64  
 12  cardio       69301 non-null  int64  
dtypes: float64(1), int64(12)
memory usage: 6.9 MB
```

Age, height, weight, ap_hi, ap_lo are continues data

cholesterol, gluc, smoke, alco, active, cardio are categorical data

id is not required column

In [4]:
```
cardio.drop(columns=['id'], inplace=True)
```

In [5]:
```
cardio.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
age	69301.0	19468.786280	2467.261818	10798.0	17664.0	19704.0	21326.0	23713.0
gender	69301.0	1.349519	0.476821	1.0	1.0	1.0	2.0	2.0
height	69301.0	164.362217	8.205337	55.0	159.0	165.0	170.0	250.0
weight	69301.0	74.203027	14.383469	10.0	65.0	72.0	82.0	200.0
ap_hi	69301.0	128.829584	154.775805	-150.0	120.0	120.0	140.0	16020.0
ap_lo	69301.0	96.650092	189.096240	-70.0	80.0	80.0	90.0	11000.0
cholesterol	69301.0	1.366806	0.680270	1.0	1.0	1.0	2.0	3.0
gluc	69301.0	1.226447	0.572246	1.0	1.0	1.0	1.0	3.0
smoke	69301.0	0.088051	0.283371	0.0	0.0	0.0	0.0	1.0
alco	69301.0	0.053881	0.225784	0.0	0.0	0.0	0.0	1.0
active	69301.0	0.803986	0.396982	0.0	1.0	1.0	1.0	1.0
cardio	69301.0	0.499589	0.500003	0.0	0.0	0.0	1.0	1.0

as looking into count column we can see there is no null values present in any column

lets verify

In [6]:

```
cardio.isna().sum()
```

Out[6]:

```
age            0
gender         0
height         0
weight         0
ap_hi          0
ap_lo          0
cholesterol    0
gluc           0
smoke          0
alco           0
active         0
cardio         0
dtype: int64
```

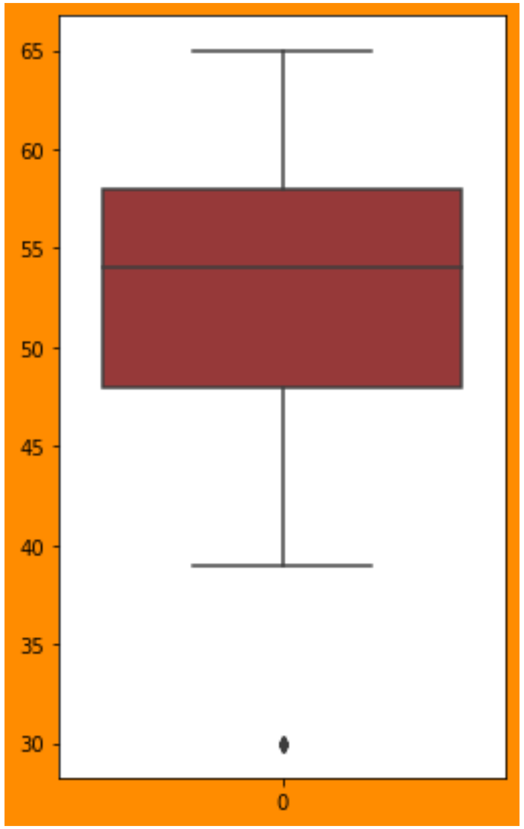
Age in days is not easy to understand

Lets make new column called year where age in days is converted into age in year

In [7]:
```
cardio['age'] = (cardio['age'] / 365).round().astype('int')
```

Lets Plot a boxplot to check age(age in year)column

In [8]:
```
plt.figure(figsize=(4,7), facecolor='DarkOrange')
sns.boxplot(cardio.age, color='Brown');
```



Describe function

Difference between mean and standard deviation shows that there so many variances in data,

Lets only consider years age above quantile 0.015, they are only few below age 40

Lets consider only 1.5% to 97.5% of weight and height and 1.5% above age

In [9]:
```
qua_low = cardio.quantile(0.015)
qua_high = cardio.quantile(0.975)

c1 = cardio[(cardio.height > qua_high.height) |
            (cardio.height < qua_low.height) |
            (cardio.weight > qua_high.weight) |
            (cardio.weight < qua_low.weight) |
            (cardio.age < qua_low.age)].index

cardio.drop(c1, inplace=True)
```

ap_hi and ap_lo represents blood pressure,

difference between ap_hi and ap_lo show the blood pressure,

while ap_hi and ap_lo cant be negative

In [10]:
```
cardio.ap_hi = cardio.ap_hi.abs()
cardio.ap_lo = cardio.ap_lo.abs()
```

There are some outlier data present in both columns

Lets consider only 1.5% to 97.5% of ap_hi and ap_lo

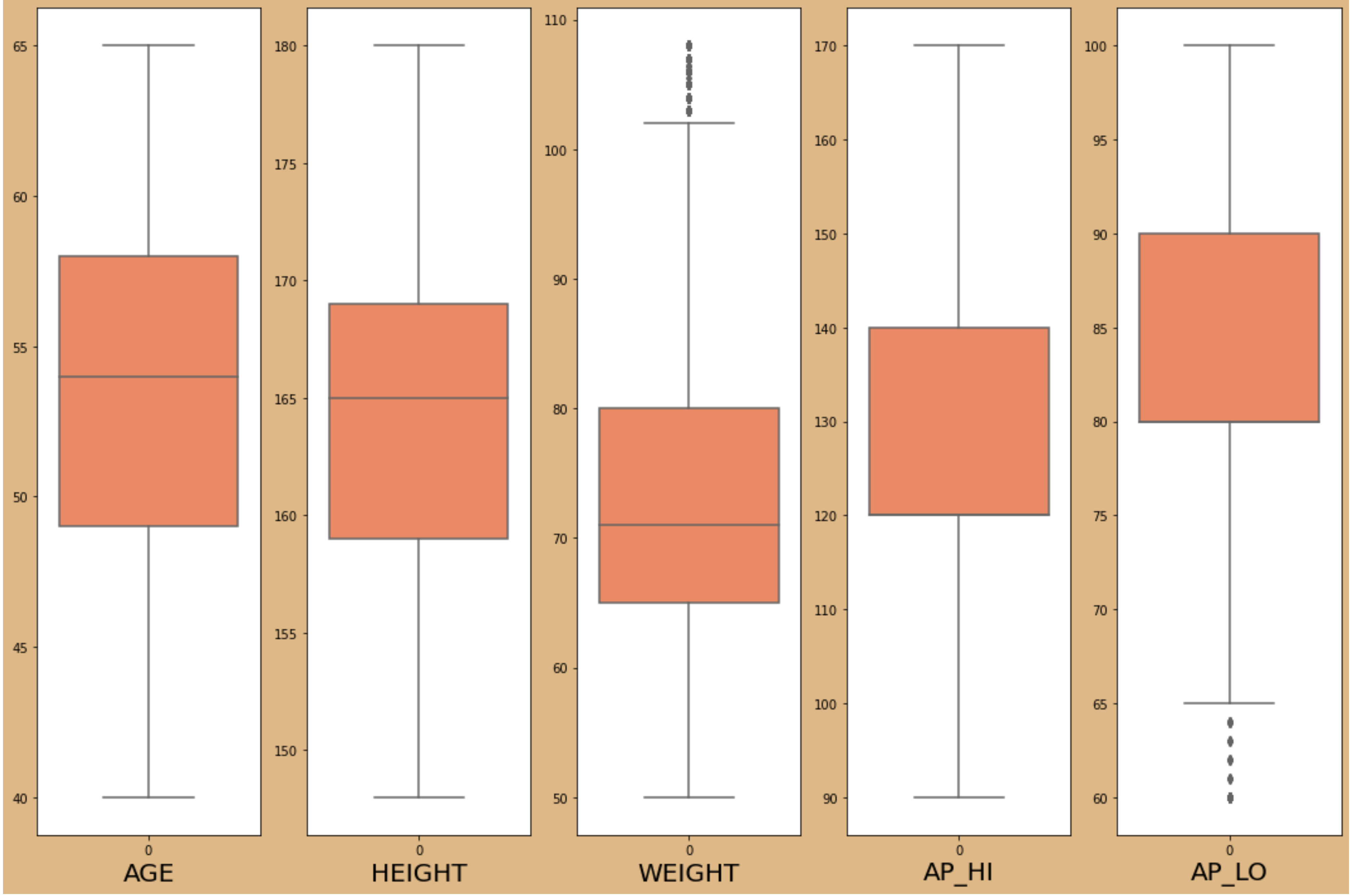
In [11]:
```
cardio.drop(cardio[(cardio.ap_hi > qua_high.ap_hi) |
                   (cardio.ap_hi < qua_low.ap_hi) |
                   (cardio.ap_lo > qua_high.ap_lo) |
                   (cardio.ap_lo < qua_low.ap_lo)].index,inplace=True)
```

In [12]:
```
cardio_cont= cardio[['age','height','weight','ap_hi','ap_lo']]

plt.figure(figsize=(15,10), facecolor='BurlyWood')
plotnumber =1

for column in cardio_cont:
    if plotnumber<=5:
        ax=plt.subplot(1,5,plotnumber)
        sns.boxplot(cardio_cont[column], color='Coral')
        plt.xlabel(column.upper(), fontsize = 20)

    plotnumber+=1
plt.tight_layout()
plt.show()
```



In [13]:

```
cardio.describe().T
```

Out[13]:

	count	mean	std	min	25%	50%	75%	max
age	61902.0	53.400827	6.686393	40.0	49.0	54.0	58.0	65.0
gender	61902.0	1.341104	0.474084	1.0	1.0	1.0	2.0	2.0
height	61902.0	164.313382	6.990518	148.0	159.0	165.0	169.0	180.0
weight	61902.0	73.212112	11.982543	50.0	65.0	71.0	80.0	108.0
ap_hi	61902.0	125.676424	14.823129	90.0	120.0	120.0	140.0	170.0
ap_lo	61902.0	80.899890	8.581824	60.0	80.0	80.0	90.0	100.0
cholesterol	61902.0	1.354205	0.671738	1.0	1.0	1.0	1.0	3.0
gluc	61902.0	1.220300	0.566947	1.0	1.0	1.0	1.0	3.0
smoke	61902.0	0.084876	0.278699	0.0	0.0	0.0	0.0	1.0
alco	61902.0	0.051501	0.221019	0.0	0.0	0.0	0.0	1.0
active	61902.0	0.804174	0.396838	0.0	1.0	1.0	1.0	1.0
cardio	61902.0	0.487916	0.499858	0.0	0.0	0.0	1.0	1.0

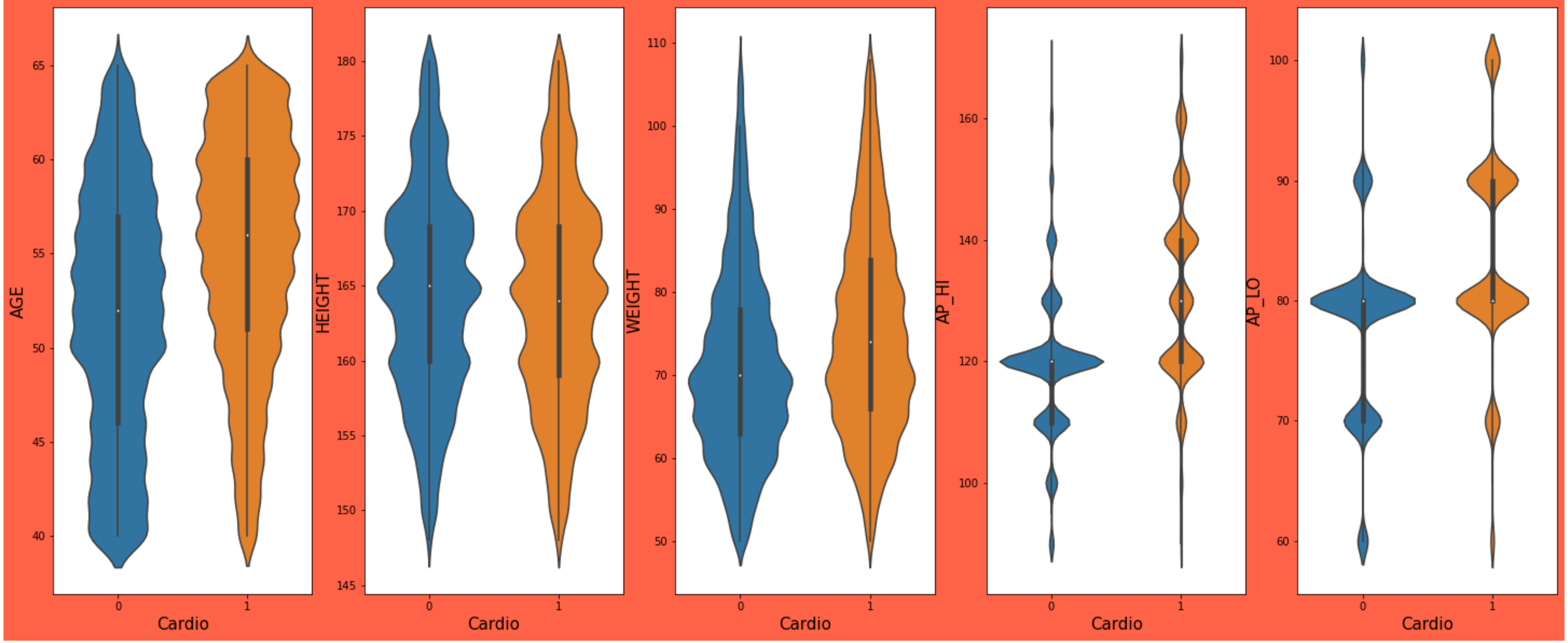
Ploting continues data vs cardio data

In [14]:

```
cont= cardio[['age','height','weight','ap_hi','ap_lo']]

plt.figure(figsize=(25,10), facecolor='Tomato')
plotnumber = 1

for columns in cont:
    if plotnumber <=5:
        ax=plt.subplot(1,5,plotnumber)
        #sns.boxenplot(cont[columns])
        sns.violinplot(data=cardio, y=cont[columns], x="cardio")
        plt.ylabel(columns.upper(), fontsize = 15)
        plt.xlabel('Cardio', fontsize= 15)
    plotnumber+=1
```

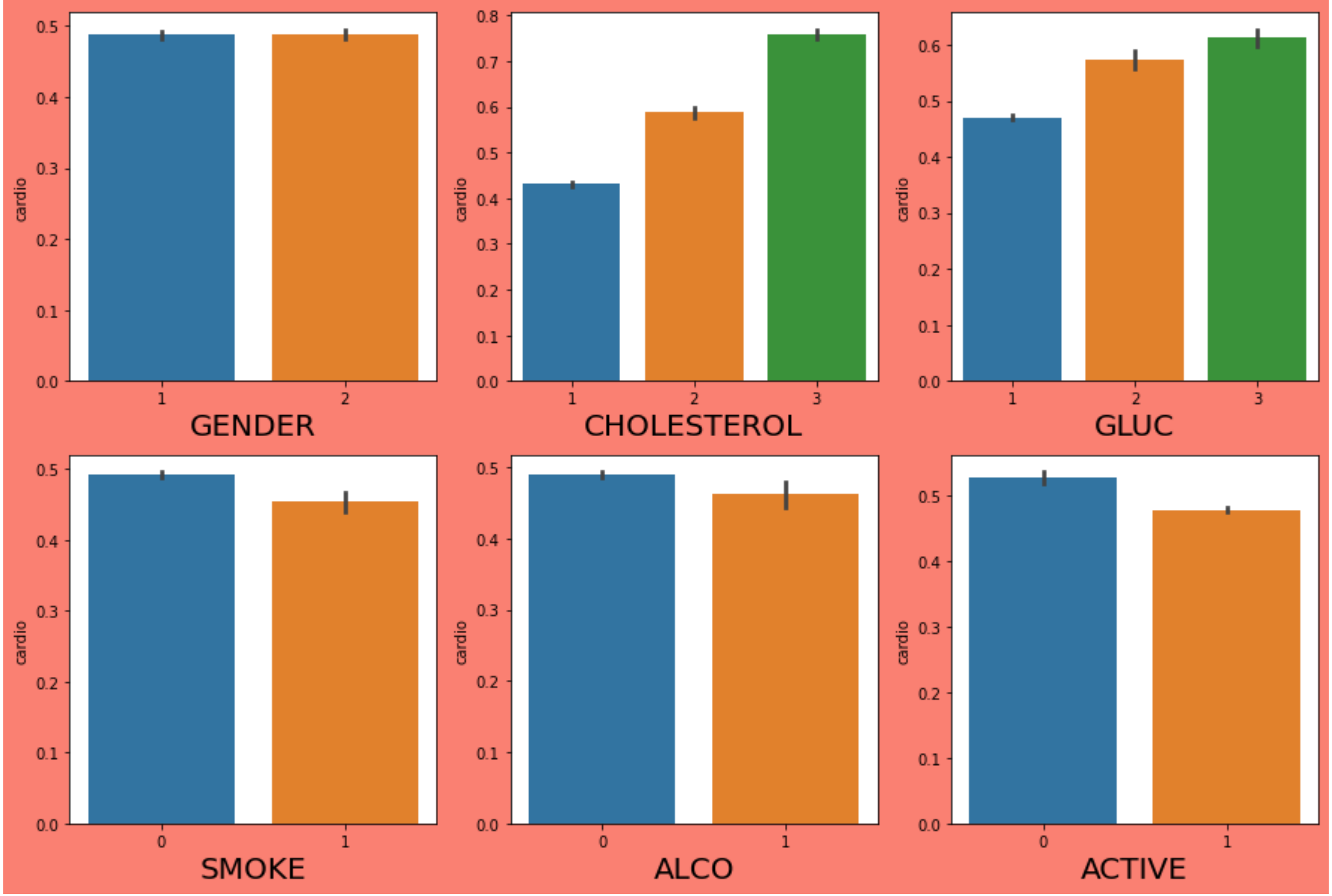


Ploting categorial data vs cardio data

In [15]:
```
cate= cardio[['gender','cholesterol','gluc','smoke','alco','active']]

plt.figure(figsize=(15,10), facecolor='Salmon')
plotnumber = 1

for columns in cate:
    if plotnumber <=6:
        ax=plt.subplot(2,3,plotnumber)
        sns.barplot(x=cate[columns], y=cardio.cardio, data= cardio)
        plt.xlabel(columns.upper(), fontsize = 20)
    plotnumber+=1
```



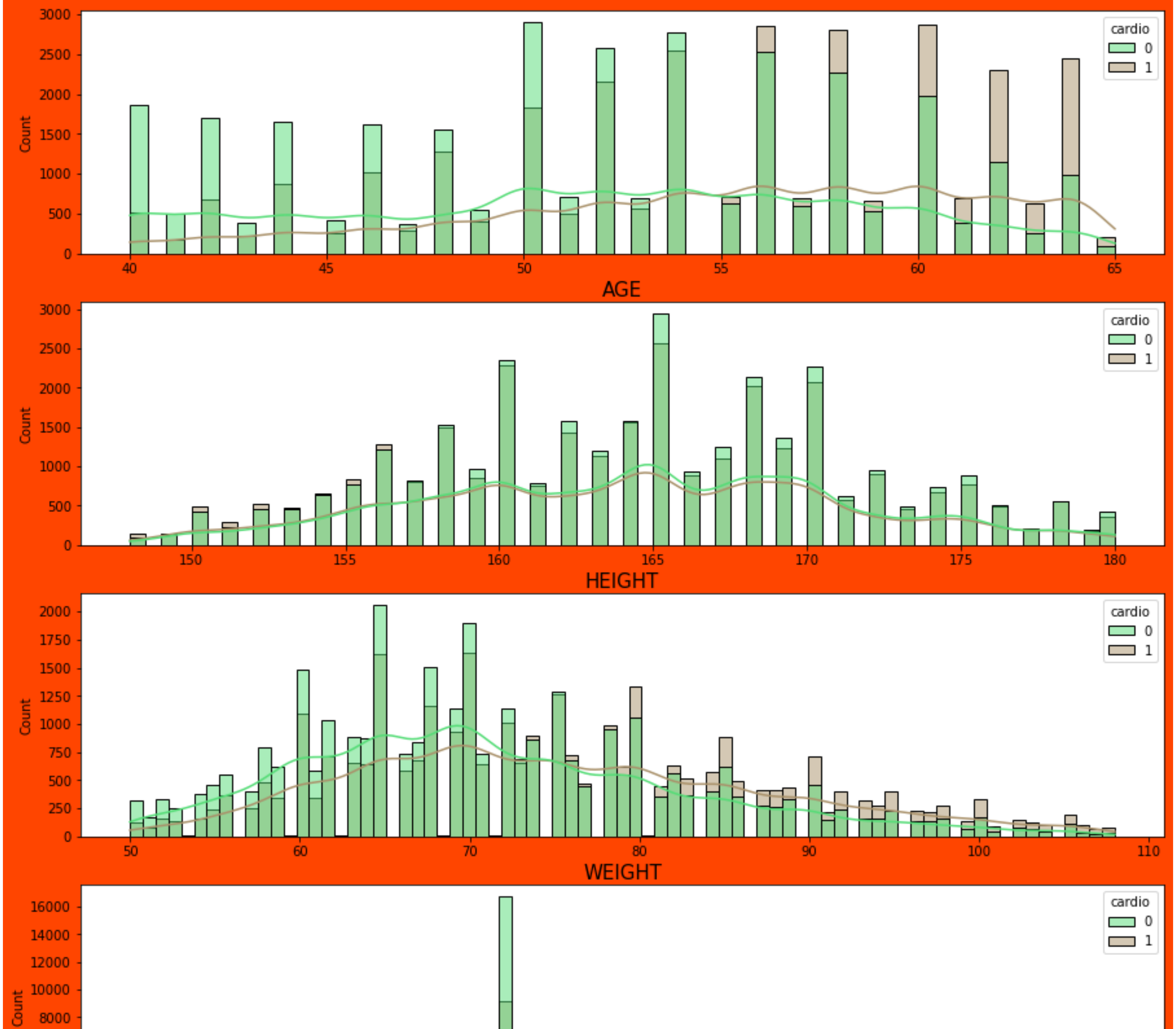
cardio
GENDER
CHOLESTEROL
GLUC
SMOKE
ALCO
ACTIVE

In [16]:

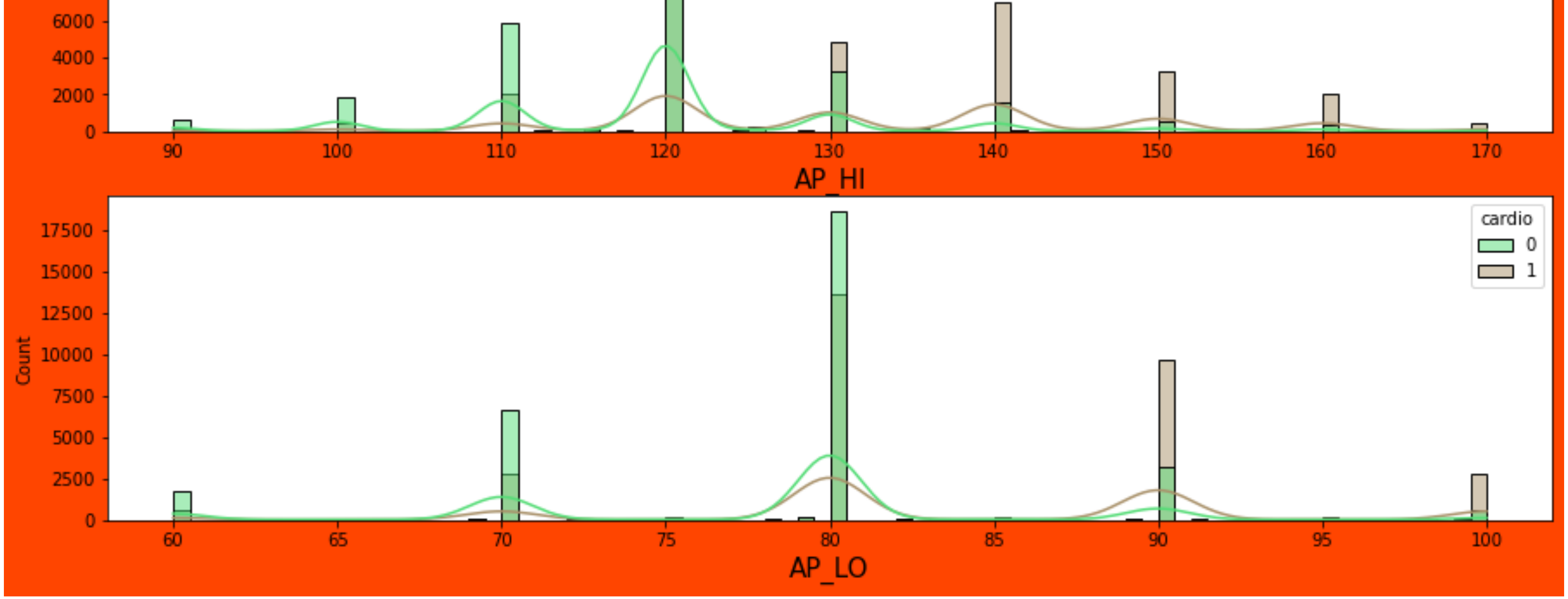
```
cont= cardio[['age','height','weight','ap_hi','ap_lo']]

plt.figure(figsize=(15,20), facecolor='OrangeRed')
plotnumber = 1

for columns in cont:
    if plotnumber <=5:
        ax=plt.subplot(5,1,plotnumber)
        sns.histplot(x= cont[columns], hue= cardio.cardio,
                     data=cardio, palette='terrain', kde=True)
        plt.xlabel(columns.upper(), fontsize = 15)
    plotnumber+=1
```

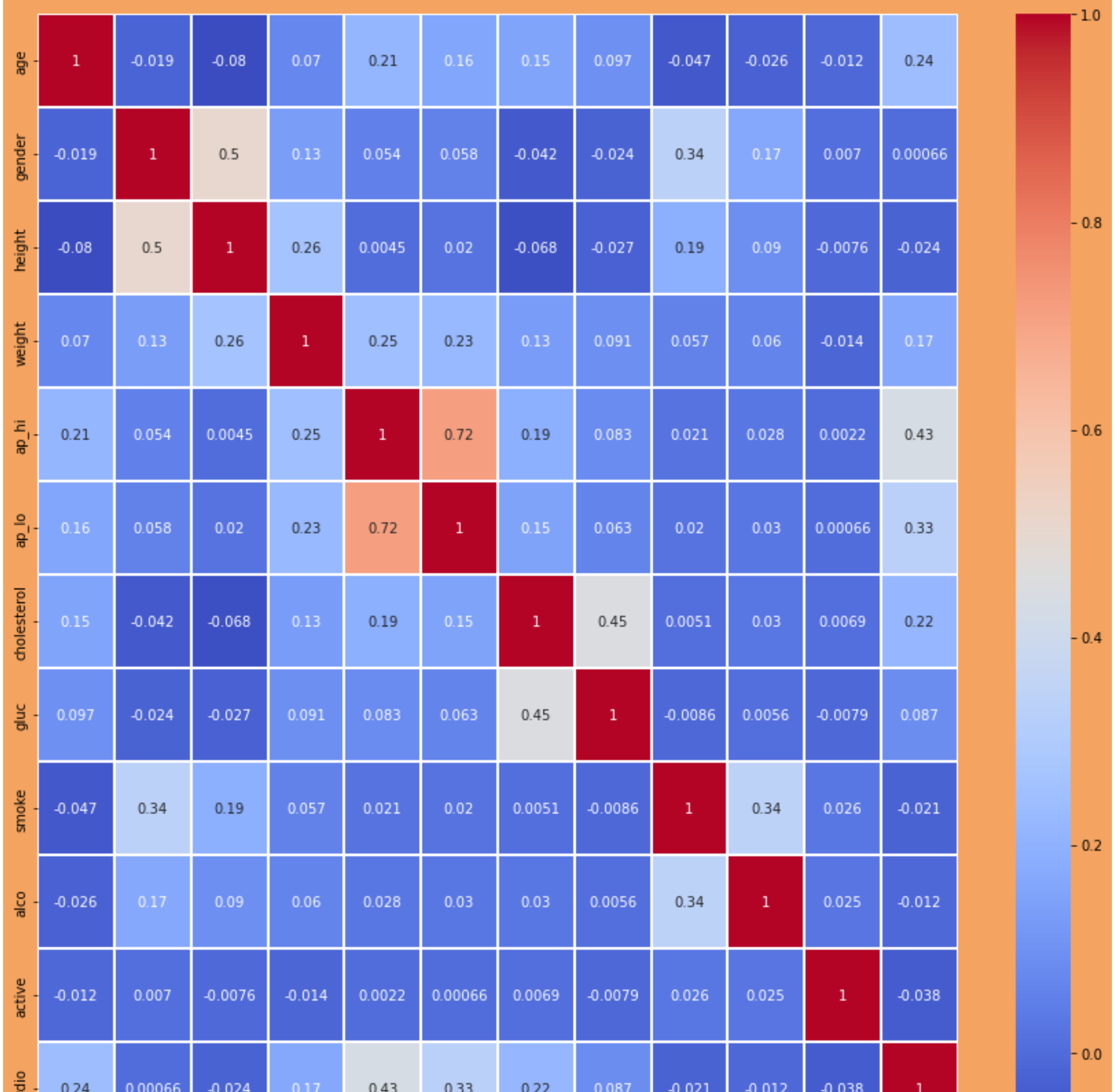


Count
cardio
0
1
AGE
HEIGHT
WEIGHT



Plot heatmap with correlation of cardio

In [17]:
```
plt.figure(figsize=(15,15), facecolor='SandyBrown')
sns.heatmap(cardio.corr(), annot=True, cmap='coolwarm',linewidths=0.05);
```


age
gender
height
weight
ap_hi
ap_lo
cholesterol
gluc
smoke
alco
active
1 -0.019 -0.08 0.07 0.21 0.16 0.15 0.097 -0.047 -0.026 -0.012 0.24
-0.019 1 0.5 0.13 0.054 0.058 -0.042 -0.024 0.34 0.17 0.007 0.00066
-0.08 0.5 1 0.26 0.0045 0.02 -0.068 -0.027 0.19 0.09 -0.0076 -0.024
0.07 0.13 0.26 1 0.25 0.23 0.13 0.091 0.057 0.06 -0.014 0.17
0.21 0.054 0.0045 0.25 1 0.72 0.19 0.083 0.021 0.028 0.0022 0.43
0.16 0.058 0.02 0.23 0.72 1 0.15 0.063 0.02 0.03 0.00066 0.33
0.15 -0.042 -0.068 0.13 0.19 0.15 1 0.45 0.0051 0.03 0.0069 0.22
0.097 -0.024 -0.027 0.091 0.083 0.063 0.45 1 -0.0086 0.0056 -0.0079 0.087
-0.047 0.34 0.19 0.057 0.021 0.02 0.0051 -0.0086 1 0.34 0.026 -0.021
-0.026 0.17 0.09 0.06 0.028 0.03 0.03 0.0056 0.34 1 0.025 -0.012
-0.012 0.007 -0.0076 -0.014 0.0022 0.00066 0.0069 -0.0079 0.026 0.025 1 -0.038
1.0
0.8
0.6
0.4
0.2
0.0

Data looks good,

Lets begin Model Training

Classification

Logistic Regression model to predict the cardio

In [18]:
```
# Separating feature and output/result
X = cardio.drop(columns=['cardio'])
y = cardio.cardio

# Splting train and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=100)

# Initializing Logistic regression
lgr = LogisticRegression()

# Fitting Logistic modle
lgr.fit(X_train, y_train)

# Predict the model
y_pred = lgr.predict(X_test)

# Model Report/results
print('Accuracy Score', (accuracy_score(y_pred,y_test))*100)
print('\n Confusion Matrix \n', confusion_matrix(y_pred, y_test))
print('\n Classfication Report \n', classification_report(y_pred,y_test))
```

```
Accuracy Score 70.99379684673042

 Confusion Matrix
 [[6100 2617]
 [1872 4887]]

 Classfication Report
               precision    recall  f1-score   support

           0       0.77      0.70      0.73      8717
           1       0.65      0.72      0.69      6759

    accuracy                           0.71     15476
   macro avg       0.71      0.71      0.71     15476
weighted avg       0.72      0.71      0.71     15476
```

Accuracy of the model is 71%

Lets try Standard Scaler to check accuracy

Standard Scaler

In [19]:
```
# Initialize Scaler Model
scaler = StandardScaler()

# Apply scaler model
X_scaled =scaler.fit_transform(X)

# Spliting data into train and test data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.25, random_state=100)


# Fitting Logistic modle
lgr.fit(X_train, y_train)

# Predict the model
y_pred = lgr.predict(X_test)

# Model Report/results
print('Accuracy Score', (accuracy_score(y_pred,y_test))*100)
print('\n Confusion Matrix \n', confusion_matrix(y_pred, y_test))
print('\n Classfication Report \n', classification_report(y_pred,y_test))
```

```
Accuracy Score 71.97596278108038

 Confusion Matrix
 [[6249 2614]
 [1723 4890]]

 Classfication Report
               precision    recall  f1-score   support

           0       0.78      0.71      0.74      8863
           1       0.65      0.74      0.69      6613

    accuracy                           0.72     15476
   macro avg       0.72      0.72      0.72     15476
weighted avg       0.73      0.72      0.72     15476
```

Accuracy is 72% using standard scaler the result variance is not that much affected

Lets try Decision Tree and see

Decision Tree

In [20]:

```
# Spliting data into train and test data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.25, random_state=250)

# Initializing Decision Tree
Class_tree= DecisionTreeClassifier(criterion= 'gini', max_depth= 3)

# Applying Decision Tree model to data
Class_tree.fit(X_train,y_train)

# Predict the model
y_pred = Class_tree.predict(X_test)

# Model Report/results
print('Accuracy Score', (accuracy_score(y_pred,y_test))*100)
print('\n Confusion Matrix \n', confusion_matrix(y_pred, y_test))
print('\n Classfication Report \n', classification_report(y_pred,y_test))
```

```
Accuracy Score 72.08581028689584

 Confusion Matrix
 [[6118 2632]
 [1688 5038]]

 Classfication Report
               precision    recall  f1-score   support

           0       0.78      0.70      0.74      8750
           1       0.66      0.75      0.70      6726

    accuracy                           0.72     15476
   macro avg       0.72      0.72      0.72     15476
weighted avg       0.73      0.72      0.72     15476
```

accuracy is still same.

lets do hyperparameter- tuning to see which tree gives best results

Hyperparameter Tuning

In [21]:

```python
# parameter's
param =  {
    'criterion': ['gini','entropy',"log_loss"],
    'max_depth' : range(6,15),
    'min_samples_leaf' : range(11,16),
    'max_features' : [ 'sqrt', 'log2' , None],
    'splitter' : ['best','random']
}

# Initializing Grid Search CV
grid_search = GridSearchCV(estimator=Class_tree,
                           param_grid=param, cv=5, n_jobs=-1)

#Applying Grid Search CV
grid_search.fit(X_train, y_train)


#Result
print('Grid Search Best Parameter',grid_search.best_params_)
print('Grid Search Best Score',grid_search.best_score_)
```

```
Grid Search Best Parameter {'criterion': 'gini', 'max_depth': 8, 'max_features': None, 'min_samples_leaf': 15, 'splitter': 'random'}
Grid Search Best Score 0.7281480496925848
```

In [22]:
```python
# Initializing Decision Tree
Class_tree = DecisionTreeClassifier(criterion= 'entropy', max_depth= 8, max_features = None,
                                    min_samples_leaf= 15, splitter='random')

# Applying Decision Tree model to data
Class_tree.fit(X_train,y_train)

# Predict the model
y_pred = Class_tree.predict(X_test)

# Model Report/results
print('Accuracy Score', (accuracy_score(y_pred,y_test))*100)
print('\n Confusion Matrix \n', confusion_matrix(y_pred, y_test))
print('\n Classfication Report \n', classification_report(y_pred,y_test))
```

```
Accuracy Score 72.40242956836391

 Confusion Matrix
 [[6338 2803]
 [1468 4867]]

 Classfication Report
               precision    recall  f1-score   support

           0       0.81      0.69      0.75      9141
           1       0.63      0.77      0.70      6335

    accuracy                           0.72     15476
   macro avg       0.72      0.73      0.72     15476
weighted avg       0.74      0.72      0.73     15476
```

Accuracy Score is 72.4, even after hyperparameter tuning the result is same