

Cardivascular Disease Prediction

The aim of this project to predict the occurence of cardiovascular disease in patients based on their medical records. The project analyzes the patients medical records and medical history to calculate the probability of the occurence of cardiovascular disease in the patient.

Data Dictionary

Feature	Description
General Health	general health condition
Checkup	Last checkup
Excercise	Does the patient excercise
Heart Disease	Does the patient have heart disease
Skin Cancer	Does the patient have skin cancer
Other Cancer	Does the patient have other cancer
Depression	Does the patient have depression
Diabetes	Does the patient have diabetes
Arthritis	Does the patient have arthritis
Sex	patient's gender
Age-Category	patient's age category
BMI	patient's BMI
Smoking History	patient's smoking history
Alcohol Consumption	patient's alcohol consumption
Fruit Consumption	patient's fruit consumption
Green Vegetable Consumption	patient's green vegetable consumption
Fried Potato Consumption	patient's fried potato consumption

```
In [ ]: # Importing the Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

```
In [ ]: # Loading the dataset
df = pd.read_csv('CVD_cleaned.csv')
df.head()
```

Out[]:

	General_Health	Checkup	Exercise	Heart_Disease	Skin_Cancer	Other_Cancer	Depre
0	Poor	Within the past 2 years	No	No	No	No	
1	Very Good	Within the past year	No	Yes	No	No	
2	Very Good	Within the past year	Yes	No	No	No	
3	Poor	Within the past year	Yes	Yes	No	No	
4	Good	Within the past year	No	No	No	No	

Data Preprocessing

In []:

```
# Checking the shape of the dataset
df.shape
```

Out[]: (308854, 19)

In []:

```
# Checking for null/missing values
df.isnull().sum()
```

Out[]:

General_Health	0
Checkup	0
Exercise	0
Heart_Disease	0
Skin_Cancer	0
Other_Cancer	0
Depression	0
Diabetes	0
Arthritis	0
Sex	0
Age_Category	0
Height_(cm)	0
Weight_(kg)	0
BMI	0
Smoking_History	0
Alcohol_Consumption	0
Fruit_Consumption	0
Green_Vegetables_Consumption	0
FriedPotato_Consumption	0

dtype: int64

In []:

```
# Checking the datatypes
df.dtypes
```

```
Out[ ]: General_Health      object
        Checkup            object
        Exercise           object
        Heart_Disease      object
        Skin_Cancer        object
        Other_Cancer       object
        Depression         object
        Diabetes           object
        Arthritis          object
        Sex                object
        Age_Category       object
        Height_(cm)        float64
        Weight_(kg)        float64
        BMI                float64
        Smoking_History    object
        Alcohol_Consumption float64
        Fruit_Consumption  float64
        Green_Vegetables_Consumption float64
        FriedPotato_Consumption float64
        dtype: object
```

The dataset has columns - weight, Height and BMI. However, the BMI column is calculated using the weight and height columns. Hence, the weight and height columns are dropped from the dataset.

```
In [ ]: # Drop Column
        df.drop(columns=['Weight_(kg)', 'Height_(cm)'], inplace=True)
```

```
In [ ]: # Unique values in each column
        for i in df.columns:
            print(i, df[i].unique())
```

```

General_Health ['Poor' 'Very Good' 'Good' 'Fair' 'Excellent']
Checkup ['Within the past 2 years' 'Within the past year' '5 or more years ago'
        'Within the past 5 years' 'Never']
Exercise ['No' 'Yes']
Heart_Disease ['No' 'Yes']
Skin_Cancer ['No' 'Yes']
Other_Cancer ['No' 'Yes']
Depression ['No' 'Yes']
Diabetes ['No' 'Yes' 'No, pre-diabetes or borderline diabetes'
        'Yes, but female told only during pregnancy']
Arthritis ['Yes' 'No']
Sex ['Female' 'Male']
Age_Category ['70-74' '60-64' '75-79' '80+' '65-69' '50-54' '45-49' '18-24' '30-34'
            '55-59' '35-39' '40-44' '25-29']
BMI [14.54 28.29 33.47 ... 63.83 19.09 56.32]
Smoking_History ['Yes' 'No']
Alcohol_Consumption [ 0.  4.  3.  8. 30.  2. 12.  1.  5. 10. 20. 17. 16.  6. 25.
28. 15.  7.
 9. 24. 11. 29. 27. 14. 21. 23. 18. 26. 22. 13. 19.]
Fruit_Consumption [ 30. 12.  8. 16.  2.  1. 60.  0.  7.  5.  3.  6.  9
 0. 28.
20.  4. 80. 24. 15. 10. 25. 14. 120. 32. 40. 17. 45. 100.
 9. 99. 96. 35. 50. 56. 48. 27. 72. 36. 84. 26. 23. 18.
21. 42. 22. 11. 112. 29. 64. 70. 33. 76. 44. 39. 75. 31.
92. 104. 88. 65. 55. 13. 38. 63. 97. 108. 19. 52. 98. 37.
68. 34. 41. 116. 54. 62. 85.]
Green_Vegetables_Consumption [ 16.  0.  3. 30.  4. 12.  8. 20.  1. 10.
 5.  2.  6. 60.
28. 25. 14. 40.  7. 22. 24. 15. 120. 90. 19. 13. 11. 80.
27. 17. 56. 18.  9. 21. 99. 29. 31. 45. 23. 100. 104. 32.
48. 75. 36. 35. 112. 26. 50. 33. 96. 52. 76. 84. 34. 97.
88. 98. 68. 92. 55. 95. 64. 124. 61. 65. 77. 85. 44. 39.
70. 93. 128. 37. 53.]
FriedPotato_Consumption [ 12.  4. 16.  8.  0.  1.  2. 30. 20. 15. 10.
 3.  7. 28.
 5.  9.  6. 120. 32. 14. 60. 33. 48. 25. 24. 21. 90. 13.
99. 17. 18. 40. 56. 34. 36. 44. 100. 11. 64. 45. 80. 29.
68. 26. 50. 22. 95. 23. 27. 112. 35. 31. 98. 96. 88. 92.
19. 76. 49. 97. 128. 41. 37. 42. 52. 72. 46. 124. 84.]

```

The diabetes column has four values - Yes, No, No pre-diabetes or borderline diabetes and Yes, but female told only during pregnancy. So replacing the last two values with pre-diabetes and gestational diabetes, respectively.

```
In [ ]: df['Diabetes'] = df['Diabetes'].map({'No, pre-diabetes or borderline diabetes':
```

Outliner removal

```
In [ ]: # columns for outlier removal
cols = ['BMI', 'Alcohol_Consumption', 'Fruit_Consumption', 'Green_Vegetables_Consumption']

#IQR for the selected columns
Q1 = df[cols].quantile(0.25)
Q3 = df[cols].quantile(0.75)
IQR = Q3 - Q1

#Threshold for outlier removal
```

```
threshold = 1.5

#Find index of outliers
index = np.where((df[cols] < (Q1 - threshold * IQR)) | (df[cols] > (Q3 + threshold * IQR)))

#Drop outliers
df = df.drop(df.index[index])
```

Descriptive Statistics

```
In [ ]: df.describe()
```

Out[]:

	BMI	Alcohol_Consumption	Fruit_Consumption	Green_Vegetables_Consumption
count	186777.000000	186777.000000	186777.000000	186777.000000
mean	28.303577	2.505287	18.446104	18.446104
std	5.433758	3.777076	10.898445	10.898445
min	12.870000	0.000000	0.000000	0.000000
25%	24.370000	0.000000	8.000000	8.000000
50%	27.550000	0.000000	16.000000	16.000000
75%	31.750000	4.000000	30.000000	30.000000
max	43.280000	15.000000	56.000000	56.000000

```
In [ ]: df.head()
```

Out[]:

	General_Health	Checkup	Exercise	Heart_Disease	Skin_Cancer	Other_Cancer	Depression
0	Poor	Within the past 2 years	No	No	No	No	No
1	Very Good	Within the past year	No	Yes	No	No	No
2	Very Good	Within the past year	Yes	No	No	No	No
3	Poor	Within the past year	Yes	Yes	No	No	No
4	Good	Within the past year	No	No	No	No	No

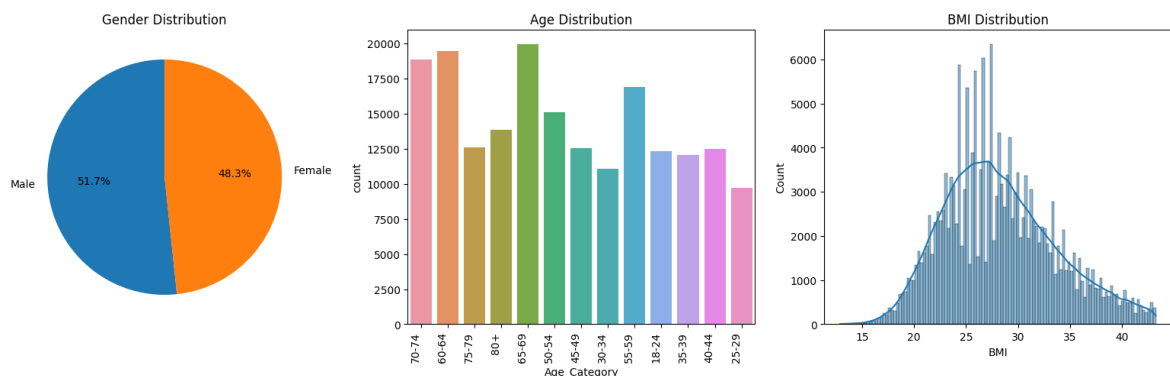
Exploratory Data Analysis

In the exploratory data analysis, I will be looking at the data and try to understand the data. I will be analyzing the data to find the relationship between the features and the target variable. I will begin with looking at the distribution of data across all the variables. Then I will look at the relationship between the features and the target variable.

Patient demographics

```
In [ ]: fig, ax = plt.subplots(1,3,figsize=(20, 5))
ax[0].pie(df['Sex'].value_counts(), labels = ['Male', 'Female'], autopct='%1.1f%%')
ax[0].set_title('Gender Distribution')
sns.countplot(x = 'Age_Category', data = df, ax = ax[1]).set_title('Age Distribution')
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation=90, ha='right')
sns.histplot(x = 'BMI', data = df, ax = ax[2], kde = True).set_title('BMI Distribution')
```

```
Out [ ]: Text(0.5, 1.0, 'BMI Distribution')
```

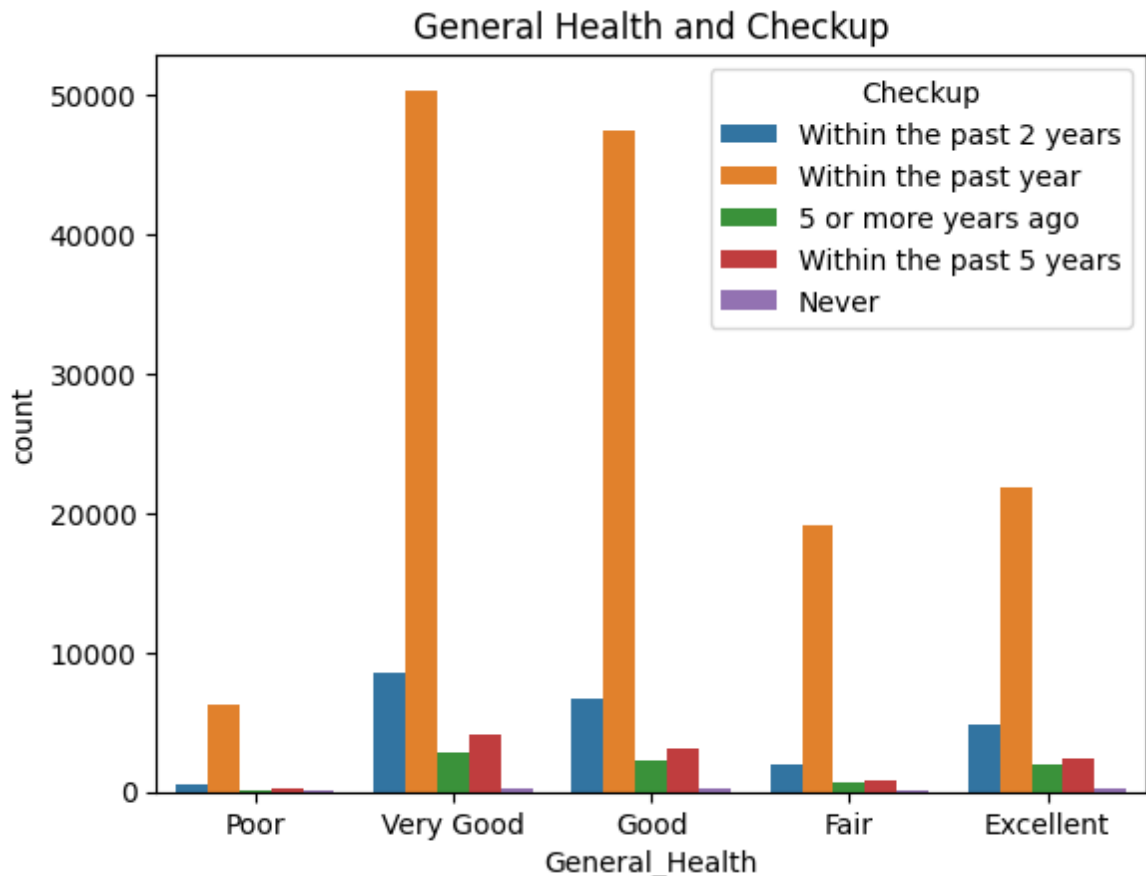


The above three graphs explain the patient demographics in the dataset. From the pie chart, it is clear that the majority of patients are male with 52% followed by females with 48%. Looking at the age distribution, we came to know that the majority of patients are older than 45 years of age, this means that the dataset is skewed towards older patients. The histogram of BMI shows that the BMI of the majority of patients is between 25 to 30. This means that the majority of patients are overweight. Therefore, I build a hypothesis that the patients with higher BMI are more likely to have cardiovascular disease.

General Health and Last Checkup

```
In [ ]: sns.countplot(x = 'General_Health', data = df, hue = 'Checkup').set_title('General Health and Last Checkup')
```

```
Out [ ]: Text(0.5, 1.0, 'General Health and Checkup')
```

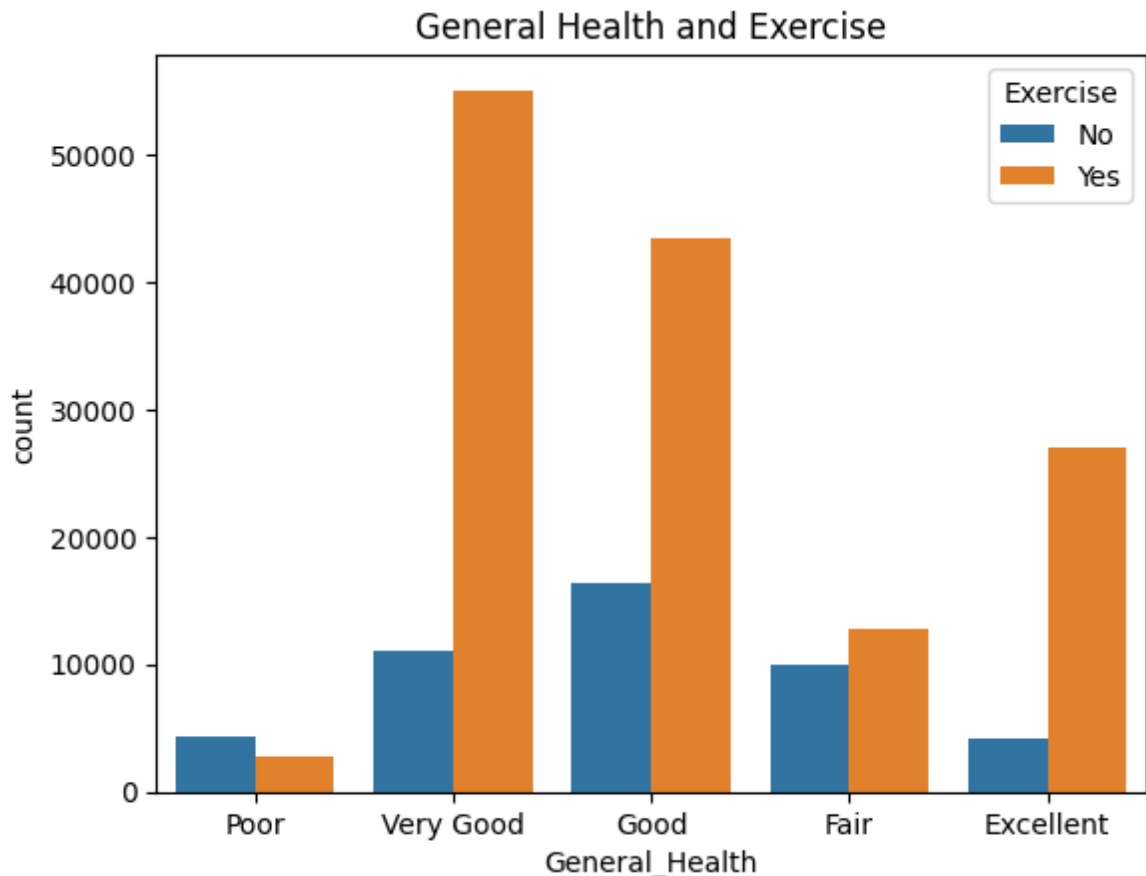


According to this graph most of the people are either in good or very good health, followed by excellent general health. This means that most of the people in the dataset are healthy. Very few of the people are poor general health. Looking at the last checkup, in all the general healths, most of the people have had their last checkup within the last year. However, there are still many people who have not had their last checkup within the last 5 years or more. This increases the chances of having a potential cardiovascular disease.

Excercise and General Health

```
In [ ]: sns.countplot(x = 'General_Health', data = df, hue = 'Exercise').set_title('Ger
```

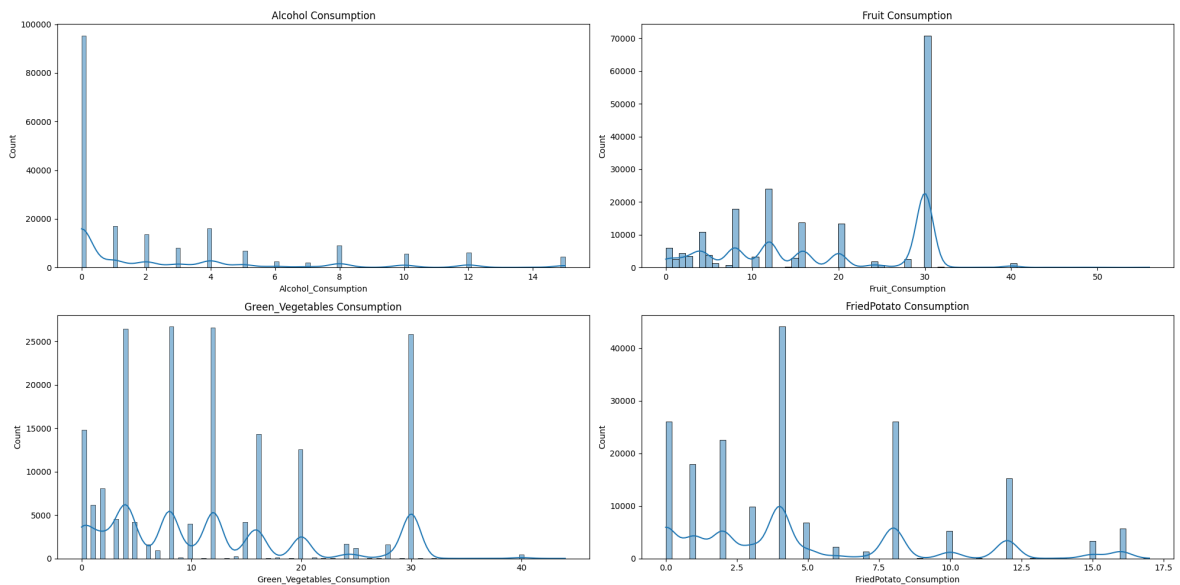
```
Out[ ]: Text(0.5, 1.0, 'General Health and Exercise')
```



The role of exercise in general health is evident through this graph. The people who exercise regularly are more likely to be in good or very good or even in excellent health. However, the people who do not exercise are more likely to be in poor health. This means that exercise plays an important role in maintaining good health.

Food Consumption

```
In [ ]: fig, ax = plt.subplots(2,2,figsize=(20, 10))
sns.histplot(x = 'Alcohol_Consumption', data = df, ax = ax[0,0], kde = True).set
sns.histplot(x = 'Fruit_Consumption', data = df, ax = ax[0,1], kde = True).set_t
sns.histplot(x = 'Green_Vegetables_Consumption', data = df, ax = ax[1,0], kde =
sns.histplot(x = 'FriedPotato_Consumption', data = df, ax = ax[1,1], kde = True)
plt.tight_layout()
```

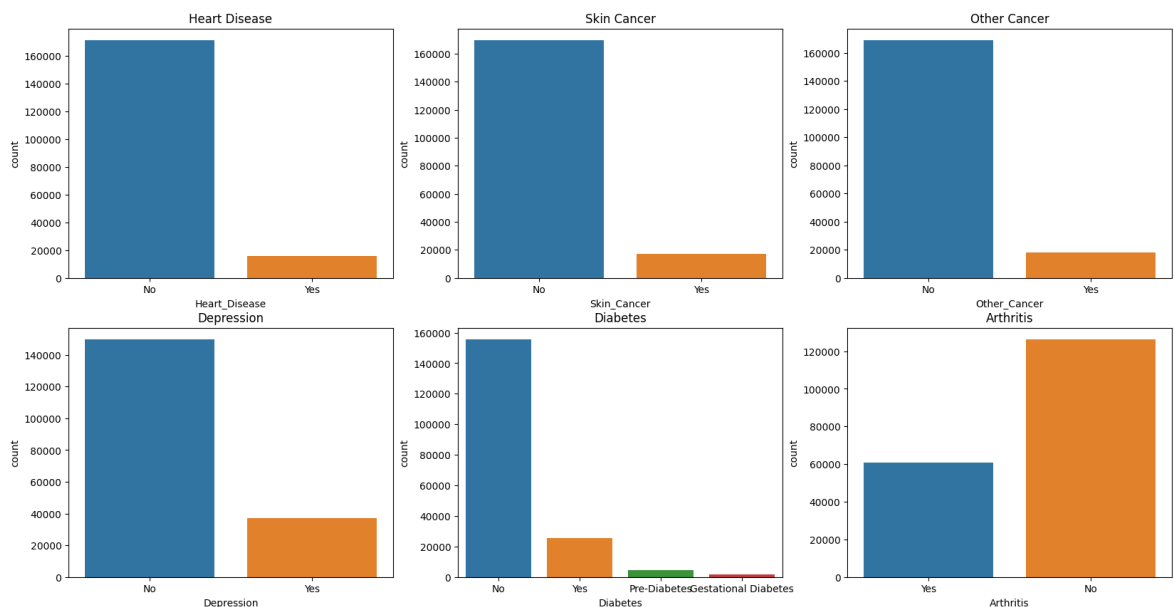



These plots visualizes the food and drinking habits of the patients. From these plots, it is clear that majority of the patients, do not consume alcohol. Coming to the food habits, most of the patients, consume higher amount of fruits and green vegetables which is good for health. However, most of the patients consume fried potatoes which is not good for health. This means that the patients who consume fried potatoes and alcohol are more likely to have cardiovascular disease.

Medical History

```
In [ ]: fig, ax = plt.subplots(2,3,figsize=(20, 10))
sns.countplot(x = 'Heart_Disease', data = df, ax = ax[0,0]).set_title('Heart Dis
sns.countplot(x = 'Skin_Cancer', data = df, ax = ax[0,1]).set_title('Skin Cancer
sns.countplot(x = 'Other_Cancer', data = df, ax = ax[0,2]).set_title('Other Canc
sns.countplot(x = 'Depression', data = df, ax = ax[1,0]).set_title('Depression')
sns.countplot(x = 'Diabetes', data = df, ax = ax[1,1]).set_title('Diabetes')
sns.countplot(x = 'Arthritis', data = df, ax = ax[1,2]).set_title('Arthritis')
```

Out[]: Text(0.5, 1.0, 'Arthritis')

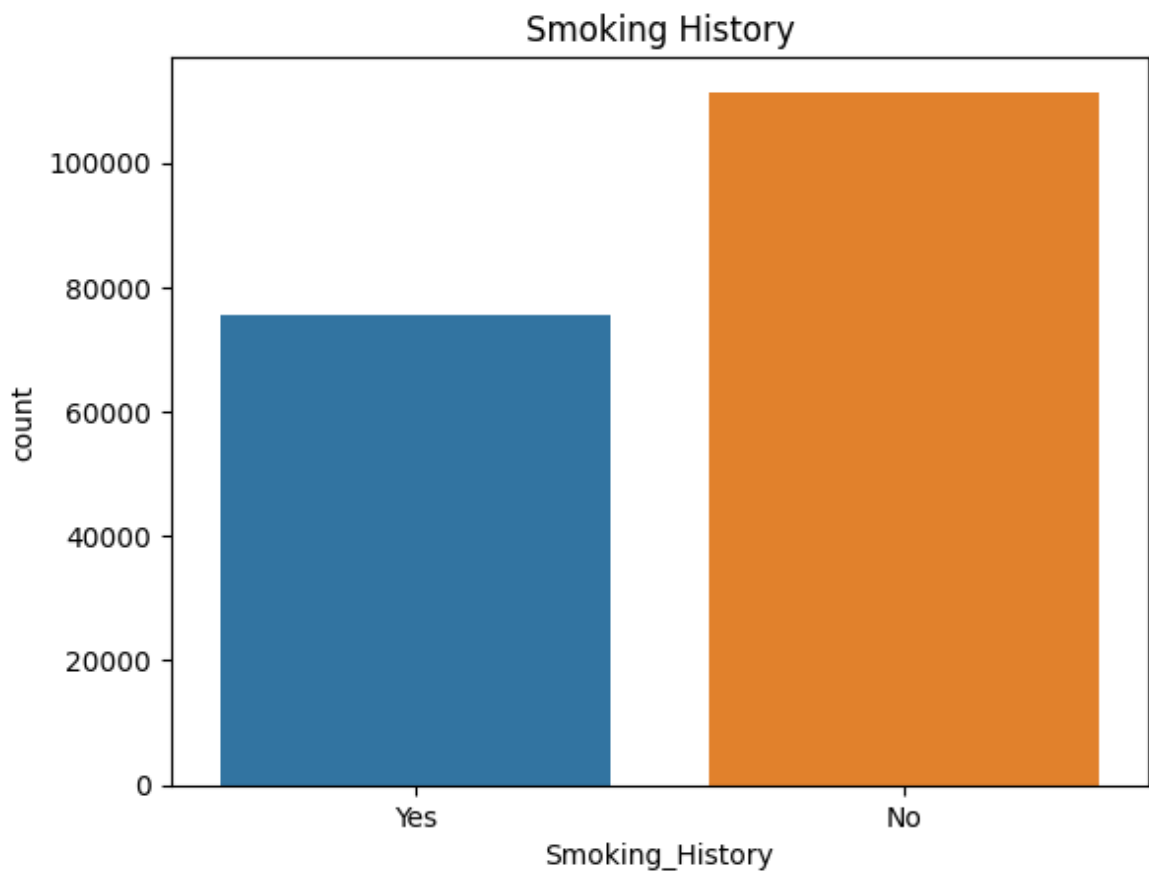


Most of the patients have no medical conditions. However, there are patients who have medical conditions like heart disease, skin cancer, other cancer, depression, diabetes and arthritis. In addition to that, there has been increased number of patients suffering from Depression as compared to other medical conditions. This means, the doctor should focus on mental health as well in addition to physical health. There certain number of patients, who are pre-diabetic and some females suffer from gestational diabetes.

Patient's Smoking History

```
In [ ]: sns.countplot(x = 'Smoking_History', data = df ).set_title('Smoking History')
```

```
Out[ ]: Text(0.5, 1.0, 'Smoking History')
```



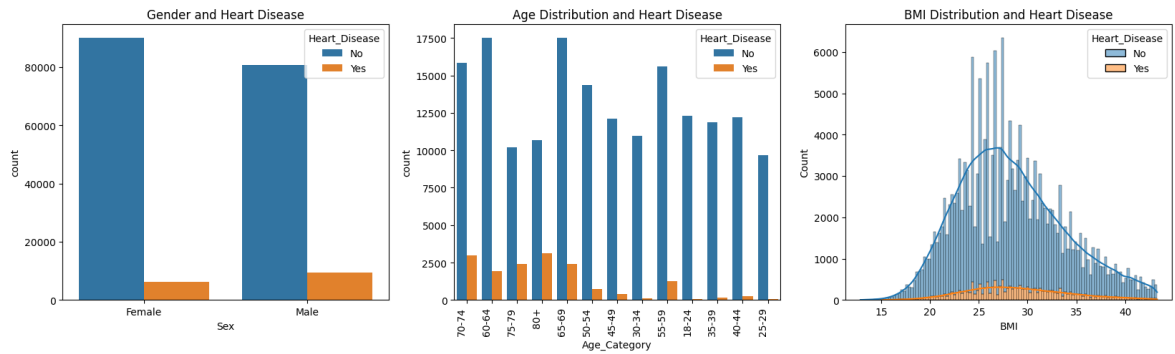
This graph shows the smoking history of the patients in the dataset. Majority of the patients have never smoked. However, there are patients in huge number who are current smokers. This means that the patients who are current smokers are more likely to have cardiovascular disease.

Target Variable and Independent Variables Visualization

Patient's Demographics and Heart Disease

```
In [ ]: fig, ax = plt.subplots(1,3,figsize=(20, 5))
sns.countplot(x = 'Sex', data = df, hue = 'Heart_Disease', ax = ax[0]).set_title('Sex')
sns.countplot(x = 'Age_Category', data = df, ax = ax[1], hue = 'Heart_Disease').
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation=90, ha='right')
sns.histplot(x = 'BMI', data = df, ax = ax[2], kde = True, hue = 'Heart_Disease')
```

```
Out[ ]: Text(0.5, 1.0, 'BMI Distribution and Heart Disease')
```

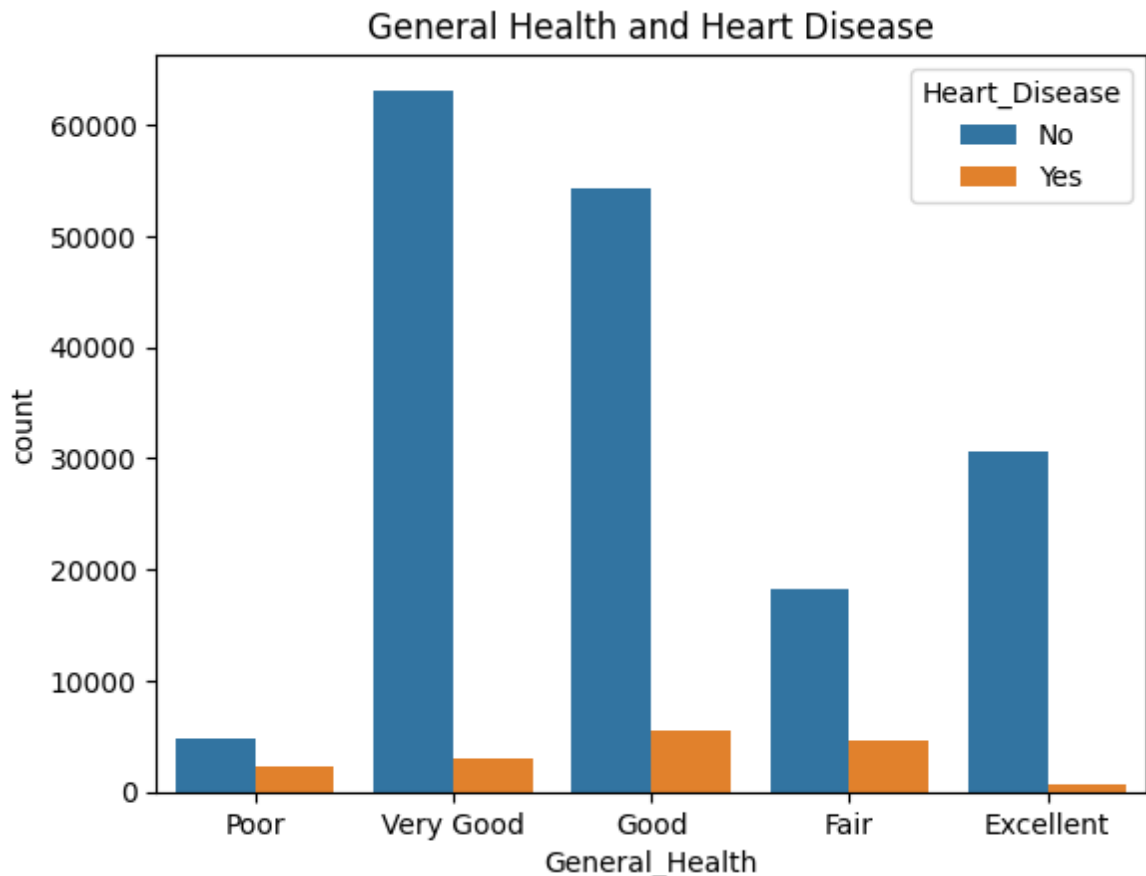


Visualizing the patient's demographics along with the heart disease, help us to know more about the relation of cardiovascular disease with patient. Firstly looking at the Gender graph, we can see that, males are more prone to heart disease as compared to females. The second graph reveals interesting facts about the data, where we can see that patients with age higher than 55 years of age have increased instances of heart diseases, as compared to other age groups, with maximum heart disease cases in 80+ years of age patient. This means that patients older age are more prone to cardiovascular disease and the risk of cardiovascular diseases increases with age. The third graph, which is about BMI, shows that, patients with BMI between 25-30 i.e. overweight, have higher chances of heart disease.

General Health and Heart Disease

```
In [ ]: sns.countplot(x = 'General_Health', data = df, hue = 'Heart_Disease').set_title
```

```
Out[ ]: Text(0.5, 1.0, 'General Health and Heart Disease')
```

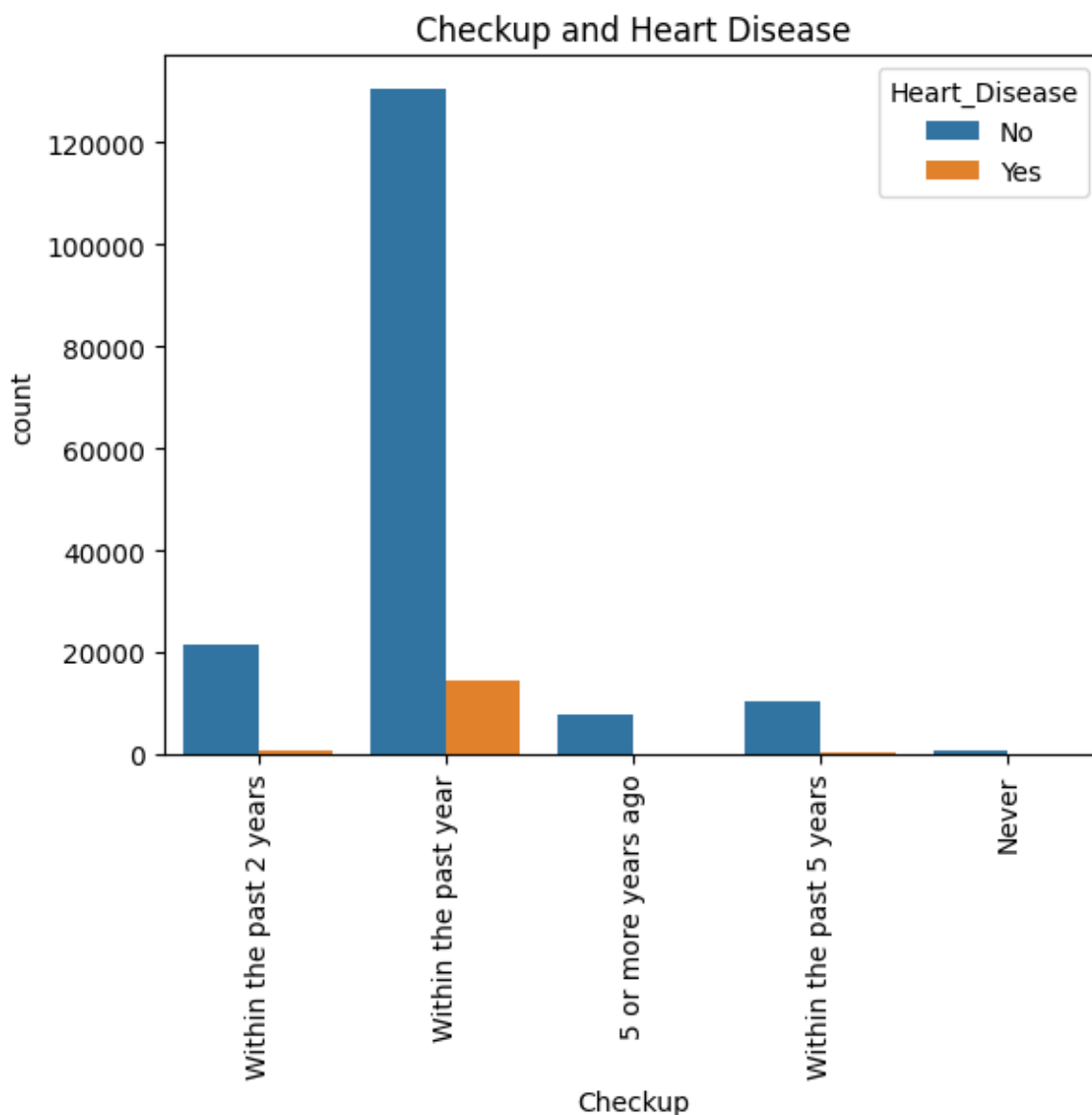


This graph is in contrast to my belief that, healthy patients are less prone to heart disease. However, this graph shows that patients with very good or good general health have more chances of heart disease as compared to patients with poor general health.

Checkup and Heart Disease

```
In [ ]: sns.countplot(x = 'Checkup', data = df, hue = 'Heart_Disease').set_title('Checkup')
plt.xticks(rotation=90)
```

```
Out[ ]: (array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'Within the past 2 years'),
  Text(1, 0, 'Within the past year'),
  Text(2, 0, '5 or more years ago'),
  Text(3, 0, 'Within the past 5 years'),
  Text(4, 0, 'Never')])
```

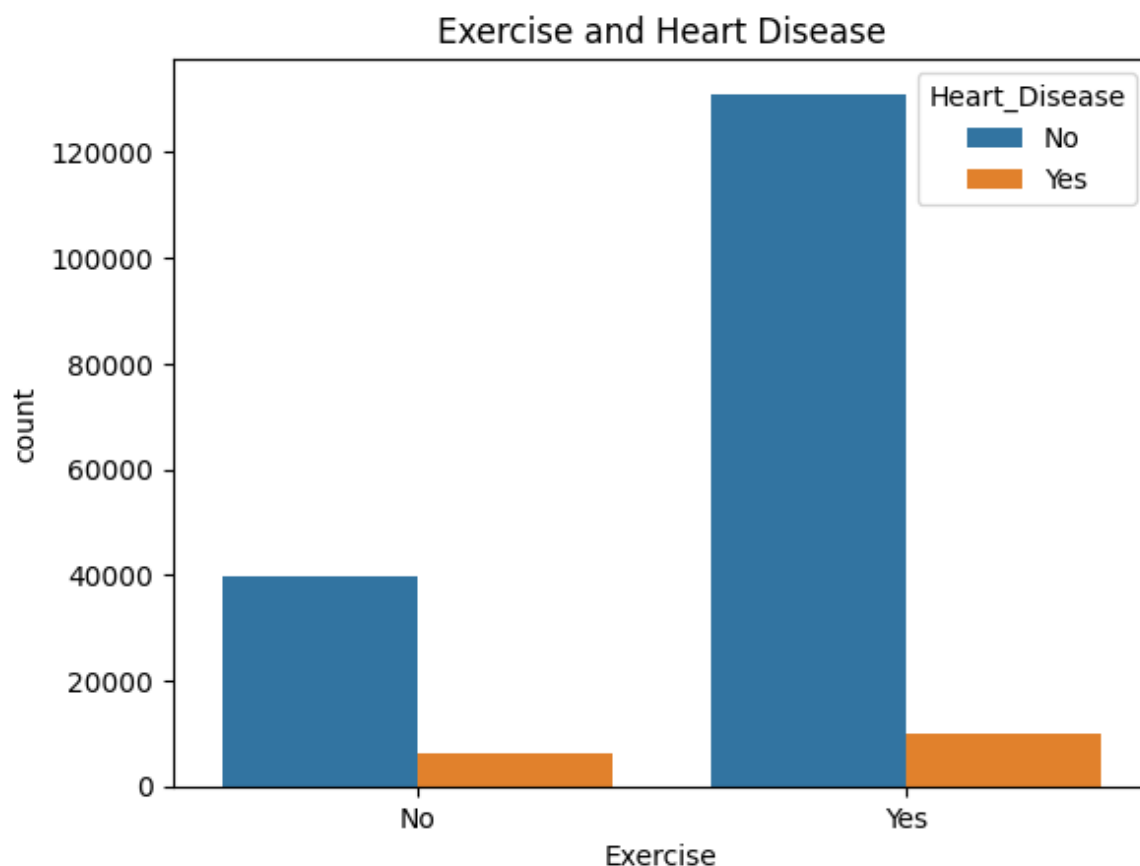


According to this graph, patients who have checkup in the last year have higher chances of having heart disease. This means that, patients who got themselves checked more often have higher chances of diagnosing cardiovascular disease at an early stage, as compared to patients who do not get themselves checked regularly.

Exercise and Heart Disease

```
In [ ]: sns.countplot(x = 'Exercise', data = df, hue = 'Heart_Disease').set_title('Exer
```

```
Out[ ]: Text(0.5, 1.0, 'Exercise and Heart Disease')
```

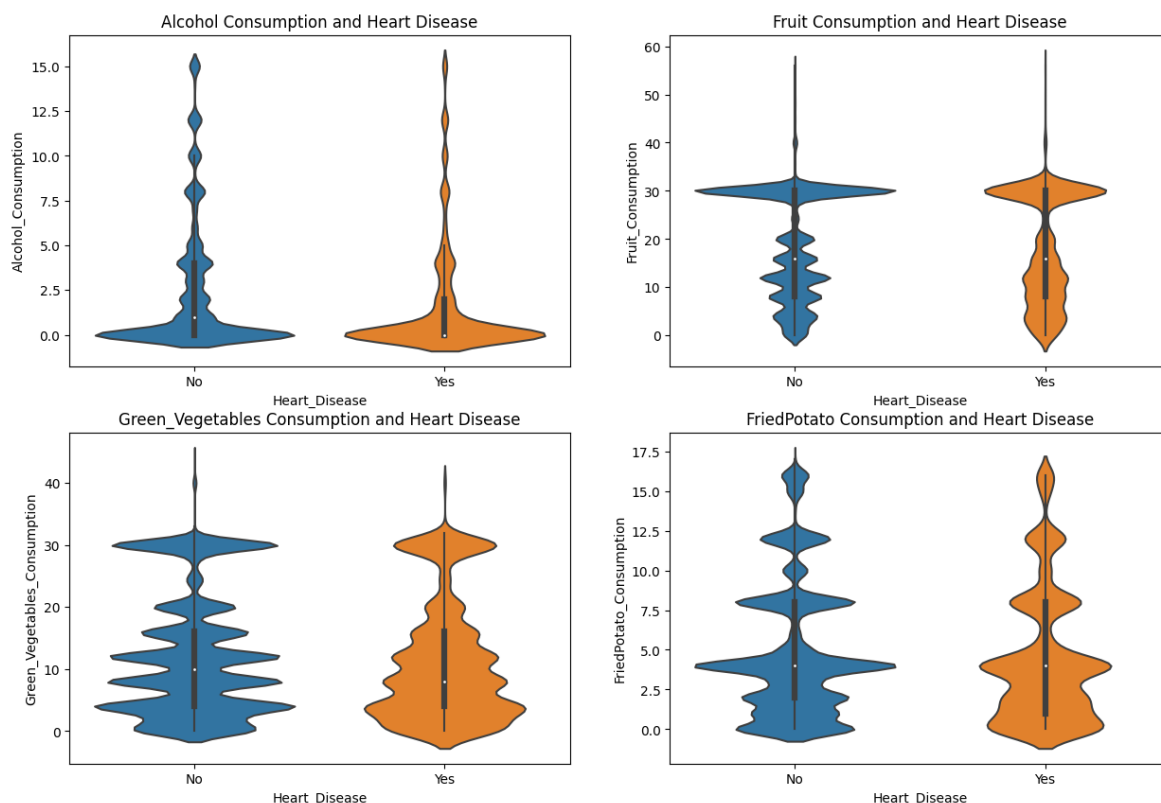


Interestingly, the patients that exercise tend to have higher rates of heart disease. This is in contrast to my belief that, patients who exercise regularly are less prone to heart disease. However, this graph shows that patients who do not exercise are less prone to heart disease. This could be possible that, patients that have weak hearts, tend to put extensive pressure on their heart by exercising, which leads to heart disease.

Food Consumption and Heart Disease

```
In [ ]: fig, ax = plt.subplots(2,2,figsize=(15, 10))
sns.violinplot(x = 'Heart_Disease', y = 'Alcohol_Consumption', data = df, ax = ax[0,0])
sns.violinplot(x = 'Heart_Disease', y = 'Fruit_Consumption', data = df, ax = ax[0,1])
sns.violinplot(x = 'Heart_Disease', y = 'Green_Vegetables_Consumption', data = df, ax = ax[1,0])
sns.violinplot(x = 'Heart_Disease', y = 'FriedPotato_Consumption', data = df, ax = ax[1,1])
```

```
Out[ ]: Text(0.5, 1.0, 'FriedPotato Consumption and Heart Disease')
```

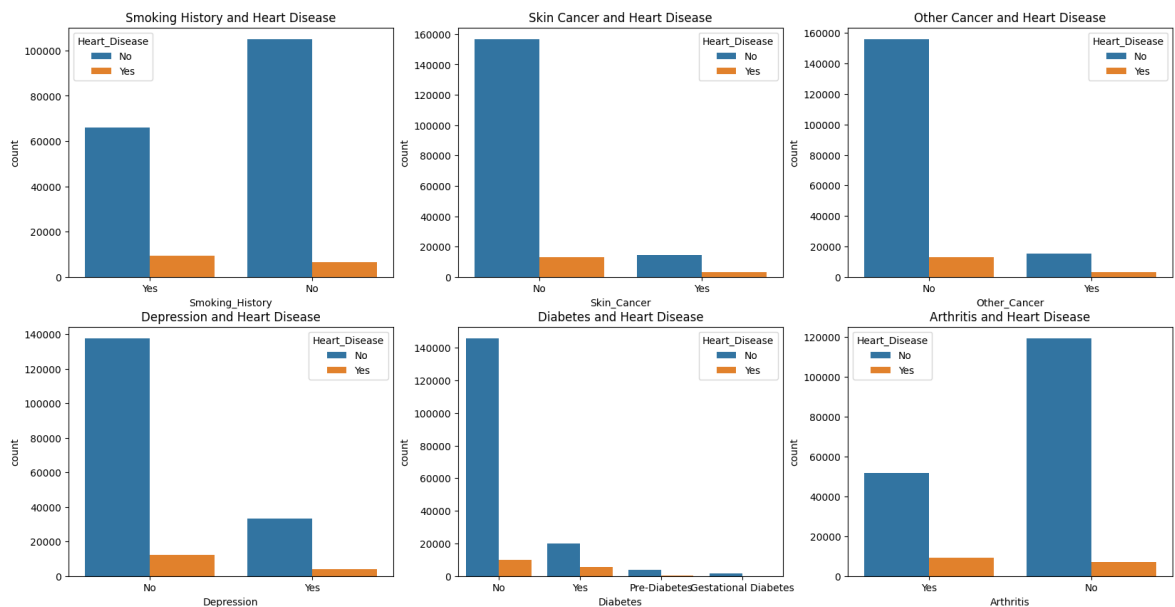


These graphs visualize the patient's food and drinking habit along with their heart disease. Looking at the alcohol consumption graph, we can see that patients with increased alcohol consumption tend to have lower chances of heart disease. However, the patients with higher consumption on fruits and green vegetables, tend to have lower risk of heart diseases. In addition to that, patients with higher consumption of fried potatoes tend to have higher risk of heart disease.

Medical History and Heart Disease

```
In [ ]: fig, ax = plt.subplots(2,3,figsize=(20, 10))
sns.countplot(x = 'Smoking_History', data = df, ax = ax[0,0], hue = 'Heart_Disease')
sns.countplot(x = 'Skin_Cancer', data = df, ax = ax[0,1], hue = 'Heart_Disease')
sns.countplot(x = 'Other_Cancer', data = df, ax = ax[0,2], hue = 'Heart_Disease')
sns.countplot(x = 'Depression', data = df, ax = ax[1,0], hue = 'Heart_Disease')
sns.countplot(x = 'Diabetes', data = df, ax = ax[1,1], hue = 'Heart_Disease')
sns.countplot(x = 'Arthritis', data = df, ax = ax[1,2], hue = 'Heart_Disease')
```

```
Out[ ]: Text(0.5, 1.0, 'Arthritis and Heart Disease')
```



These graphs visualize patient's medical history and its relation with heart disease. In the first graph, which is about smoking history, we can see that patients who smoke or used to smoke tend to have higher instances of having cardiovascular disease. In the second graph, we can see that patients with no skin cancer have higher cases of having heart disease as compared to its counterpart. In addition to that it is evident from the third graph, that patient without any kind of cancer have higher cases of having a cardiovascular disease. In the fourth graph, we can see that patients with no depression have higher cases of having heart disease as compared to its counterpart. In the fifth graph, we can see that patients with no diabetes have higher cases of having heart disease and pre-diabetes or gestational diabetes have zero or no effect on heart diseases. In the last graph, we can see that patients with no arthritis have higher cases of having heart disease as compared to its counterpart.

From this, I conclude that, patients with medical history have no major effect on having a cardiovascular disease.

Data Preprocessing 2

Label Encoding the Categorical Variables

```
In [ ]: from sklearn.preprocessing import LabelEncoder

# List of categorical variables
cols = ['General_Health', 'Checkup', 'Exercise', 'Heart_Disease', 'Skin_Cancer', 'Other_Cancer']

# Label encoding object
le = LabelEncoder()

for i in cols:
    le.fit(df[i])
    df[i] = le.transform(df[i])
    print(i, df[i].unique())
```



```

General_Health [3 4 2 1 0]
Checkup [2 4 0 3 1]
Exercise [0 1]
Heart_Disease [0 1]
Skin_Cancer [0 1]
Other_Cancer [0 1]
Depression [0 1]
Diabetes [1 3 2 0]
Arthritis [1 0]
Sex [0 1]
Age_Category [10 8 11 12 9 6 5 2 7 0 3 4 1]
Smoking_History [1 0]

```

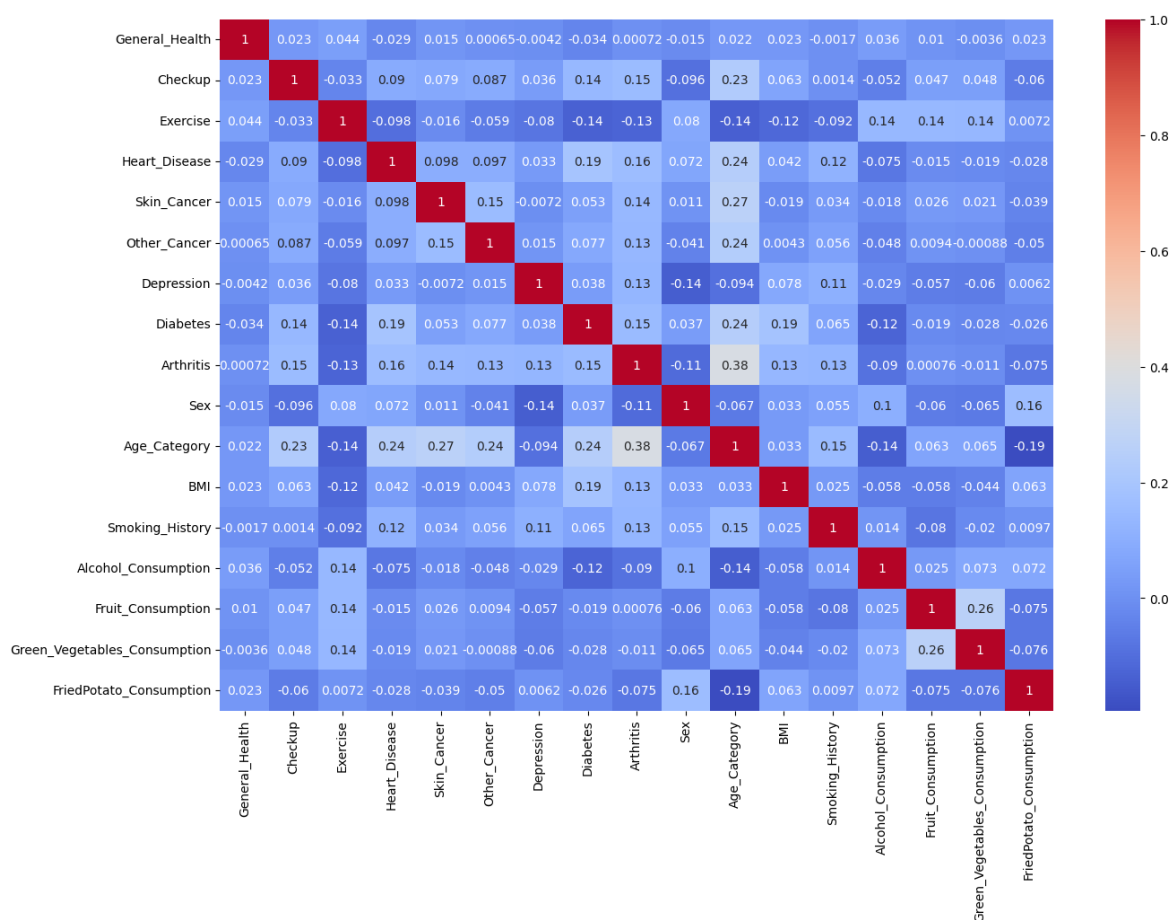
Coorelation Matrix Heatmap

```

In [ ]: plt.figure(figsize=(15,10))
sns.heatmap(df.corr(), annot = True, cmap = 'coolwarm')

```

Out[]: <Axes: >



There is no major coorelation among the variales.

Train Test Split

```

In [ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop(columns = ['Heart_Di

```

Cardiovascular Disease Prediction

For predicting the cardiovascular disease, I have used the following classification models:

1. Random Forest Classifier
2. Decision Tree Classifier

Random Forest Classifier

```
In [ ]: from sklearn.ensemble import RandomForestClassifier

# Create Random Forest object
rfc = RandomForestClassifier(random_state=0, max_features='sqrt', n_estimators=200)
```

```
In [ ]: # Training the model
rfc.fit(X_train, y_train)
```

```
Out[ ]: ▼                                RandomForestClassifier
RandomForestClassifier(class_weight='balanced', n_estimators=200,
                        random_state=0)
```

```
In [ ]: # Training accuracy
rfc.score(X_train, y_train)
```

```
Out[ ]: 0.9999866150005688
```

```
In [ ]: # Predicting the test set results
rfc_pred = rfc.predict(X_test)
```

Decision Tree Classifier

```
In [ ]: from sklearn.tree import DecisionTreeClassifier

# Create Decision Tree object
dtc = DecisionTreeClassifier(random_state=0, max_depth=12, min_samples_leaf=2,
```

```
In [ ]: # Training the model
dtc.fit(X_train, y_train)
```

```
Out[ ]: ▼                                DecisionTreeClassifier
DecisionTreeClassifier(class_weight='balanced', max_depth=12,
                        min_samples_leaf=2, random_state=0)
```

```
In [ ]: # Training accuracy
dtc.score(X_train, y_train)
```

```
Out[ ]: 0.73877835110192
```

```
In [ ]: # Predicting the test set results
dtc_pred = dtc.predict(X_test)
```

Logistic Regression

```
In [ ]: from sklearn.linear_model import LogisticRegression

lr = LogisticRegression()
```

```
In [ ]: #Training the model
lr.fit(X_train, y_train)
```

```
Out[ ]: ▼ LogisticRegression
LogisticRegression()
```

```
In [ ]: #Training accuracy
lr.score(X_train, y_train)
```

```
Out[ ]: 0.914101766150675
```

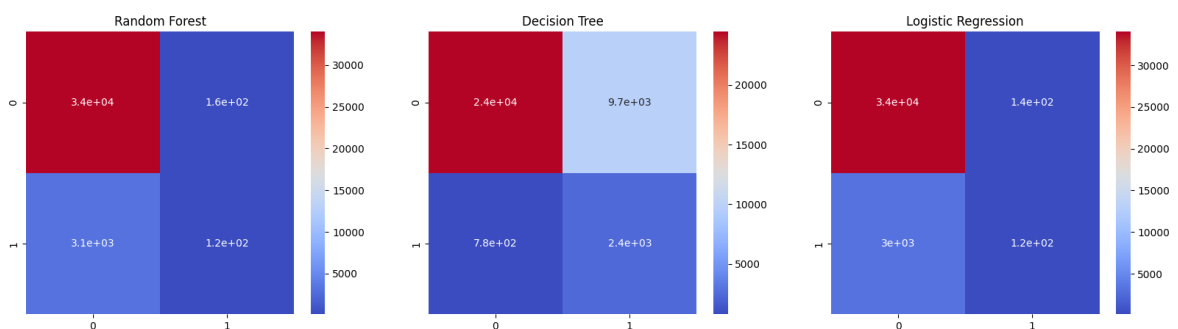
```
In [ ]: #Predicting the test set results
lr_pred = lr.predict(X_test)
```

Model Evalution

Confusion Matrix

```
In [ ]: from sklearn.metrics import confusion_matrix
fig, ax = plt.subplots(1,3, figsize = (20,5))
sns.heatmap(confusion_matrix(y_test, rfc_pred), annot = True, cmap = 'coolwarm',
sns.heatmap(confusion_matrix(y_test, dtc_pred), annot = True, cmap = 'coolwarm',
sns.heatmap(confusion_matrix(y_test, lr_pred), annot = True, cmap = 'coolwarm',
```

```
Out[ ]: Text(0.5, 1.0, 'Logistic Regression')
```



```
In [ ]: from sklearn.metrics import accuracy_score, precision_score, recall_score, r2_score
print('Random Forest')
print('Accuracy Score: ', accuracy_score(y_test, rfc_pred))
print('Precision Score: ', precision_score(y_test, rfc_pred))
print('Recall Score: ', recall_score(y_test, rfc_pred))
print('F1 Score: ', f1_score(y_test, rfc_pred))
```

Random Forest
Accuracy Score: 0.9137755648356355
Precision Score: 0.4166666666666667
Recall Score: 0.03622047244094488
F1 Score: 0.06664734859461026

```
In [ ]: print('Decision Tree')
print('Accuracy Score: ', accuracy_score(y_test, dtc_pred))
print('Precision Score: ', precision_score(y_test, dtc_pred))
print('Recall Score: ', recall_score(y_test, dtc_pred))
print('F1 Score: ', f1_score(y_test, dtc_pred))
```

Decision Tree
Accuracy Score: 0.718920655316415
Precision Score: 0.19753902056321745
Recall Score: 0.7533858267716536
F1 Score: 0.31300706621303326

```
In [ ]: print('Logistic Regression')
print('Accuracy Score: ', accuracy_score(y_test, lr_pred))
print('Precision Score: ', precision_score(y_test, lr_pred))
print('Recall Score: ', recall_score(y_test, lr_pred))
print('F1 Score: ', f1_score(y_test, lr_pred))
```

Logistic Regression
Accuracy Score: 0.9147124959845808
Precision Score: 0.4789272030651341
Recall Score: 0.03937007874015748
F1 Score: 0.07275902211874273

Conclusion

From the exploratory data analysis, it was found the risk of having a cardiovascular disease increases with increasing age and the people with age above 55 are more prone to this disease, with maximum number patients with cardiovascular disease in 80+ years of age. In addition to that, the patients with higher BMI are more likely to have cardiovascular disease. The patients of older age who exercise are prone cardiovascular disease, which may be due to extensive pressure on the heart. The dietary habits of the patient also have some contribution to the cardiovascular disease. The patients who consume higher amount of fruits and green vegetables are less prone to cardiovascular disease. However, the patients who consume fried potatoes are more prone to cardiovascular disease. The patients who smoke or used to smoke are more prone to cardiovascular disease. But in contrast to my belief, any of the previous medical history such as cancer, arthritis, diabetes or depression have no major effect on cardiovascular disease.