TOPS TECHNOLOGIES

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Predicting Heart Disease: A Case Study Using the UCI Dataset

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1) Introduction: -

Heart Disease is one of the leading causes of Mortality Worldwide. Early Detection plays a Critical role in preventing severe outcomes and improving patient care. This case study uses the UCI Heart Disease Dataset to simulate a real-world scenario, analysing key medical indicators to assess the likelihood of cardiovascular disease.

2) Dataset Overview: -

- **Source**: UCI Machine Learning Repository
- **Records**: 303
- **Attributes Used**: 14 clinical features (e.g., age, chest pain type, cholesterol, etc.)
- **Purpose**: Predict the presence and severity of heart disease

3) Explanation of Column: -

Column	Description
age	Age in years
sex	1 = Male, 0 = Female
cp	Chest pain type (1–4)
trestbps	Resting blood pressure (mm Hg)
chol	Serum cholesterol (mg/dl)
fbs	Fasting blood sugar > 120 mg/dl (1 = true, 0 = false)
restecg	Resting ECG results (0–2)
thalach	Maximum heart rate achieved
exang	Exercise-induced angina (1 = yes, 0 = no)
oldpeak	ST depression from exercise relative to rest
slope	Slope of peak ST segment (1–3)
ca	Number of major vessels (0–3) collared by fluoroscopy
thal	Thalassemia status (3 = normal, 6 = fixed defect, 7 = reversible defect)
num	Diagnosis of heart disease (0 = no disease to 4 = severe)

4)Patient Scenario :-

Patient Name: John M.

Age: 56

Sex: Male

Chest Pain Type: Asymptomatic

Resting BP: 150 mm Hg

Cholesterol: 260 mg/dl

Fasting Blood Sugar: Normal

ECG: Left ventricular hypertrophy

Max HR: 120 bpm

Exercise Angina: Yes

ST Depression: 2.3

ST Slope: Flat

Major Vessels: 2

Thalassemia: Reversible defect

Predicted Heart Disease Level: 3 (Moderate to severe)

Exploratory Analysis on John M.'s Report:- John M. is a 56-year-old male with high blood pressure and cholesterol levels. Though asymptomatic, exercise tests and ECG indicate signs of heart strain, placing him at moderate to severe risk.

5) Analysis: -

5.1) Data Collection: -

- **Source:**
  UCI Machine Learning Repository — Heart Disease Dataset
- **Format:**
  CSV file (`heart.csv` or similar)
- **Data Fields Include:**
  - `age` – Age of the patient
  - `sex` – Male (1), Female (0)
  - `cp` – Chest pain type
  - `trestbps` – Resting blood pressure
  - `chol` – Serum cholesterol in mg/dl
  - `fbs` – Fasting blood sugar > 120 mg/dl
  - `restecg` – Resting ECG results
  - `thalach` – Max heart rate achieved
  - `exang` – Exercise-induced angina
  - `oldpeak` – ST depression
  - `thal` – Thalassemia status
  - `target` – Presence of heart disease (1 = yes, 0 = no)

5.2) Data Understanding 🔍

- **Initial Exploration:**
  - Checked dataset shape: e.g., `(303, 14)`
  - Viewed data types and column meanings
  - `target` is our outcome variable (binary classification)
- **Insights Gathered:**
  - `cp`, `thal`, `sex`, `fbs`, `exang`, etc. are categorical
  - Some features are continuous (`chol`, `age`, `oldpeak`)
- **Techniques Used:**
  - `df.describe()` for summary statistics
  - `df.info ()` for data types and null checks
  - Histograms and boxplots for distribution

5.3) Data Cleaning:-

Fill the NaN Values to Mean

```
mean_value = heart_df['ca'].mean()
heart_df['ca'] = heart_df['ca'].fillna(mean_value)
heart_df['ca']
heart_df


mean_value = heart_df['thal'].mean()
heart_df['thal'] = heart_df['thal'].fillna(mean_value)
heart_df['thal']
heart_df

 mode_value = heart_df['num'].mode()
 mode_value
 heart_df['num'] = heart_df['num'].fillna(mode_value, inplace = True)
 heart_df['num']
 heart_df

 heart_df['num'].fillna(heart_df['num'].mode())
 heart_df['num']
```

Over here, we are not removing the NaN value; instead that we are using the fillna method to replace the NaN value with the column mean or the Mode

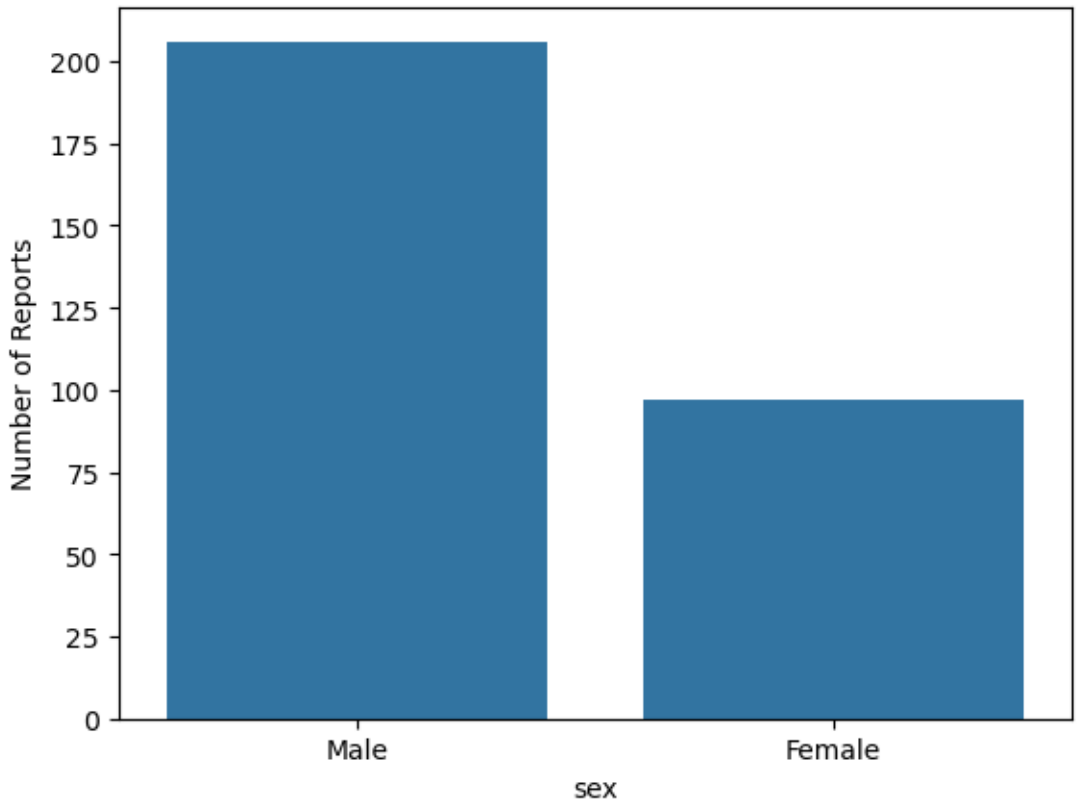
Convert the Numeric Value to Categorical Value:- By using Replace

```
import numpy as np
heart_df['sex'] = heart_df['sex'].replace({1: 'Male', 0: 'Female'})
heart_df

heart_df['cp'] = heart_df['cp'].replace({1: 'typical angina', 2: 'atypical angina',3:'non-anginal pain',4:'asymptomatic'})
heart_df

heart_df['fbs'] = heart_df['fbs'].replace({1 : "true" , 0 : "false"})
heart_df

heart_df['restecg'] = heart_df['restecg'].replace({0:"normal",1: "abnormality",2 : "LVH"})
heart_df


heart_df['exang'] = heart_df['exang'].replace({1 : "yes" , 0 : "no"})
heart_df

heart_df['slope'] = heart_df['slope'].replace({1:"upsloping",2: "flat",3 : "downsloping"})
heart_df

heart_df['thal'] = heart_df['thal'].replace({3:"normal",6: "fixed defect",7 : " reversable defect"})
heart_df
```

5.4) Data Analysis:

5.4.1) Count the number of Reports Gender-wise :-

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(data=heart_df,x='sex')
plt.ylabel('Number of Reports')
plt.savefig("count_Reports_from_gender.png", dpi=300, bbox_inches='tight')
plt.show()
```

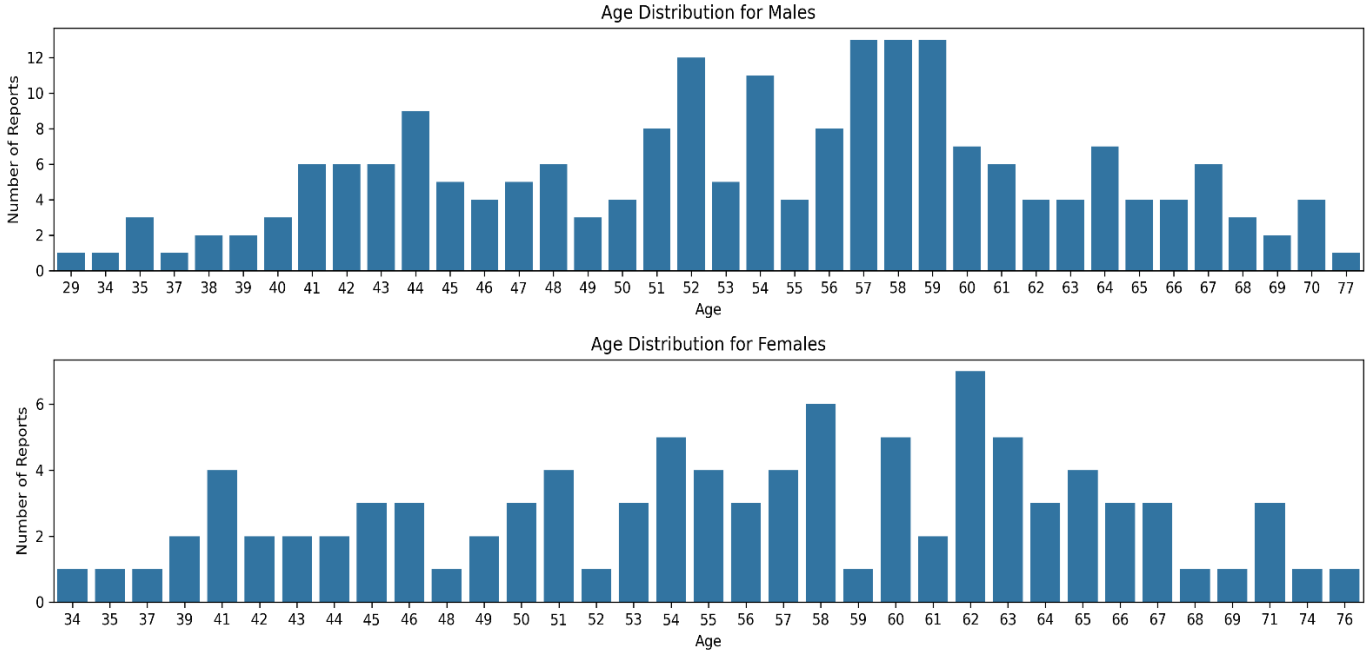


From the Above Charts, we can easily identify that Males have more Reports in comparison to females

This shows that approximately 68.3% (207) **of the dataset consists of male patient records, while the remaining** 31.7% (96) **are female. This imbalance in gender representation is important to note**

5.4.2) Number_of_reports_age-wise_for_each_gender:

```
import os
print(os.getcwd())

fig, axes = plt.subplots(2, 1, figsize=(14, 6))

sns.countplot(data=heart_df[heart_df['sex'] == "Male"], x='age', ax=axes[0])
axes[0].set_title('Age Distribution for Males')
axes[0].set_ylabel('Number of Reports')
axes[0].set_xlabel('Age')


sns.countplot(data=heart_df[heart_df['sex'] == "Female"], x='age', ax=axes[1])
axes[1].set_title('Age Distribution for Females')
axes[1].set_ylabel('Number of Reports')
axes[1].set_xlabel('Age')

plt.tight_layout()
plt.savefig("D:/personal_Skill_inhancing/Project/Health/Documentation/photos/Number_of_reports_agewise_for_each_gender.png"
            ,dpi=300, bbox_inches='tight')
plt.show()
```



The first chart shows the age distribution for males, and the Second one tells about the Females

In Males, we can see that a nice spike or wave came in the age of 52 to 62, and in females, we can see the spike between the ages of 52 to 67

In the males, in just 10 years (age of 52 to 62), we can see 107 Reports, which is nearly 55 % of the total Reports.

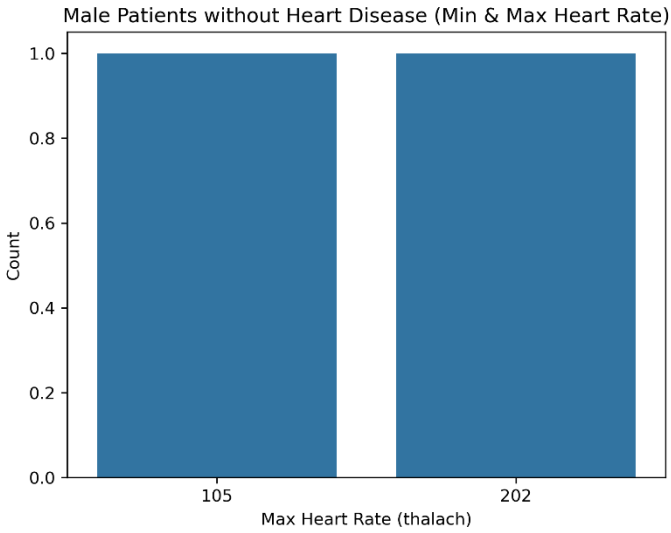
In females in this 15 age range (ages of 52 to 67), we can see 58 reports, which is exactly 55% of the Total Reports

In short, we can find out from this that the plot is that as the age increases, the number of reports also increases

5.4.3) Minimum and Maximum Heart Rate during each stage of Diagnosis (Males) :

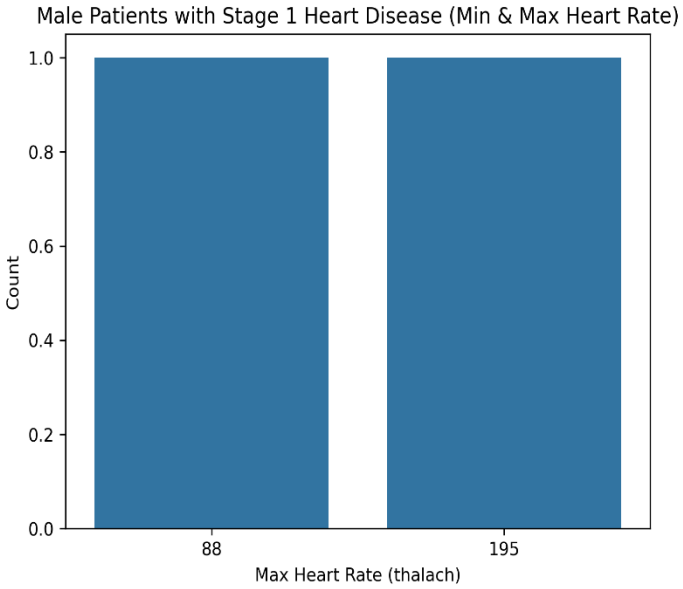
```
male_healthy = heart_df[(heart_df['num'] == 0 ) &
               (heart_df['sex'] == "Male")]

# Find min and max thalach
min_hr = male_healthy['thalach'].min()
max_hr = male_healthy['thalach'].max()

# Filter for only those rows with min or max thalach
filtered = male_healthy[(male_healthy['thalach'] == min_hr) |
           (male_healthy['thalach'] == max_hr)]

# Plot
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(data=filtered, x='thalach')
plt.title('Male Patients without Heart Disease (Min & Max Heart Rate)')
plt.xlabel('Max Heart Rate (thalach)')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

The above code is for stage 0 to see another stage, you need to change in male healthy in which you need to change 0 to (1,2,3,4). Any of them

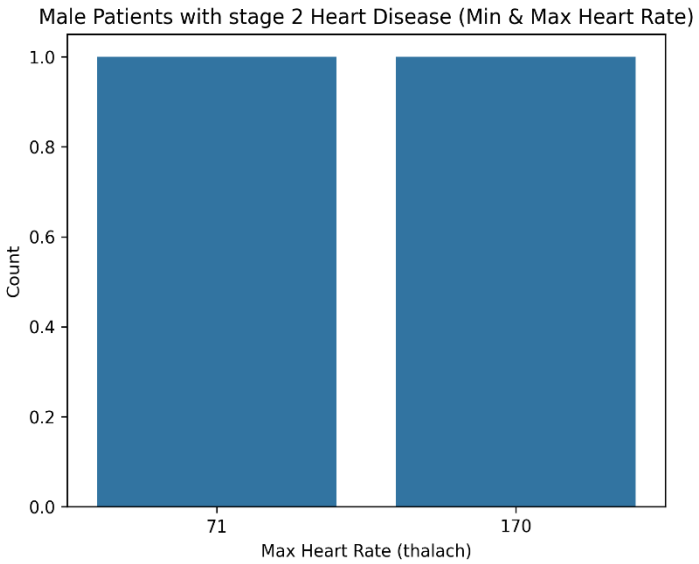


In stage 0, the minimum heart rate is 105, and the maximum heart rate is 202

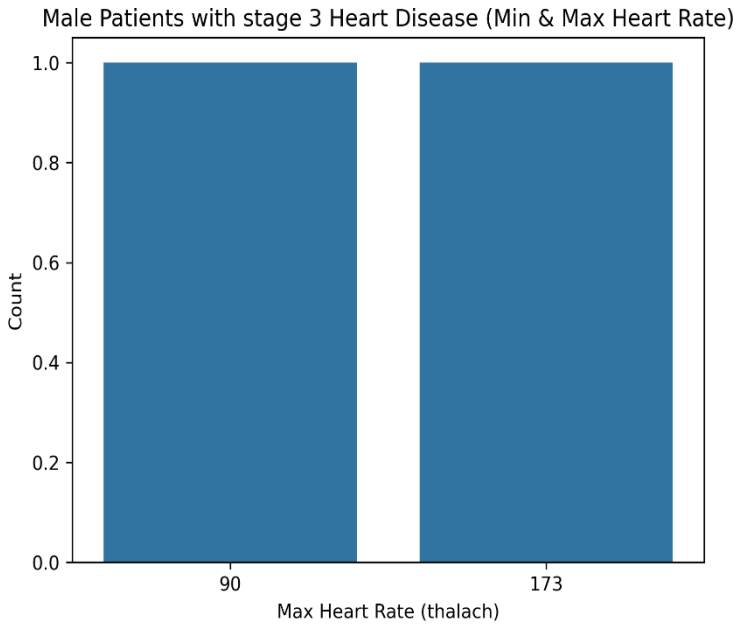
202 is an outlier value over here; an official value should be around 187



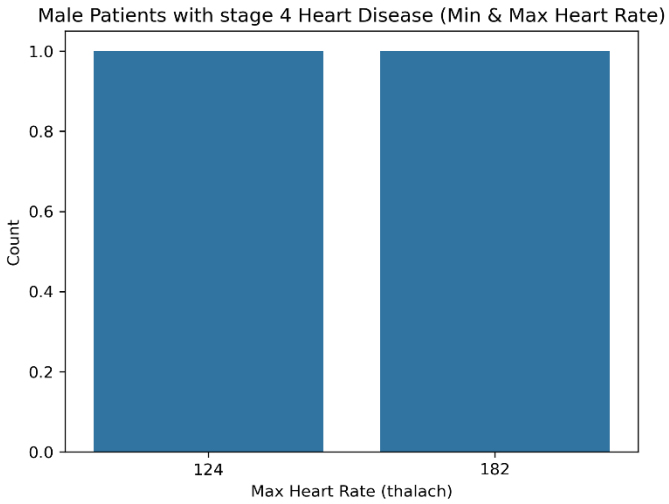
In stage 1 of diagnosis, we can see over here that the minimum is 88 only, and the maximum is 195



in stage 2, the maximum heart rate is 170, but when we see that the minimum heart rate is 71, which shows that a patient might have symptoms of Heart Disease



In the stage 3 diagnosis of the male patients, the minimum heart rate is 90 and the maximum heart rate is 173



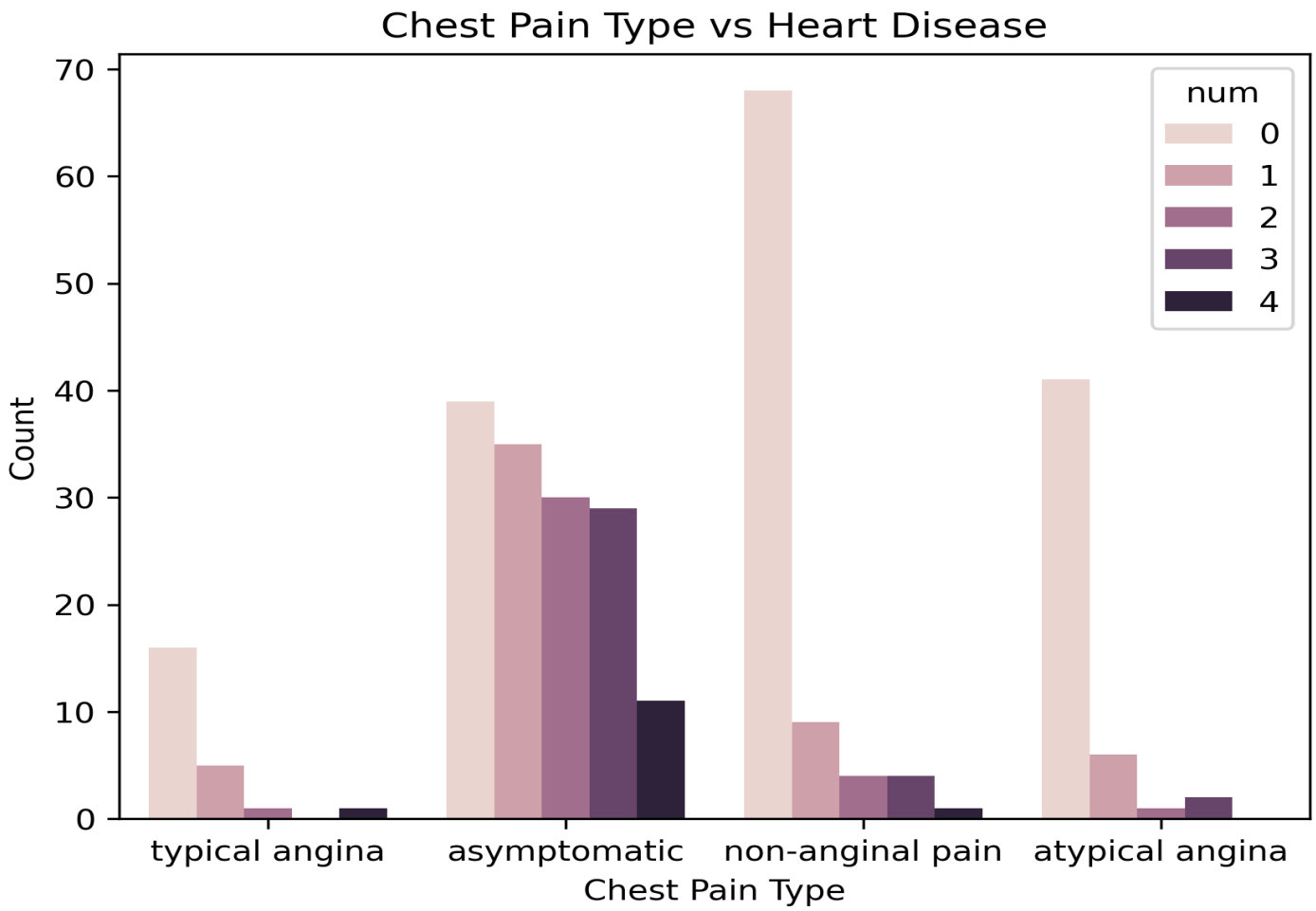
In stage 4 of diagnosis, the minimum heart rate is 124, and the maximum will be 182

AS we can see, all the above stages of Diagnosis, in which we can see a great increment in heart rate, with the minimum heart rate per stage. Majorly, the 80 to 100 is normal in the adult body

But when we talk about below 80, it might show several heart diseases. And if it is above 100, it is not normal; it is happening due to a high amount of exercise stress, and anxiety

5.4.4) Chest Pain Type **vs**. Heart Disease**:** -

```
sns.countplot(data=heart_df, x='cp', hue='num')
plt.title('Chest Pain Type vs Heart Disease')
plt.xlabel('Chest Pain Type')
plt.ylabel('Count')
```



1 Typical Angina:- Chest discomfort related to physical exertion or stress

2 Atypical Angina:- Unusual chest pain not related to physical exertion

3 Non-Angina:- Pain Chest pain not related to the heart

4 Asymptomatic:- No chest pain; may still have underlying heart issues

The visualization of chest pain types against heart disease severity reveals a critical insight—asymptomatic individuals are significantly more likely to have heart disease **than those with typical or non-angina chest pain. While it's common to associate chest pain with heart issues, the data shows that** relying solely on chest discomfort is not sufficient for diagnosis**. Most patients with classic symptoms (typical angina) were not diagnosed with heart disease. On the other hand, asymptomatic patients had the highest share of diagnoses, emphasizing the importance of** regular screening and use of diagnostic tools **even when symptoms aren't present.**

5.4.5) Problem Statement: -

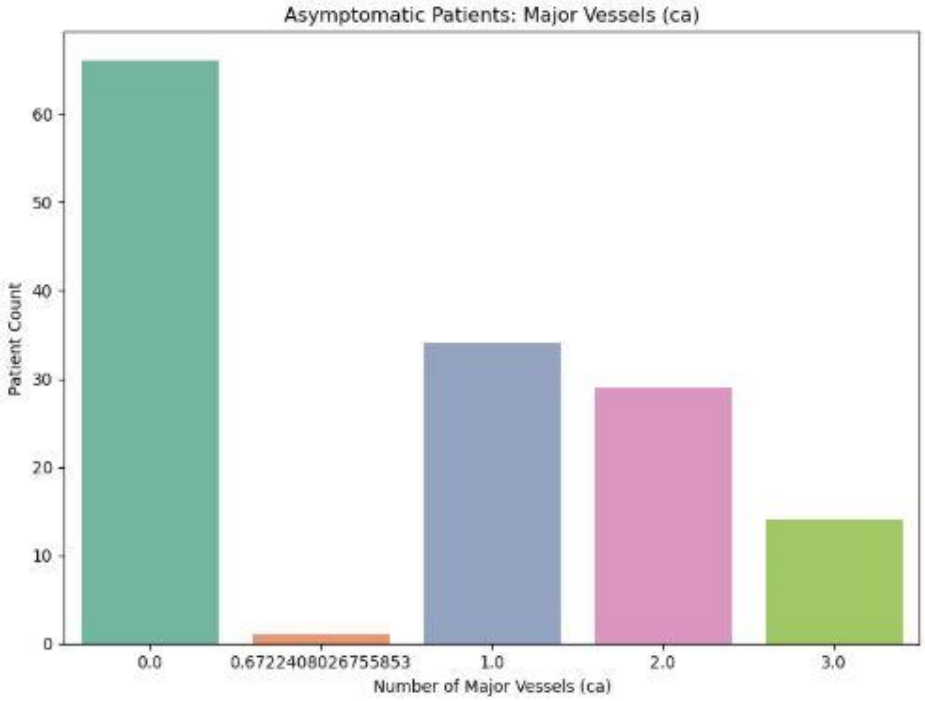
Why do we have the Highest number of Heart disease patients who have Asymptomatic Chest Pain?

Normally, in the heart's anatomy, we find multiple vessels, and these vessels are used to circulate blood in the heart. If it does not circulate blood freely, there might be a chance that a person can develop heart problems

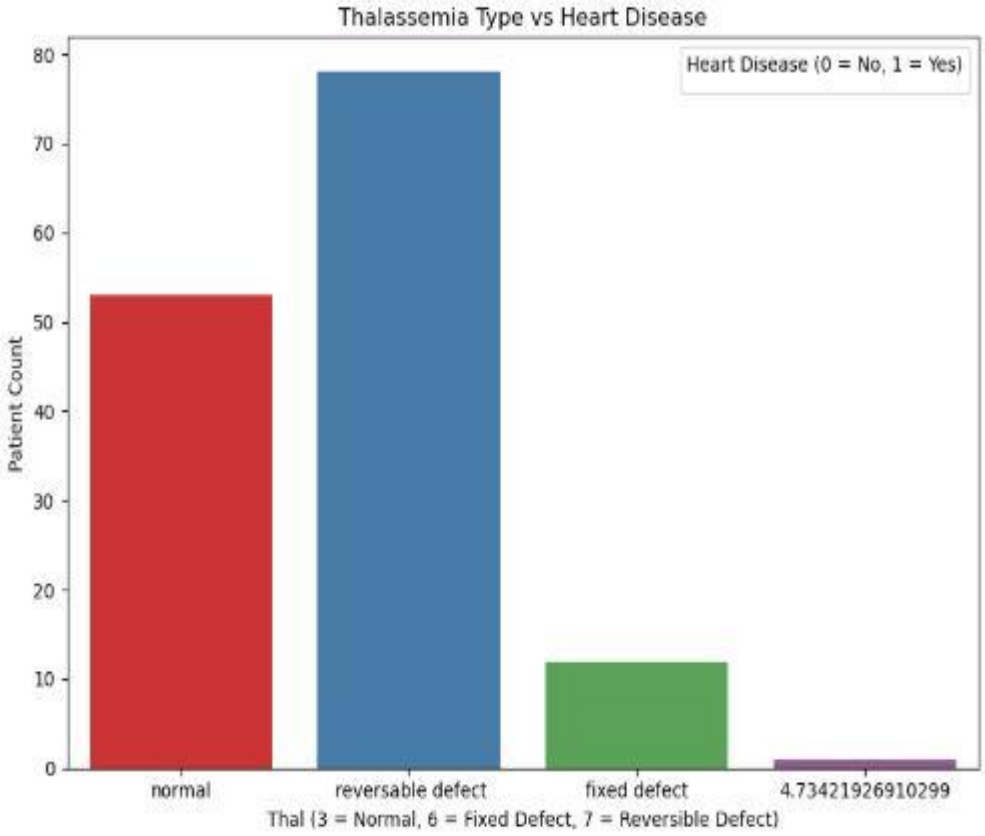
In the same way as we mentioned above, the blood. Let's take an Example (if we eat healthy food, does it make us unhealthy? No, it always makes us healthy). The same way to run a Heart smoothly, the blood also needs to be of good quality.

But there is a blood disorder called thalassemia. In which the Blood's quality gets very Bad, and if a patient has the thalassemia of 6 **(Fixed Defect)** or 7 **(Reversible Defect)** means the Patient is at Risk

```
sns.countplot(data=heart_df[heart_df['cp'] == "asymptomatic"], x='ca', palette='Set2', ax=axes[0])
# asymptomatic, typical angina, non-anginal pain, atypical angina
axes[0].set_title('Asymptomatic Patients: Major Vessels (ca)')
axes[0].set_xlabel('Number of Major Vessels (ca)')
axes[0].set_ylabel('Patient Count')
```



As we can see over here, this is a vessel blockage plot of Asymptomatic Patients. In which we can see that the maximum number of people have no blockage, but on the other side, 32 patients have 1 vessel blocked, 28 patients have 2 blockages of vessels, and in the last, there are 13 to 15 patients who have 3 vessel blockages. Which shows more risk of heart problems



Thalassemia is a type of blood disease in which the quality of the blood gets so bad that it is basically a blood disorder. Now, Normal Thalassemia is not leading to heart problems over here. It considers a healthy heart. But if the patients are having a Reversible or Fixed defect, it definitely indicates the heart problems

5.4.6) Correlation Matrix: -

• Age**, cholesterol levels, and blood pressure** are likely significant factors contributing to heart disease.

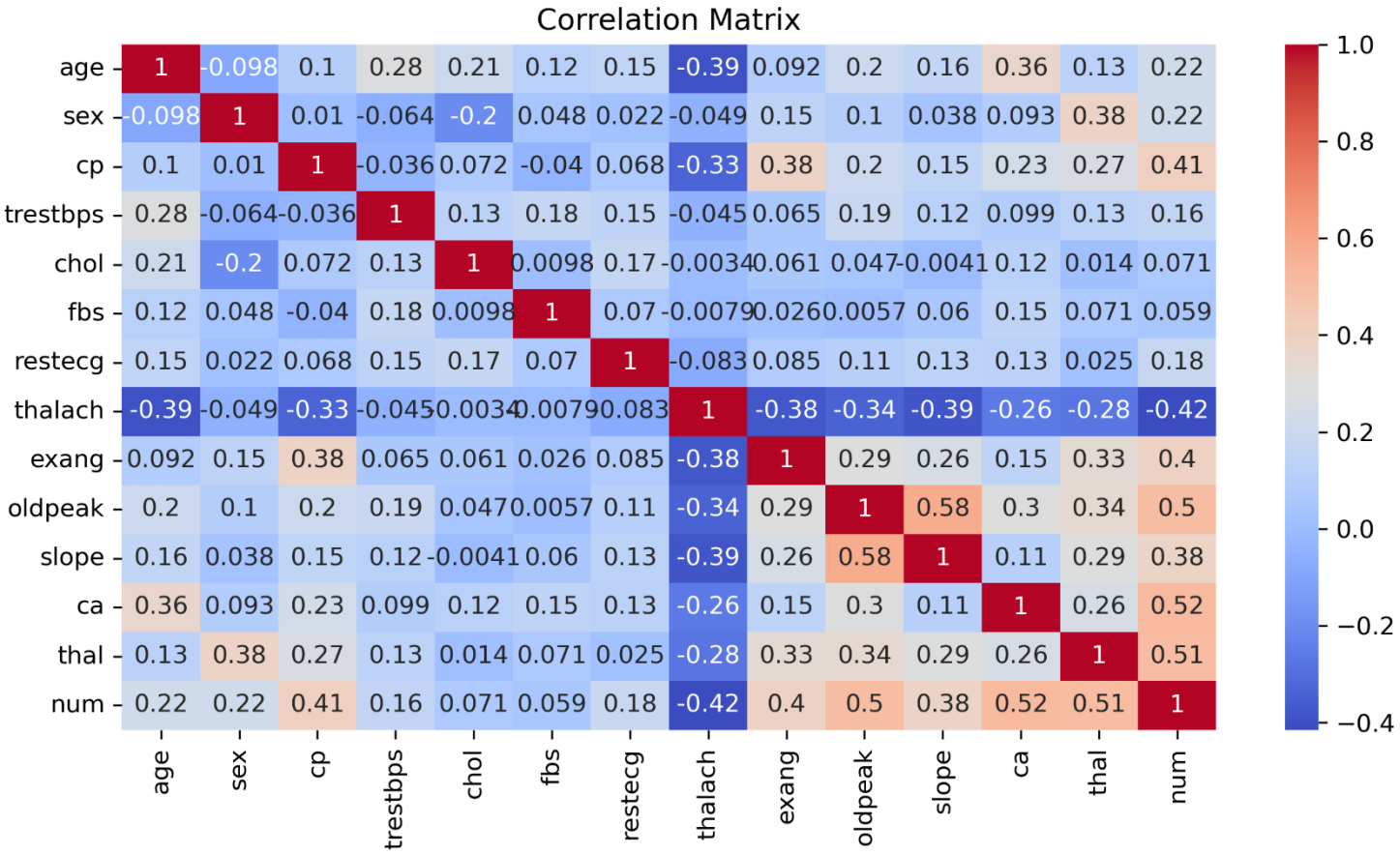
• Thalassemia **defects** (if included as "thal") may increase the risk, especially if there are defects.

• High **cholesterol and high blood pressure** are often related, and together they could be major contributors to heart disease.

• Multicollinearity **issues** could arise between features like cholesterol and blood pressure, which may require further data pre-processing or feature engineering.

• Lifestyle **factors** (if available) like smoking, exercise, and diet could play an important role.

```
hdf['thal'] = hdf['thal'].replace({
    'normal': 3,
    'fixed defect': 6,
    'reversible defect': 7
})

# Generate correlation matrix
corr = hdf.corr()

# Plot the heatmap
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 5))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')

plt.tight_layout()
plt.show()
```



6) Interpretation & Communication :-

The analysis reveals that heart disease is most prevalent in males aged 52–67, with a surprising number of cases among asymptomatic individuals. Key contributing factors include high cholesterol, abnormal heart rate, elevated ST depression (oldpeak), and thalassemia defects. Asymptomatic patients with blocked vessels are at high risk, showing that symptoms alone are not reliable indicators. Age, chest pain type, and thalassemia status are strong predictors of heart issues. These insights highlight the importance of regular screening, early diagnosis, and proactive lifestyle interventions to reduce risk and improve patient outcomes—even in the absence of noticeable symptoms.

6.1) Tools Used:

→Matplotlib / Seaborne for visual storytelling

➔ Numpy for Numerical Computation

➔ Pandas for Data Manipulation

➔ Microsoft Word for Documentation

➔ Jupiter Notebook for Python code

7) Conclusion:-

The UCI Heart Disease dataset analysis highlights that heart disease can occur even without typical symptoms, particularly in males aged 52–67. Critical risk indicators include thalassemia defects, high cholesterol, abnormal heart rates, and silent conditions like asymptomatic chest pain. Therefore, relying solely on symptoms is insufficient—regular health check-ups, early screening, and awareness of hidden risk factors are essential for timely diagnosis and prevention. Data-driven insights can support better clinical decisions and targeted interventions to reduce heart disease risk and improve patient care.

Keep Exploring ….