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the dataset related to heart disease. The target field refers to the presence of heart disease in the patient. It is integer valued 0 = no disease and 1 = disease. These features cover a range of demographic, physiological, and diagnostic indicators that are commonly associated with heart health. Here's a brief description of each feature:

- 1. Age: The age of the patient.
- 2. Sex: The gender of the patient (0 = female, 1 = male).
- 3. Chest Pain Type: Describes the type of chest pain experienced by the patient. It's categorized into four values.
- 4. Resting Blood Pressure: The blood pressure of the patient while at rest.
- 5. Serum Cholesterol: Serum cholesterol level in mg/dl.
- 6. Fasting Blood Sugar: Indicates whether the patient's fasting blood sugar level is above 120 mg/dl (1 = yes, 0 = no).
- 7. Resting Electrocardiographic Results: Results of resting electrocardiogram, categorized into three values (0, 1, 2).
- 8. Maximum Heart Rate Achieved: The maximum heart rate achieved during exercise.
- 9. Exercise Induced Angina: Indicates whether exercise induced angina is present (1 = yes, 0 = no).
- 10. Oldpeak: ST depression induced by exercise relative to rest.
- 11. Slope of the Peak Exercise ST Segment: Describes the slope of the peak exercise ST segment.
- 12. Number of Major Vessels Colored by Fluoroscopy: The number of major vessels (0-3) colored by fluoroscopy.
- 13. Thal: Thalassemia, categorized into three values (0 = normal, 1 = fixed defect, 2 = reversible defect).

Link: Heart Disease Dataset (kaggle.com)

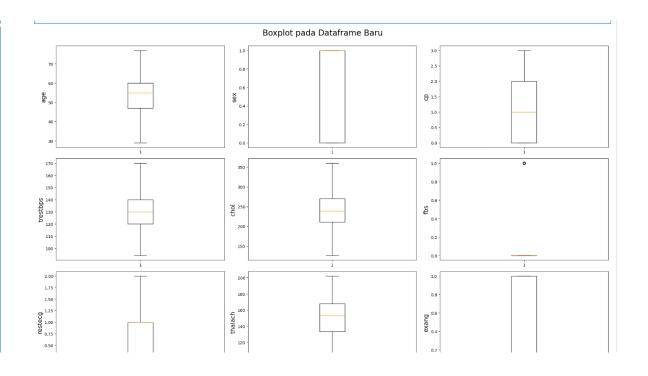
- Checking Missing Values:
- missing\_values = df.isnull().sum()calculates the total number of missing values in each column of the DataFrame df.
- print(missing\_values) displays the count of missing values for each column.

```
[ ]: #Checkin for missing values
[6]: missing_values = df.isnull().sum()
     print(missing_values)
     age
     sex
                0
                0
     ср
     trestbps
                0
                0
     chol
     fbs
                0
     restecg
     thalach
                0
     exang
     oldpeak
     slope
     ca
     thal
     target
     dtype: int64
```

- Handling Duplicate Rows:
- df.duplicated() identifies duplicate rows in the DataFrame.
- df.duplicated().sum() calculates the total number of duplicate rows.
- data = df.drop\_duplicates() removes duplicate rows from the DataFrame and stores the cleaned data in data.
- data.duplicated().sum() = 0 verifies that there are no duplicate rows in the cleaned data.

```
# Duplicate values
[28]:
[7]:
      df.duplicated()
[7]: 0
               False
      1
               False
      2
               False
      3
               False
               False
               . . .
      1020
               True
      1021
               True
      1022
               True
      1023
               True
      1024
               True
      Length: 1025, dtype: bool
[8]: df.duplicated().sum()
[8]: 723
      data = df.drop_duplicates()
[10]: data.duplicated().sum()
[10]: 0
```

- Detecting Outliers:
- Quartiles and IQR are calculated for the numerical columns ("trestbps", "chol", "thalach", "oldpeak") using quantile ().
- Lower and upper bounds for outliers are determined based on the calculated quartiles and IQR.
- Outliers are identified using conditions based on the calculated bounds.
- Outliers are handled by removing them from the DataFrame and storing the cleaned data in "data2".
- Boxplots are created for each column in the cleaned DataFrame "data2" to visualize the distribution and identify outliers.
- The loop iterates through each column, creating subplots for visualization.
- Output handle outliers.



- Checking Data Consistency and Distribution:
- Categorical variables (categorical\_vars ) and numerical variables ( numerical\_vars ) are defined.
- The loop checks for inconsistencies in categorical variables by printing unique values for each column.
- Summary statistics are printed for numerical variables using describe ().
- Boxplots are created to visually inspect the distribution of numerical variables and identify potential outliers.
- Count plots are generated to visualize the distribution of categorical variables.

```
[18]: categorical_vars = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'target']
      numerical_vars = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
      # Check for inconsistencies in categorical variables
      for column in categorical vars:
          print(f"Unique values in {column}: {data2[column].unique()}")
      # Check for inconsistencies in numerical variables
      for column in numerical_vars:
          print(f"Summary statistics for {column}:")
          print(data2[column].describe())
      # Check for unexpected values or outliers in numerical variables using box plots
      plt.figure(figsize=(12, 8))
      for i, column in enumerate(numerical_vars, 1):
          plt.subplot(3, 2, i) # Adjusting layout to 3 rows and 2 columns
          plt.boxplot(data2[column])
          plt.title(column)
      plt.tight_layout()
      plt.show()
      # Check for distribution of categorical variables using count plots
      plt.figure(figsize=(12, 8))
      for column in categorical_vars:
          plt.subplot(3, 3, categorical_vars.index(column) + 1)
          sns.countplot(data2[column])
          plt.title(column)
      plt.tight_layout()
      plt.show()
```

Unique values in sex: [1 0]
Unique values in cp: [0 1 2 3]
Unique values in fbs: [0 1]
Unique values in restecg: [1 0 2]
Unique values in exang: [0 1]

## • Feature Engineering:

# 1. Age Group:

- Categorizes individuals into different age groups based on their age.
- Creates a new column called age\_group using the pd.cut() function, binning the 'age' column into specified ranges.
  - Labels for age groups: '<40', '40-59', '60-79', '80+'.

### 2. Total Cholesterol:

- Combines chol (cholesterol) and fbs (fasting blood sugar) to calculate total cholesterol.
  - Creates a new column total\_chol by summing 'chol' and 'fbs' for everyone.
- 3. Exercise Induced Angina & Max Heart Rate Interaction:
- Captures interaction between exang (exercise-induced angina) and thalach (maximum heart rate achieved).
  - Creates exang\_thalach\_interaction by multiplying exang and thalach.
- 4. Age and Cholesterol Interaction:
  - Represents interaction between age and cholesterol levels.
  - Creates age\_chol\_interaction by multiplying age and chol.
- 5. Max Heart Rate and Exercise Induced Angina Interaction:
- Captures interaction between maximum heart rate achieved and exercise-induced angina.
  - Creates thalach\_exang\_interaction by multiplying thalach and exang.

#### • Evaluation Results:

Using the evaluation metrics that were derived from the models:

### **Performance Metrics Overview**

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Logistic Regression	0.842105	0.823529	0.903226	0.861538	0.836228
Random Forest	0.789474	0.771429	0.870968	0.818182	0.781638
Support Vector Machine	0.614035	0.588235	0.967742	0.731707	0.580025
Gradient Boosting	0.789474	0.787879	0.838710	0.812500	0.784739

#### • Conclusion:

Based on its superior accuracy, precision, recall, F1 score, and ROC-AUC, the analysis shows that Logistic Regression is the best-performing model for predicting heart disease. Based on a good balance between sensitivity and specificity, this suggests that the most dependable model for accurately identifying positive and negative cases of heart disease is Logistic Regression.

In situations where interpretability and particular model attributes—such as managing non-linear relationships and interactions—are critical, Random Forest and Gradient Boosting also demonstrate strong performance and may be taken into consideration as viable alternatives.

Support Vector Machine performs poorly in other metrics, even with its high recall, which makes it less appropriate for this specific application without more fine-tuning or data preprocessing.

• GUI using streamlit

