ai-ml-tasks

June 5, 2025

https://colab.research.google.com/drive/1SR0yLmwUS68UMHsDGHSB1Ofzt_kNPzYY?usp=sharing

1 Github Repository

```
[61]: %cd https://github.com/zoya4477/AI-Ml.git
      git clone!
      git config --global user.email "zoyahafeez785@gmail.com"
      !git config --global user.name "zoya4477"
     [Errno 2] No such file or directory: 'https://github.com/zoya4477/AI-Ml.git'
     fatal: You must specify a repository to clone.
     usage: git clone [<options>] [--] <repo> [<dir>]
         -v, --verbose
                               be more verbose
         -q, --quiet
                               be more quiet
         --progress
                               force progress reporting
         --reject-shallow
                             don't clone shallow repository
         -n, --no-checkout
                               don't create a checkout
         --bare
                               create a bare repository
                               create a mirror repository (implies bare)
         --mirror
         -1, --local
                               to clone from a local repository
         --no-hardlinks
                               don't use local hardlinks, always copy
         -s, --shared
                               setup as shared repository
         --recurse-submodules[=<pathspec>]
                               initialize submodules in the clone
                             alias of --recurse-submodules
         --recursive ...
         -j, --jobs <n>
                               number of submodules cloned in parallel
         --template <template-directory>
                               directory from which templates will be used
         --reference <repo>
                               reference repository
         --reference-if-able <repo>
                               reference repository
                               use --reference only while cloning
         --dissociate
         -o, --origin <name> use <name> instead of 'origin' to track upstream
         -b, --branch <branch>
```

```
checkout <branch> instead of the remote's HEAD
   -u, --upload-pack <path>
                          path to git-upload-pack on the remote
    --depth <depth>
                          create a shallow clone of that depth
    --shallow-since <time>
                          create a shallow clone since a specific time
   --shallow-exclude <revision>
                          deepen history of shallow clone, excluding rev
                          clone only one branch, HEAD or --branch
    --single-branch
                          don't clone any tags, and make later fetches not to
    --no-tags
follow them
    --shallow-submodules any cloned submodules will be shallow
    --separate-git-dir <gitdir>
                          separate git dir from working tree
   -c, --config <key=value>
                          set config inside the new repository
   --server-option <server-specific>
                          option to transmit
   -4, --ipv4
                          use IPv4 addresses only
   -6, --ipv6
                          use IPv6 addresses only
                         object filtering
   --filter <args>
    --remote-submodules any cloned submodules will use their remote-tracking
branch
                          initialize sparse-checkout file to include only files
    --sparse
at root
```

2 Task 1: Exploring and Visualizing the Iris Dataset

3 Load the Dataset

```
[30]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load the Iris dataset directly from seaborn
df = pd.read_csv('/content/Iris.csv')
```

4 Inspect the dataset

```
[31]: # Shape of the dataset
print("Shape of the dataset:", df.shape)

# Column names
print("Column names:", df.columns.tolist())
```

```
# First few rows
print(df.head())

# Info summary
print("\nDataset Info:")
print(df.info())

# Descriptive statistics
print("\nDescriptive Statistics:")
print(df.describe())
```

Shape of the dataset: (152, 6)

 ${\tt Column\ names:\ ['Id',\ 'SepalLengthCm',\ 'SepalWidthCm',\ 'PetalLengthCm',\ 'P$

'PetalWidthCm', 'Species']

	Id	${\tt SepalLengthCm}$	${ t SepalWidthCm}$	${\tt PetalLengthCm}$	${\tt PetalWidthCm}$	Species
0	1	5.1	3.5	NaN	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	NaN	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	NaN	Iris-setosa
4	5	5.0	NaN	1.4	0.2	Iris-setosa

Dataset Info:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 152 entries, 0 to 151 Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	Id	152 non-null	int64
1	${\tt SepalLengthCm}$	151 non-null	float64
2	${\tt SepalWidthCm}$	151 non-null	float64
3	${\tt PetalLengthCm}$	151 non-null	float64
4	${\tt PetalWidthCm}$	151 non-null	float64
5	Species	152 non-null	object
4+	og. floo+64(4)	in+6/(1) object	+(1)

dtypes: float64(4), int64(1), object(1)

memory usage: 7.3+ KB

None

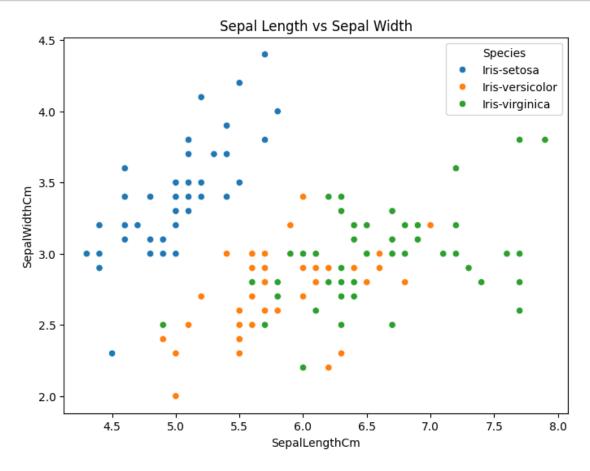
Descriptive Statistics:

	Id	${\tt SepalLengthCm}$	${\tt SepalWidthCm}$	${\tt PetalLengthCm}$	${\tt PetalWidthCm}$
count	152.000000	151.000000	151.000000	151.000000	151.000000
mean	75.414474	5.849007	3.055629	3.770861	1.206623
std	43.866813	0.823073	0.432302	1.764902	0.766870
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	37.750000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.400000	1.300000
75%	113.250000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

#Visualize the Dataset

```
[32]: #Scatter Plot -- Sepal Length vs Sepal Width

plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='SepalLengthCm', y='SepalWidthCm', hue='Species')
plt.title('Sepal Length vs Sepal Width')
plt.show()
```



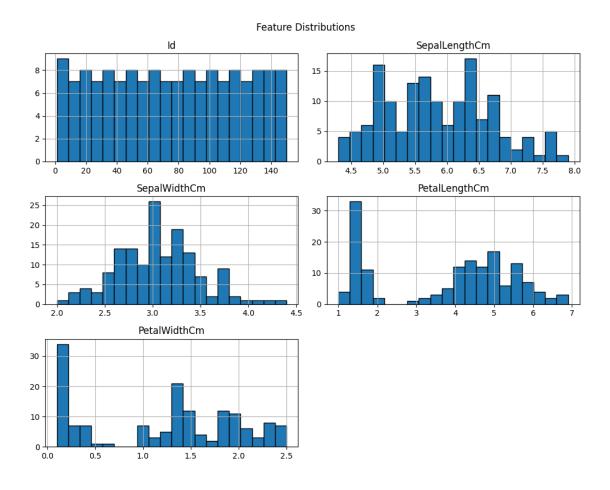
```
[33]: #Histograms -- Distribution of Each Feature

df.hist(figsize=(10, 8), bins=20, edgecolor='black')

plt.suptitle('Feature Distributions')

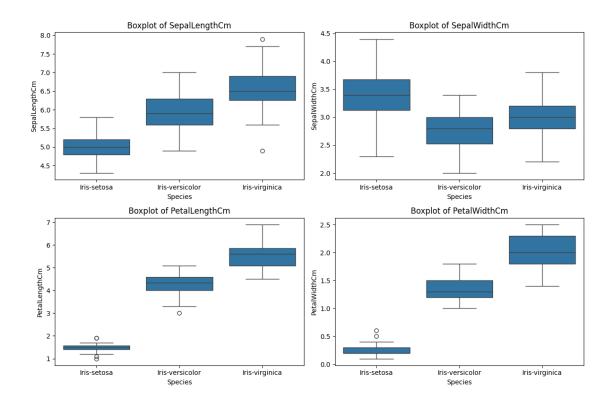
plt.tight_layout()

plt.show()
```



```
[34]: #Boxplot -- To Identify Outlier
plt.figure(figsize=(12, 8))
features = ['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']

for i, column in enumerate(features):
   plt.subplot(2, 2, i + 1)
    sns.boxplot(x='Species', y=column, data=df)
   plt.title(f'Boxplot of {column}')
plt.tight_layout()
plt.show()
```



[34]:

5 Task 2: Predict Future Stock Prices (Short-Term)

[35]: pip install yfinance

Requirement already satisfied: yfinance in /usr/local/lib/python3.11/dist-packages (0.2.61)

Requirement already satisfied: pandas>=1.3.0 in /usr/local/lib/python3.11/dist-packages (from yfinance) (2.2.2)

Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib/python3.11/dist-packages (from yfinance) (2.0.2)

Requirement already satisfied: requests>=2.31 in /usr/local/lib/python3.11/dist-packages (from yfinance) (2.32.3)

Requirement already satisfied: multitasking>=0.0.7 in

/usr/local/lib/python3.11/dist-packages (from yfinance) (0.0.11)

Requirement already satisfied: platformdirs>=2.0.0 in

/usr/local/lib/python3.11/dist-packages (from yfinance) (4.3.8)

Requirement already satisfied: pytz>=2022.5 in /usr/local/lib/python3.11/dist-packages (from yfinance) (2025.2)

Requirement already satisfied: frozendict>=2.3.4 in

/usr/local/lib/python3.11/dist-packages (from yfinance) (2.4.6)

Requirement already satisfied: peewee>=3.16.2 in /usr/local/lib/python3.11/dist-

```
Requirement already satisfied: beautifulsoup4>=4.11.1 in
     /usr/local/lib/python3.11/dist-packages (from yfinance) (4.13.4)
     Requirement already satisfied: curl_cffi>=0.7 in /usr/local/lib/python3.11/dist-
     packages (from vfinance) (0.11.1)
     Requirement already satisfied: protobuf>=3.19.0 in
     /usr/local/lib/python3.11/dist-packages (from yfinance) (5.29.5)
     Requirement already satisfied: websockets>=13.0 in
     /usr/local/lib/python3.11/dist-packages (from yfinance) (15.0.1)
     Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.11/dist-
     packages (from beautifulsoup4>=4.11.1->yfinance) (2.7)
     Requirement already satisfied: typing-extensions>=4.0.0 in
     /usr/local/lib/python3.11/dist-packages (from beautifulsoup4>=4.11.1->yfinance)
     (4.13.2)
     Requirement already satisfied: cffi>=1.12.0 in /usr/local/lib/python3.11/dist-
     packages (from curl_cffi>=0.7->yfinance) (1.17.1)
     Requirement already satisfied: certifi>=2024.2.2 in
     /usr/local/lib/python3.11/dist-packages (from curl_cffi>=0.7->yfinance)
     (2025.4.26)
     Requirement already satisfied: python-dateutil>=2.8.2 in
     /usr/local/lib/python3.11/dist-packages (from pandas>=1.3.0->yfinance)
     (2.9.0.post0)
     Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
     packages (from pandas>=1.3.0->yfinance) (2025.2)
     Requirement already satisfied: charset-normalizer<4,>=2 in
     /usr/local/lib/python3.11/dist-packages (from requests>=2.31->yfinance) (3.4.2)
     Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
     packages (from requests>=2.31->yfinance) (3.10)
     Requirement already satisfied: urllib3<3,>=1.21.1 in
     /usr/local/lib/python3.11/dist-packages (from requests>=2.31->yfinance) (2.4.0)
     Requirement already satisfied: pycparser in /usr/local/lib/python3.11/dist-
     packages (from cffi>=1.12.0->curl_cffi>=0.7->yfinance) (2.22)
     Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
     packages (from python-dateutil>=2.8.2->pandas>=1.3.0->yfinance) (1.17.0)
     #Import libraries and load data
[36]: import yfinance as yf
      import pandas as pd
      import numpy as np
      from sklearn.model_selection import train_test_split
      from sklearn.ensemble import RandomForestRegressor
      from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean squared error
      import matplotlib.pyplot as plt
      # Download historical data for Apple (AAPL)
      ticker = 'AAPL'
```

packages (from yfinance) (3.18.1)

```
df = yf.download(ticker, start='2020-01-01', end='2024-01-01')
# Display first rows
print(df.head())
```

```
[******** 100%*********** 1 of 1 completed
                                                     Volume
Price
              Close
                         High
                                             Open
                                    Low
Ticker
               AAPL
                         AAPL
                                   AAPL
                                             AAPL
                                                       AAPL
Date
2020-01-02 72.620834 72.681281 71.373211 71.627084
                                                  135480400
2020-01-03 71.914795 72.676423 71.689935 71.847095
                                                  146322800
2020-01-06 72.487839 72.526526 70.783241 71.034702 118387200
2020-01-07 72.146950 72.753831 71.926922 72.497537
                                                  108872000
2020-01-08 73.307510 73.609745 71.849533 71.849533 132079200
```

6 Prepare features and target

```
[37]: # Shift the Close column up by 1 to represent next day close price
df['Next_Close'] = df['Close'].shift(-1)

# Drop last row with NaN target
df = df[:-1]

# Features and target
features = ['Open', 'High', 'Low', 'Volume']
X = df[features]
y = df['Next_Close']
```

#Split data into train/test sets

7 Train the model

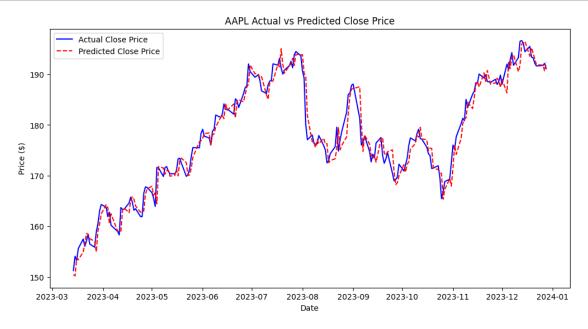
```
[39]: #Linear Regression
model = LinearRegression()
model.fit(X_train, y_train)
```

[39]: LinearRegression()

```
[40]: y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse:.4f}")
```

Mean Squared Error: 4.9761

#Plot actual vs predicted closing prices



[41]:

8 Task 3: Heart Disease Prediction

9 Import Libraries

```
[42]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve, u confusion_matrix, ConfusionMatrixDisplay
```

10 Load Dataset

```
[43]: data = pd.read_csv('/content/archive.zip')
      data.head()
[43]:
                                               restecg
                                                                          oldpeak slope \
         age
               sex
                    ср
                        trestbps
                                   chol fbs
                                                         thalach exang
      0
          69
                     0
                              160
                                    234
                                                      2
                                                                              0.1
                                                                                        1
                 1
                                            1
                                                             131
                                                                       0
      1
          69
                              140
                                    239
                                            0
                                                     0
                                                             151
                                                                       0
                                                                              1.8
                                                                                        0
                 0
                     0
                                                                              2.6
                                                                                        2
      2
          66
                                    226
                                                     0
                                                             114
                                                                       0
                 0
                     0
                              150
                                            0
      3
          65
                              138
                                    282
                                            1
                                                     2
                                                             174
                                                                       0
                                                                              1.4
                 1
                     0
                                                                                        1
                                                      2
                                                                              1.8
          64
                              110
                                    211
                                            0
                                                             144
                                                                       1
         ca thal
                    condition
      0
          1
                 0
      1
          2
                 0
                             0
      2
                             0
          0
                 0
      3
          1
                 0
                             1
      4
          0
                 0
                             0
```

10.1 Check Missing Values

```
[44]: print("Missing values in each column:")
print(data.isnull().sum())
```

```
Missing values in each column:
              0
age
              0
sex
              0
ср
              0
trestbps
chol
              0
fbs
              0
              0
restecg
thalach
              0
              0
exang
              0
oldpeak
slope
              0
ca
              0
thal
              0
              0
condition
dtype: int64
```

11 Basic Info and Description

max

2.000000

202.000000

```
[45]: print(data.info())
      print(data.describe())
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 297 entries, 0 to 296
     Data columns (total 14 columns):
           Column
                       Non-Null Count
                                        Dtype
      0
           age
                       297 non-null
                                        int64
      1
                       297 non-null
                                        int64
           sex
      2
                       297 non-null
                                        int64
           ср
      3
           trestbps
                       297 non-null
                                        int64
      4
           chol
                       297 non-null
                                        int64
      5
           fbs
                       297 non-null
                                        int64
      6
                       297 non-null
           restecg
                                        int64
      7
           thalach
                       297 non-null
                                        int64
      8
                       297 non-null
                                        int64
           exang
      9
           oldpeak
                                        float64
                       297 non-null
      10
           slope
                       297 non-null
                                        int64
      11
           ca
                       297 non-null
                                        int64
      12
                       297 non-null
           thal
                                        int64
      13
           condition
                      297 non-null
                                        int64
     dtypes: float64(1), int64(13)
     memory usage: 32.6 KB
     None
                                                      trestbps
                                                                       chol
                                                                                     fbs
                                                                                           \
                    age
                                 sex
                                                ср
     count
             297.000000
                          297.000000
                                       297.000000
                                                    297.000000
                                                                 297.000000
                                                                              297.000000
              54.542088
                            0.676768
                                         2.158249
                                                    131.693603
                                                                 247.350168
                                                                                0.144781
     mean
     std
               9.049736
                            0.468500
                                         0.964859
                                                     17.762806
                                                                  51.997583
                                                                                0.352474
     min
              29.000000
                            0.000000
                                         0.000000
                                                     94.000000
                                                                 126.000000
                                                                                0.000000
     25%
              48.000000
                            0.000000
                                         2.000000
                                                    120.000000
                                                                 211.000000
                                                                                0.000000
     50%
              56.000000
                            1.000000
                                         2.000000
                                                    130.000000
                                                                 243.000000
                                                                                0.000000
     75%
                            1.000000
                                         3.000000
                                                    140.000000
              61.000000
                                                                 276.000000
                                                                                0.000000
              77.000000
                            1.000000
                                         3.000000
                                                    200.000000
                                                                 564.000000
                                                                                1.000000
     max
                                                       oldpeak
                restecg
                             thalach
                                            exang
                                                                      slope
                                                                                      ca
             297.000000
                          297.000000
                                                    297.000000
                                                                 297.000000
     count
                                       297.000000
                                                                              297.000000
     mean
               0.996633
                          149.599327
                                         0.326599
                                                      1.055556
                                                                   0.602694
                                                                                0.676768
     std
               0.994914
                           22.941562
                                         0.469761
                                                      1.166123
                                                                   0.618187
                                                                                0.938965
     min
               0.000000
                           71.000000
                                         0.000000
                                                      0.00000
                                                                   0.000000
                                                                                0.000000
     25%
               0.000000
                          133.000000
                                         0.000000
                                                      0.00000
                                                                   0.000000
                                                                                0.000000
     50%
               1.000000
                          153.000000
                                         0.000000
                                                      0.800000
                                                                   1.000000
                                                                                0.00000
     75%
                          166.000000
                                         1.000000
                                                      1.600000
                                                                   1.000000
                                                                                1.000000
               2.000000
```

6.200000

2.000000

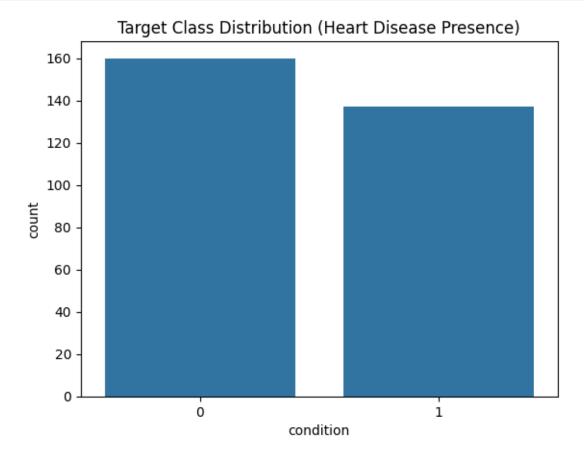
3.000000

1.000000

	thal	condition
count	297.000000	297.000000
mean	0.835017	0.461279
std	0.956690	0.499340
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	2.000000	1.000000
max	2.000000	1.000000

12 Visualize Target Distribution

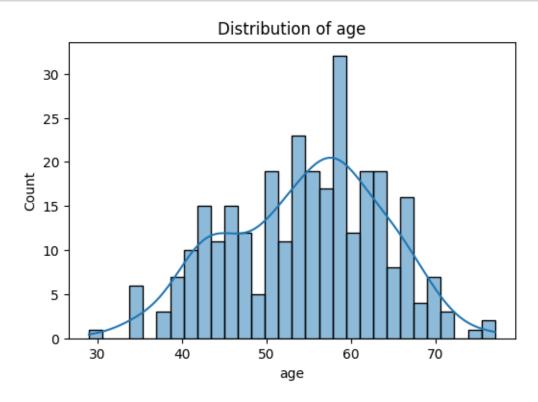
```
[48]: sns.countplot(x='condition', data=data)
  plt.title('Target Class Distribution (Heart Disease Presence)')
  plt.show()
```

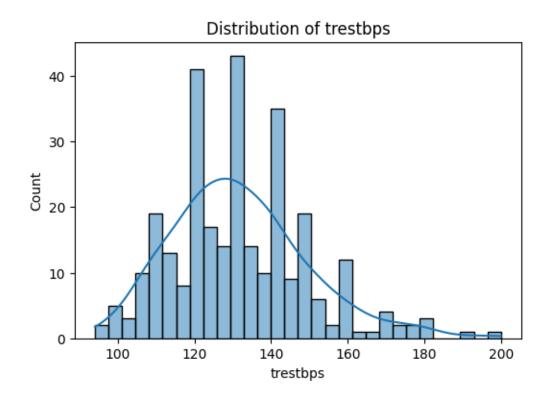


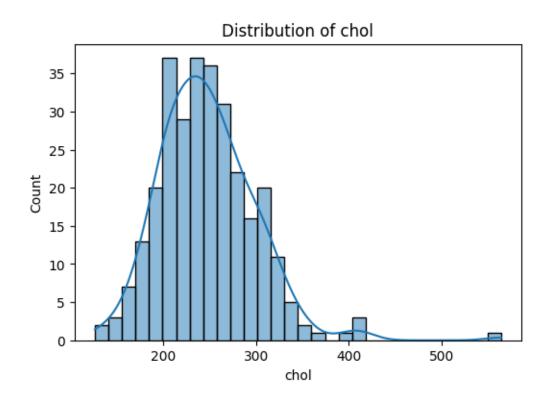
13 Distribution of Numerical Features

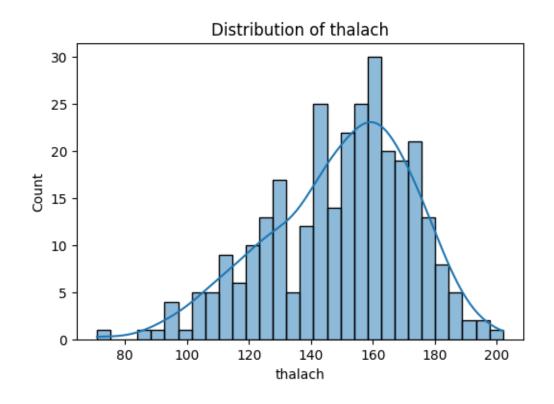
```
[59]: numerical_cols = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']

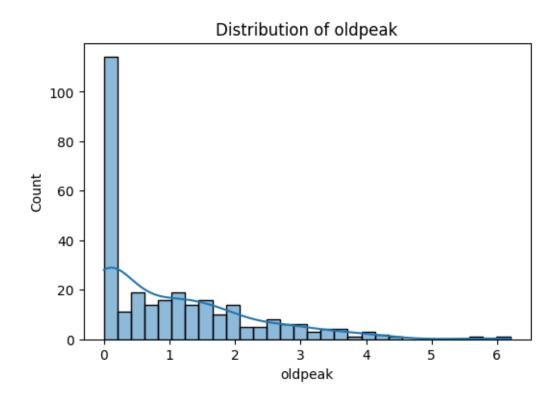
for col in numerical_cols:
   plt.figure(figsize=(6, 4))
   sns.histplot(data[col], kde=True, bins=30)
   plt.title(f'Distribution of {col}')
   plt.show()
```





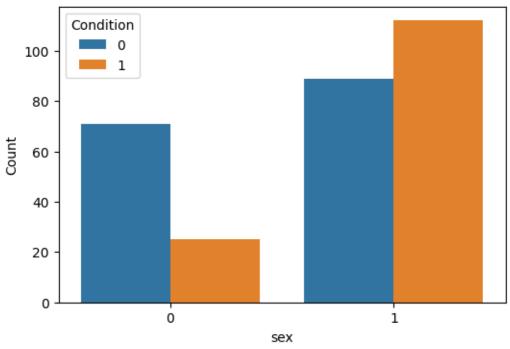


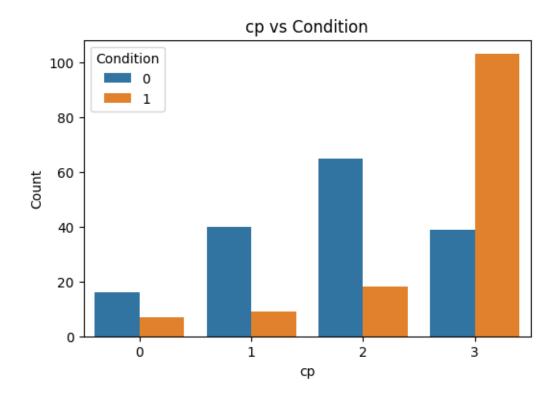


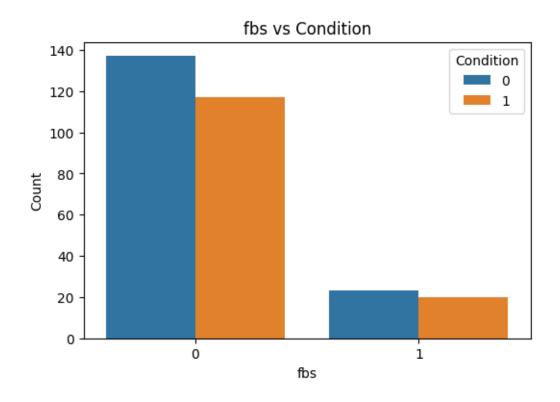


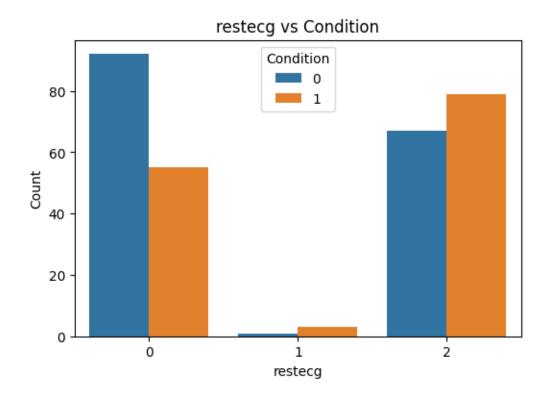
14 Categorical Features vs Target

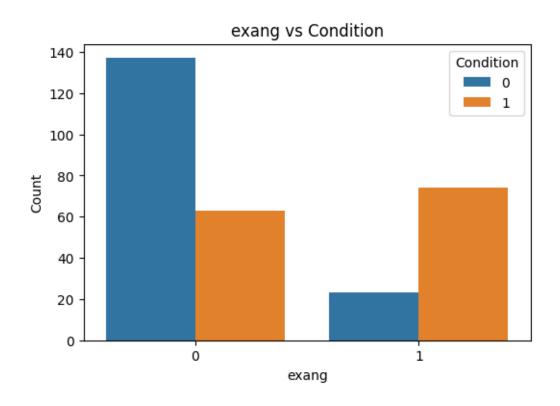
sex vs Condition

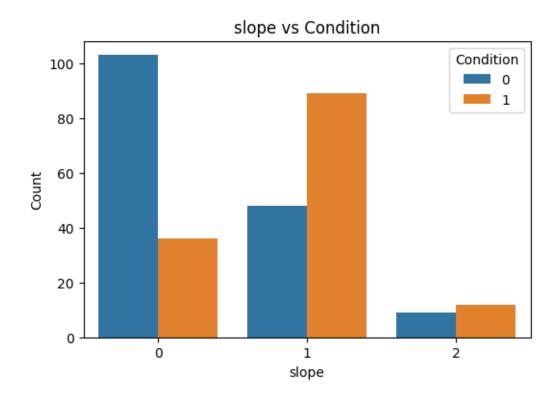


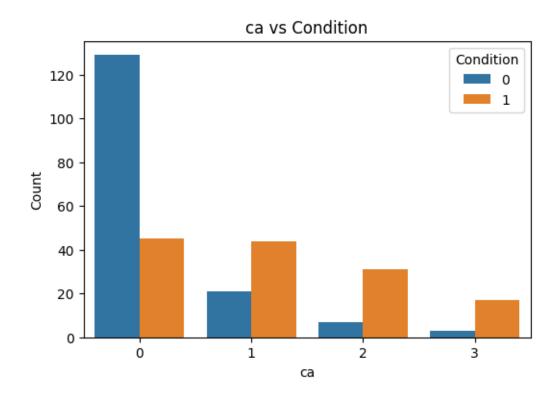


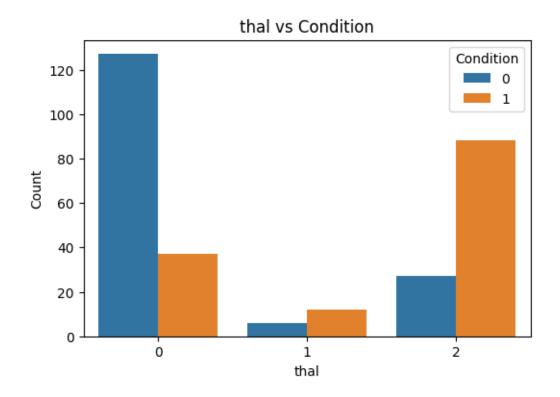






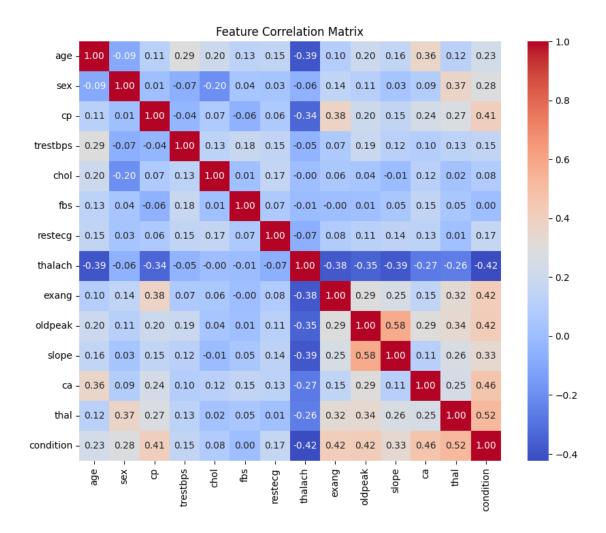






15 Correlation Heatmap

```
[49]: plt.figure(figsize=(10,8))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Feature Correlation Matrix')
plt.show()
```



16 Prepare Data for Modeling

17 Train Logistic Regression Model

```
[53]: model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

```
[53]: LogisticRegression(max_iter=1000)
```

18 Make Predictions and Evaluate

```
[54]: y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

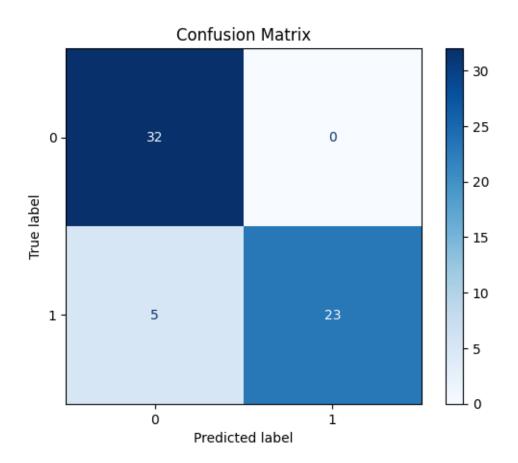
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_prob)

print(f'Accuracy: {accuracy:.4f}')
print(f'ROC AUC: {roc_auc:.4f}')
```

Accuracy: 0.9167 ROC AUC: 0.9509

19 Plot Confusion Matrix

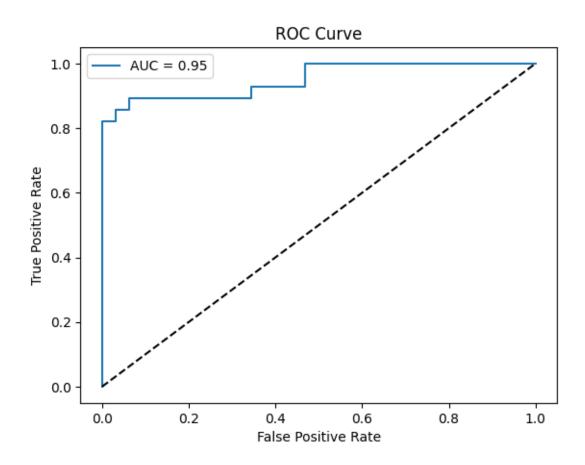
```
[55]: cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot(cmap='Blues')
    plt.title('Confusion Matrix')
    plt.show()
```



20 Plot ROC Curve

```
[56]: fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')
plt.plot([0,1], [0,1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```



21 Feature Importance (Logistic Regression Coefficients)

```
[57]: features = X.columns
    coefficients = model.coef_[0]

importance_df = pd.DataFrame({'Feature': features, 'Coefficient': coefficients})
importance_df['AbsCoefficient'] = importance_df['Coefficient'].abs()
importance_df = importance_df.sort_values(by='AbsCoefficient', ascending=False)

print("Important Features (based on logistic regression coefficients):")
print(importance_df[['Feature', 'Coefficient']])
```

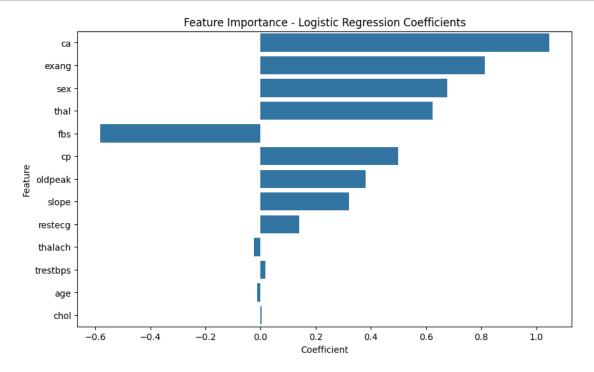
Important Features (based on logistic regression coefficients):

```
Feature
              Coefficient
11
                  1.046757
          ca
8
       exang
                  0.812330
1
                  0.675442
         sex
12
        thal
                  0.623016
5
         fbs
                 -0.582774
```

```
2
                  0.498075
           ср
9
     oldpeak
                  0.379411
10
       slope
                  0.320660
6
     restecg
                  0.139551
7
     thalach
                 -0.023170
3
    trestbps
                  0.017056
0
         age
                 -0.013472
                  0.002924
4
         chol
```

22 Visualize Feature Importance

```
[58]: plt.figure(figsize=(10,6))
    sns.barplot(x='Coefficient', y='Feature', data=importance_df)
    plt.title('Feature Importance - Logistic Regression Coefficients')
    plt.show()
```



```
[62]: import getpass
username = "zoya4477"
token = getpass.getpass("Enter your GitHub token: ")

Enter your GitHub token: ........
```