Connect With Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

This is Necessery Library and other resoursc

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
```

Read Data from CSV File

```
csv_file_path = '/content/drive/MyDrive/DIU/Registured Course /7th Semester/Artificial Intelligence Lab/Lab Performance 2/UCI H
df = pd.read_csv(csv_file_path)
df.head()
```

	id	age	sex	dataset	cp	trestbps	chol	fbs	restecg	thalch	exang	oldpeak	slope	ca	thal	r
0	1	63	Male	Cleveland	typical angina	145.0	233.0	True	lv hypertrophy	150.0	False	2.3	downsloping	0.0	fixed defect	
1	2	67	Male	Cleveland	asymptomatic	160.0	286.0	False	lv hypertrophy	108.0	True	1.5	flat	3.0	normal	
2	3	67	Male	Cleveland	asymptomatic	120.0	229.0	False	lv hypertrophy	129.0	True	2.6	flat	2.0	reversable defect	

Next steps: Generate code with df New interactive sheet

Data Cleaning , Drop Unnecessery Data

```
df = df.drop(['id'], axis=1)
```

Checking null Value

```
print(df.isnull().sum())
df.shape
```

```
age          0
sex          0
dataset      0
cp           0
trestbps    59
chol        30
fbs         90
restecg      2
thalch      55
```

```
exang        55
oldpeak      62
slope       309
ca          611
thal        486
num           0
dtype: int64
(920, 15)
```

Delete Null Value of of the row

```
df = df.dropna()
print(df.isnull().sum())
df.shape
```

```
age         0
sex         0
dataset     0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalch      0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
num         0
dtype: int64
(299, 15)
```

Remove Duplicate row

```
print(f"Shape before removing duplicates: {df.shape}")
df = df.drop_duplicates()
print(f"Shape after removing duplicates: {df.shape}")
```

```
Shape before removing duplicates: (299, 15)
Shape after removing duplicates: (299, 15)
```

Current Data Type

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 299 entries, 0 to 748
Data columns (total 15 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       299 non-null    int64  
 1   sex       299 non-null    object 
 2   dataset   299 non-null    object 
 3   cp        299 non-null    object 
 4   trestbps  299 non-null    float64
 5   chol      299 non-null    float64
 6   fbs       299 non-null    object 
 7   restecg   299 non-null    object 
 8   thalch    299 non-null    float64
 9   exang     299 non-null    object 
 10  oldpeak   299 non-null    float64
 11  slope     299 non-null    object 
 12  ca        299 non-null    float64
 13  thal      299 non-null    object 
 14  num       299 non-null    int64  
dtypes: float64(5), int64(2), object(8)
memory usage: 37.4+ KB
```

Set Feature X and Target Y

```
X = df.drop(['num'], axis=1)
Y= df['num']
```

LabelEncoder

```
from sklearn.preprocessing import LabelEncoder

categorical_cols = X.select_dtypes(include=['object', 'bool']).columns

binary_cols = []
multi_class_cols = []

for col in categorical_cols:
    if X[col].nunique() <= 2:
        binary_cols.append(col)
    else:
        multi_class_cols.append(col)

print(f"Binary categorical columns: {binary_cols}")
print(f"Multi-class categorical columns: {multi_class_cols}")
```

```
Binary categorical columns: ['sex', 'fbs', 'exang']
Multi-class categorical columns: ['dataset', 'cp', 'restecg', 'slope', 'thal']
```

```
label_encoder = LabelEncoder()
for col in binary_cols:
    X[col] = label_encoder.fit_transform(X[col])

X = pd.get_dummies(X, columns=multi_class_cols, drop_first=True)

display(X.head())
```

	age	sex	trestbps	chol	fbs	thalch	exang	oldpeak	ca	dataset_Hungary	dataset_VA Long Beach	cp_atypical angina	cp_non-anginal	cp_typical angina	rest
0	63	1	145.0	233.0	1	150.0	0	2.3	0.0	False	False	False	False	True	
1	67	1	160.0	286.0	0	108.0	1	1.5	3.0	False	False	False	False	False	
2	67	1	120.0	229.0	0	129.0	1	2.6	2.0	False	False	False	False	False	
3	37	1	130.0	250.0	0	187.0	0	3.5	0.0	False	False	False	True	False	
4	41	0	130.0	204.0	0	172.0	0	1.4	0.0	False	False	True	False	False	

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 299 entries, 0 to 748
Data columns (total 20 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   age                      299 non-null    int64
 1   sex                      299 non-null    int64
 2   trestbps                 299 non-null    float64
 3   chol                     299 non-null    float64
 4   fbs                      299 non-null    int64
 5   thalch                   299 non-null    float64
 6   exang                    299 non-null    int64
 7   oldpeak                  299 non-null    float64
 8   ca                       299 non-null    float64
 9   dataset_Hungary          299 non-null    bool
 10  dataset_VA Long Beach    299 non-null    bool
 11  cp_atypical angina       299 non-null    bool
 12  cp_non-anginal           299 non-null    bool
 13  cp_typical angina        299 non-null    bool
 14  restecg_normal           299 non-null    bool
 15  restecg_st-t abnormality  299 non-null    bool
 16  slope_flat               299 non-null    bool
 17  slope_upsloping          299 non-null    bool
 18  thal_normal              299 non-null    bool
 19  thal_reversable defect   299 non-null    bool
dtypes: bool(11), float64(5), int64(4)
memory usage: 26.6 KB
```

Feature Scaling with StandardScaler

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Convert the scaled array back to a DataFrame with original column names
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)

display(X_scaled.head())
```

	age	sex	trestbps	chol	fbs	thalch	exang	oldpeak	ca	dataset_Hungary	dataset_VA Long Beach	cp_aty a
0	0.940446	0.687682	0.749760	-0.262867	2.439977	0.029124	-0.703562	1.069475	-0.718306	-0.057928	-0.057928	-0.4
1	1.384143	0.687682	1.596354	0.747722	-0.409840	-1.790447	1.421338	0.380309	2.487269	-0.057928	-0.057928	-0.4
2	1.384143	0.687682	-0.661231	-0.339138	-0.409840	-0.880662	1.421338	1.327912	1.418744	-0.057928	-0.057928	-0.4
3	-1.943588	0.687682	-0.096835	0.061285	-0.409840	1.632079	-0.703562	2.103224	-0.718306	-0.057928	-0.057928	-0.4
4	-1.499891	-1.454161	-0.096835	-0.815830	-0.409840	0.982232	-0.703562	0.294163	-0.718306	-0.057928	-0.057928	2.2

Training Dataset

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2 , random_state=42)
```

4. Apply Five Machine Learning Algorithms

Logistic Regression

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
logistic_model = LogisticRegression(max_iter=1000, random_state=42)
logistic_model.fit(X_train_scaled, Y_train)
Y_pred_lr = logistic_model.predict(X_test_scaled)

accuracy_lr = accuracy_score(Y_test, Y_pred_lr)
print(f"Accuracy: {accuracy_lr}")
```

```
Accuracy: 0.6166666666666667
```

K-Nearest Neighbors (KNN)

```
from sklearn.neighbors import KNeighborsClassifier

scaler = StandardScaler()
X_train_scaled_knn = scaler.fit_transform(X_train)
X_test_scaled_knn = scaler.transform(X_test)

knn_model = KNeighborsClassifier()

knn_model.fit(X_train_scaled_knn, Y_train)
Y_pred_knn = knn_model.predict(X_test_scaled_knn)

accuracy_knn = accuracy_score(Y_test, Y_pred_knn)
print(f"KNN Accuracy: {accuracy_knn}")
```

```
KNN Accuracy: 0.5833333333333334
```

Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier

decision_tree_model = DecisionTreeClassifier(random_state=42)
decision_tree_model.fit(X_train_scaled, Y_train)
Y_pred_dt = decision_tree_model.predict(X_test_scaled)
accuracy_dt = accuracy_score(Y_test, Y_pred_dt)
print(f"Decision Tree Accuracy: {accuracy_dt}")
```

```
Decision Tree Accuracy: 0.5166666666666667
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

random_forest_model = RandomForestClassifier(random_state=42)
random_forest_model.fit(X_train_scaled, Y_train)
Y_pred_rf = random_forest_model.predict(X_test_scaled)

accuracy_rf = accuracy_score(Y_test, Y_pred_rf)
print(f"Random Forest Accuracy: {accuracy_rf}")
```

```
Random Forest Accuracy: 0.6166666666666667
```

Support Vector Machine (SVM)

```
from sklearn.svm import SVC
svm_model = SVC(random_state=42)
svm_model.fit(X_train_scaled, Y_train)
Y_pred_svm = svm_model.predict(X_test_scaled)
accuracy_svm = accuracy_score(Y_test, Y_pred_svm)
print(f"SVM Accuracy: {accuracy_svm}")
```

```
SVM Accuracy: 0.6
```

5. Model Result Analysis (Mandatory)

Confusion Matrix for Logistic Regression

```
print("Confusion Matrix for Logistic Regression:\n", confusion_matrix(Y_test, Y_pred_lr))
```

```
Confusion Matrix for Logistic Regression:
 [[32  2  1  0  0]
 [ 2  5  2  4  0]
 [ 1  2  0  1  1]
 [ 0  2  1  0  1]
 [ 1  0  1  1  0]]
```

Confusion Matrix for K-Nearest Neighbors

```
print("Confusion Matrix for K-Nearest Neighbors:\n", confusion_matrix(Y_test, Y_pred_knn))
```

```
Confusion Matrix for K-Nearest Neighbors:
 [[31  2  1  1  0]
 [ 4  3  3  3  0]
 [ 1  2  1  0  1]
 [ 1  1  2  0  0]
 [ 0  2  0  1  0]]
```

Confusion Matrix for Decision Tree

```
print("Confusion Matrix for Decision Tree:\n", confusion_matrix(Y_test, Y_pred_dt))
```

```
Confusion Matrix for Decision Tree:
 [[28  4  2  1  0]
 [ 3  0  5  3  2]
 [ 0  1  2  2  0]
 [ 0  2  1  1  0]
 [ 0  2  1  0  0]]
```

Confusion Matrix for Random Forest Classifier

```
print("Confusion Matrix for Decision Tree:\n", confusion_matrix(Y_test, Y_pred_rf))
```

```
Confusion Matrix for Decision Tree:
 [[33  2  0  0  0]
 [ 7  1  4  1  0]
 [ 1  1  3  0  0]
 [ 1  2  1  0  0]
 [ 0  1  2  0  0]]
```

Precision, Recall, F1-score

Logistic Regression

```
report_lr = classification_report(Y_test, Y_pred_lr, output_dict=True)
precision_lr = report_lr['weighted avg']['precision']
recall_lr = report_lr['weighted avg']['recall']
f1_score_lr = report_lr['weighted avg']['f1-score']

print(f"Logistic Regression Precision (weighted avg): {precision_lr:.2f}")
print(f"Logistic Regression Recall (weighted avg): {recall_lr:.2f}")
print(f"Logistic Regression F1-score (weighted avg): {f1_score_lr:.2f}")
```

```
Logistic Regression Precision (weighted avg): 0.62
Logistic Regression Recall (weighted avg): 0.62
Logistic Regression F1-score (weighted avg): 0.62
```

K-Nearest Neighbors

```
report_knn = classification_report(Y_test, Y_pred_knn, output_dict=True)
precision_knn = report_knn['weighted avg']['precision']
recall_knn = report_knn['weighted avg']['recall']
f1_score_knn = report_knn['weighted avg']['f1-score']

print(f"K-Nearest Neighbors Precision (weighted avg): {precision_knn:.2f}")
print(f"K-Nearest Neighbors Recall (weighted avg): {recall_knn:.2f}")
print(f"K-Nearest Neighbors F1-score (weighted avg): {f1_score_knn:.2f}")
```

```
K-Nearest Neighbors Precision (weighted avg): 0.57
K-Nearest Neighbors Recall (weighted avg): 0.58
K-Nearest Neighbors F1-score (weighted avg): 0.57
```

Decision Tree Precision

```
report_dt = classification_report(Y_test, Y_pred_dt, output_dict=True)
precision_dt = report_dt['weighted avg']['precision']
recall_dt = report_dt['weighted avg']['recall']
f1_score_dt = report_dt['weighted avg']['f1-score']

print(f"Decision Tree Precision (weighted avg): {precision_dt:.2f}")
print(f"Decision Tree Recall (weighted avg): {recall_dt:.2f}")
print(f"Decision Tree F1-score (weighted avg): {f1_score_dt:.2f}")
```

```
Decision Tree Precision (weighted avg): 0.55
Decision Tree Recall (weighted avg): 0.52
Decision Tree F1-score (weighted avg): 0.53
```

Random Forest Classifier

```
report_rf = classification_report(Y_test, Y_pred_dt, output_dict=True)
precision_rf = report_rf['weighted avg']['precision']
```

```
recall_rf = report_rf['weighted avg']['recall']
f1_score_rf = report_rf['weighted avg']['f1-score']

print(f"Decision Tree Precision (weighted avg): {precision_rf:.2f}")
print(f"Decision Tree Recall (weighted avg): {recall_rf:.2f}")
print(f"Decision Tree F1-score (weighted avg): {f1_score_rf:.2f}")
```

```
Decision Tree Precision (weighted avg): 0.55
Decision Tree Recall (weighted avg): 0.52
Decision Tree F1-score (weighted avg): 0.53
```

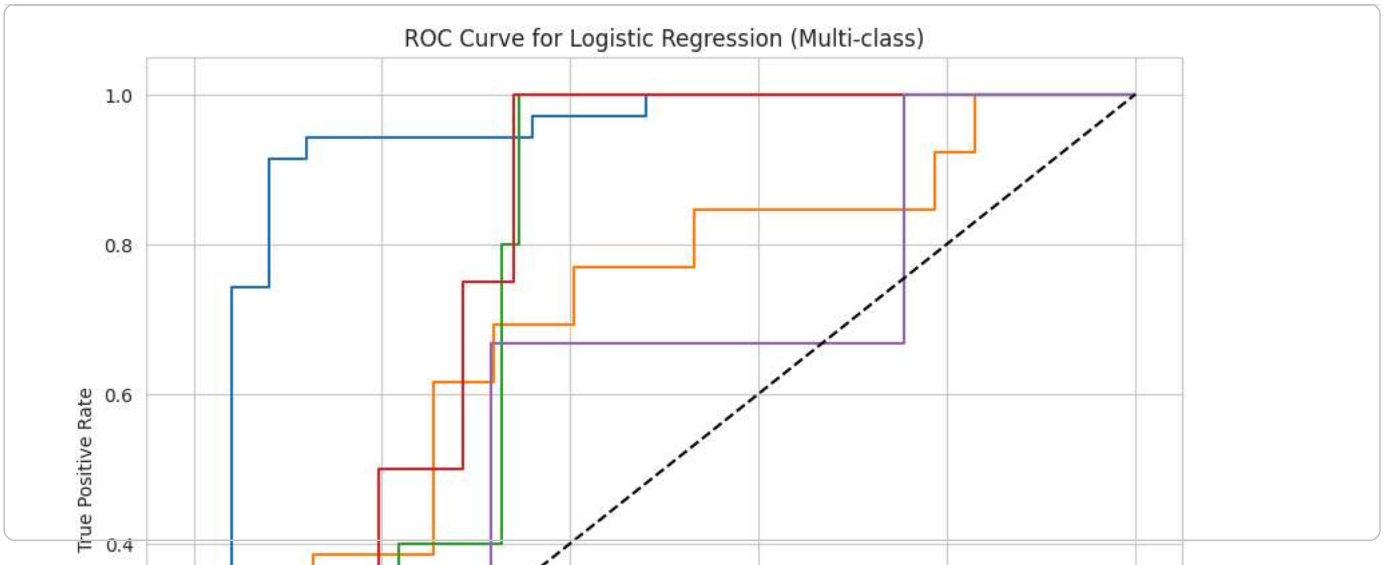
Support Vector Machine Precision

```
report_svm = classification_report(Y_test, Y_pred_svm, output_dict=True)
precision_svm = report_svm['weighted avg']['precision']
recall_svm = report_svm['weighted avg']['recall']
f1_score_svm = report_svm['weighted avg']['f1-score']

print(f"Support Vector Machine Precision (weighted avg): {precision_svm:.2f}")
print(f"Support Vector Machine Recall (weighted avg): {recall_svm:.2f}")
print(f"Support Vector Machine F1-score (weighted avg): {f1_score_svm:.2f}")
```

```
Support Vector Machine Precision (weighted avg): 0.54
Support Vector Machine Recall (weighted avg): 0.60
Support Vector Machine F1-score (weighted avg): 0.56
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-define
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-define
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-define
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

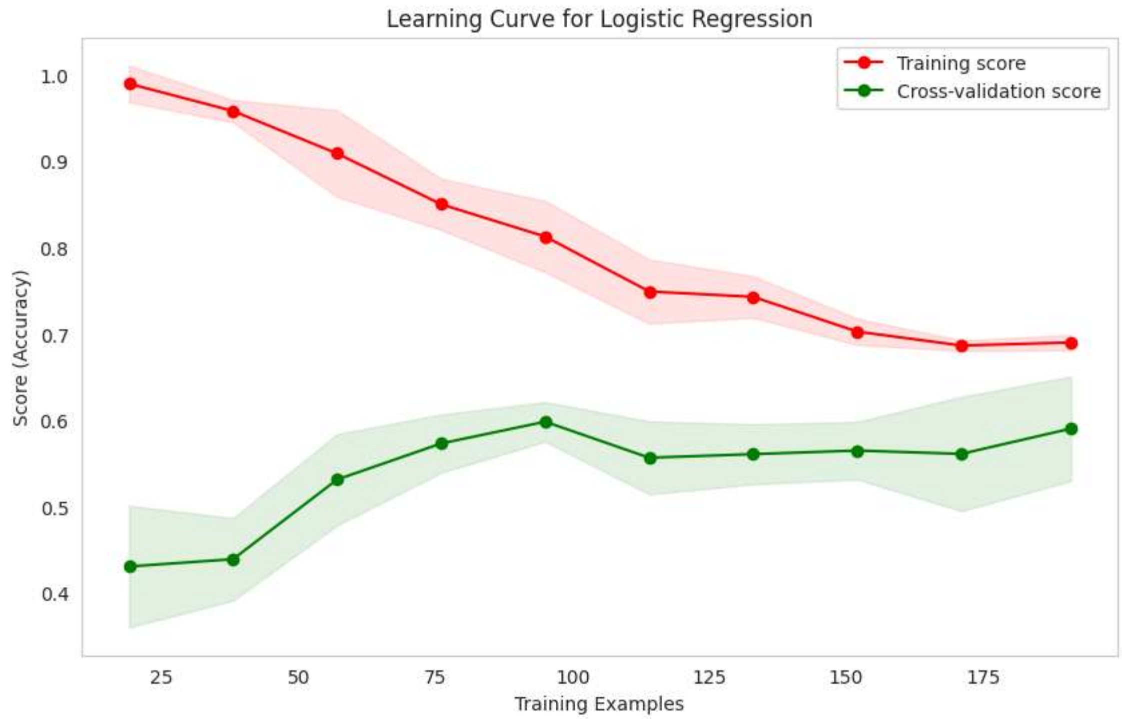
ROC Curve (at least one classifier)

```
from sklearn.metrics import roc_curve, auc

# Get predicted probabilities for each class
Y_pred_proba_lr = logistic_model.predict_proba(X_test_scaled)
# Get the number of classes
n_classes = Y.nunique()
fpr = dict()
tpr = dict()
roc_auc = dict()
plt.figure(figsize=(10, 8))
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(Y_test, Y_pred_proba_lr[:, i], pos_label=i)
    roc_auc[i] = auc(fpr[i], tpr[i])

    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Logistic Regression (Multi-class)')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Loss vs Validation Loss Curve (or Learning Curve)

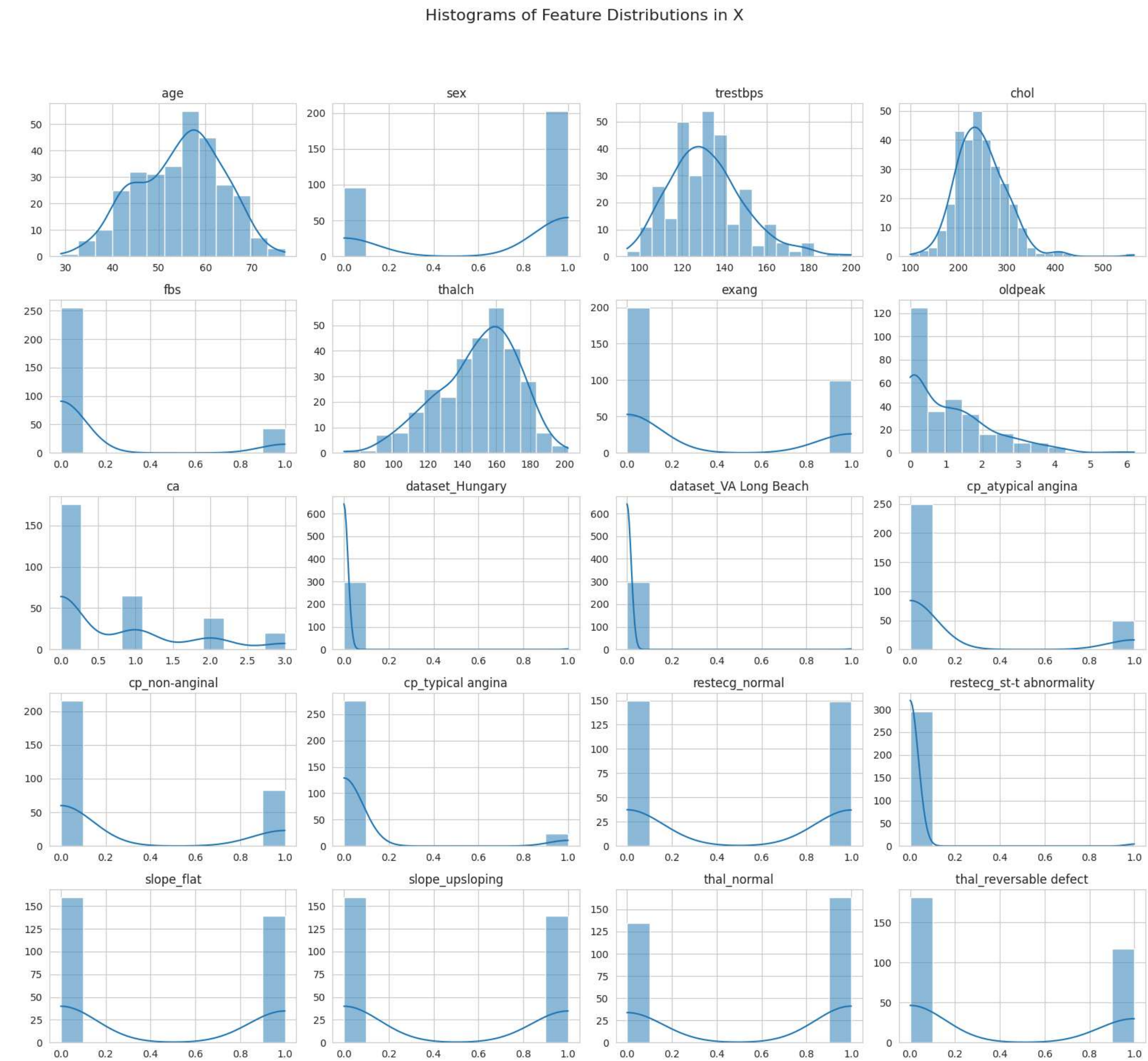
```
from sklearn.model_selection import learning_curve
import numpy as np
import matplotlib.pyplot as plt

# Define the model (Logistic Regression in this case)
model_lr = LogisticRegression(max_iter=1000, random_state=42)

train_sizes, train_scores, test_scores = learning_curve(
    model_lr, X_train_scaled, Y_train, cv=5, n_jobs=-1, scoring='accuracy',
    train_sizes=np.linspace(0.1, 1.0, 10), random_state=42
)

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

# Plot the learning curve
plt.figure(figsize=(10, 6))
plt.title('Learning Curve for Logistic Regression')
plt.xlabel('Training Examples')
plt.ylabel('Score (Accuracy)')
plt.grid()

plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1, color='r')
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color='g')
plt.plot(train_sizes, train_scores_mean, 'o-', color='r', label='Training score')
plt.plot(train_sizes, test_scores_mean, 'o-', color='g', label='Cross-validation score')

plt.legend(loc='best')
plt.show()
```



6. Visualization Requirements

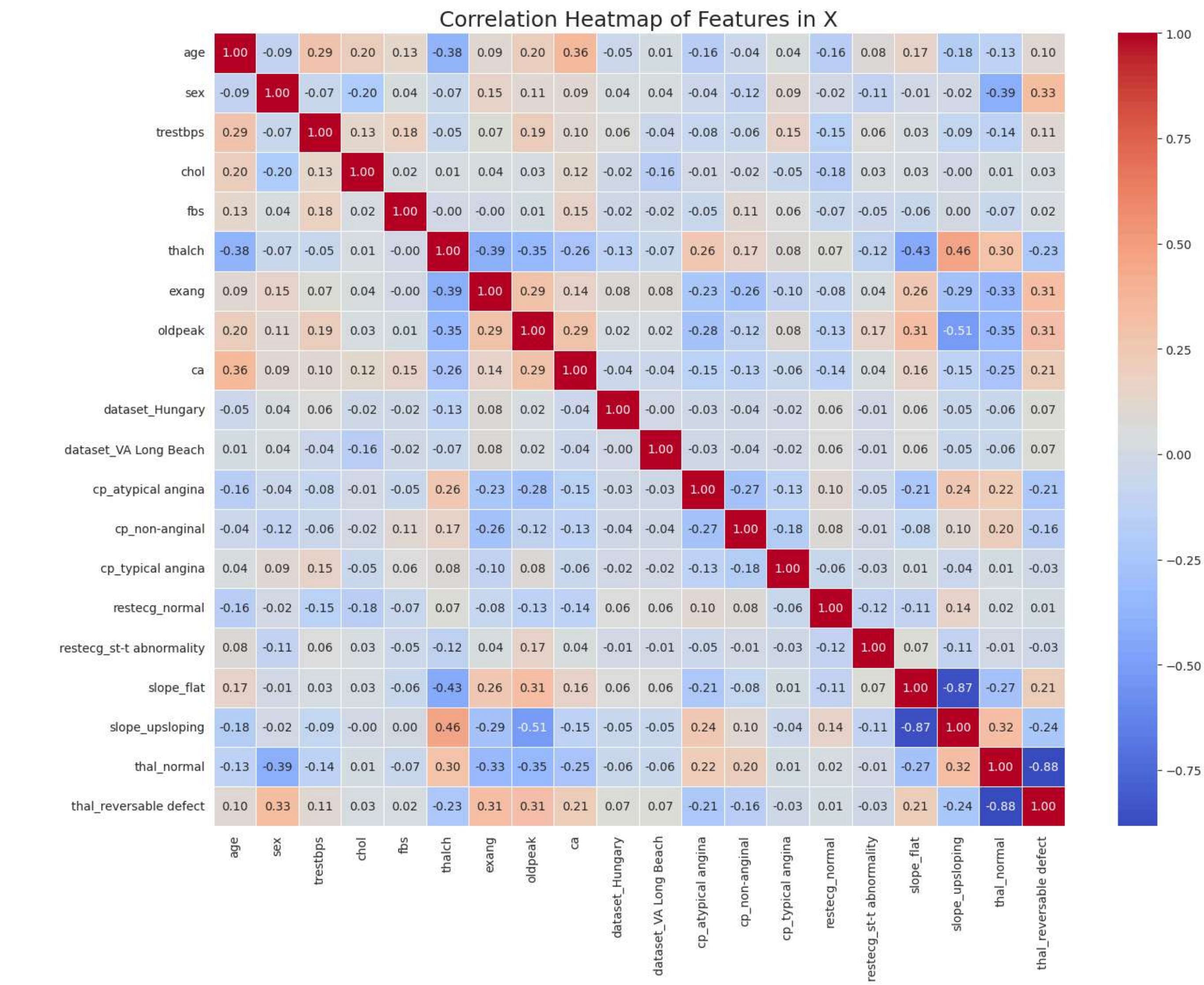
Histograms for Feature Distribution

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style("whitegrid")

num_features = X.shape[1]
n_cols = 4  # You can adjust this for optimal layout
n_rows = (num_features + n_cols - 1) // n_cols

plt.figure(figsize=(n_cols * 4, n_rows * 3))
plt.suptitle('Histograms of Feature Distributions in X', y=1.02, fontsize=16)

for i, column in enumerate(X.columns):
    plt.subplot(n_rows, n_cols, i + 1)
    sns.histplot(X[column], kde=True)
    plt.title(column)
    plt.xlabel('') # Remove x-label to avoid clutter
    plt.ylabel('')

plt.tight_layout(rect=[0, 0.03, 1, 0.98])
plt.show()
```



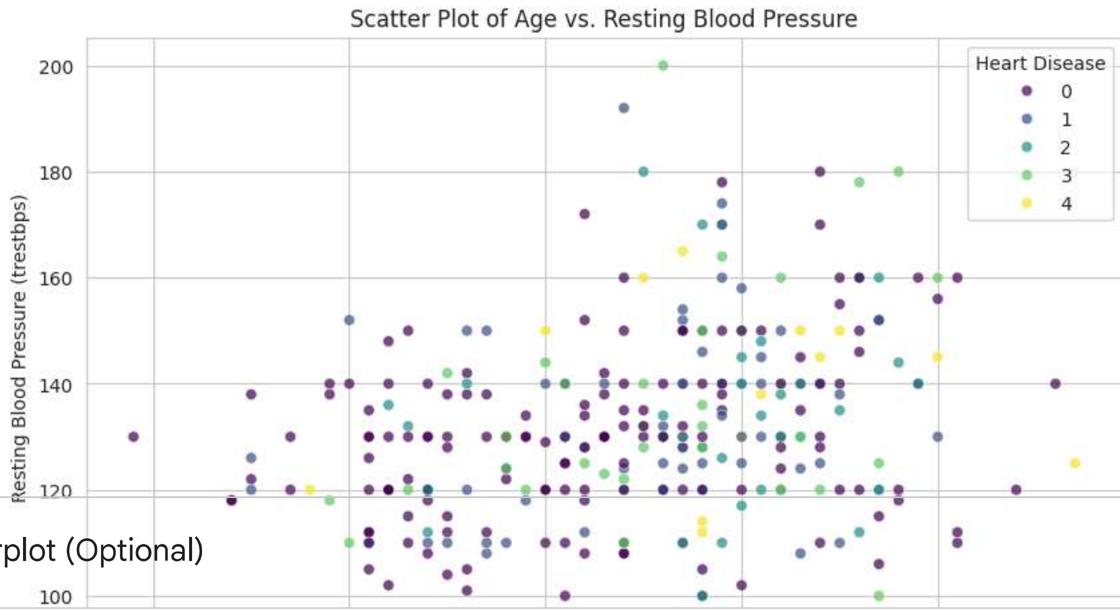
Correlation Heatmap

```
import seaborn as sns
import matplotlib.pyplot as plt

correlation_matrix = X.corr()

plt.figure(figsize=(16, 12))

sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Heatmap of Features in X', fontsize=18)
plt.show()
```



Scatter Plots

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.scatterplot(x='age', y='trestbps', data=X, hue=Y, palette='viridis', alpha=0.7)
plt.title('Scatter Plot of Age vs. Resting Blood Pressure')
plt.xlabel('Age')
plt.ylabel('Resting Blood Pressure (trestbps)')
plt.grid(True)
plt.legend(title='Heart Disease')
plt.show()
```



Pairplot (Optional)

```
import seaborn as sns
import matplotlib.pyplot as plt

selected_features = ['age', 'trestbps', 'chol', 'thalch', 'oldpeak', 'sex', 'fbs']
df_subset = X[selected_features].copy()
df_subset['num'] = Y # Add the target variable to color the points

plt.figure(figsize=(15, 15))
sns.pairplot(df_subset, hue='num', palette='viridis', diag_kind='kde')
plt.suptitle('Pairplot of Selected Features in X', y=1.02, fontsize=18)
plt.show()
```

```
<Figure size 1500x1500 with 0 Axes>
```