```
In [283]: import numpy as np # linear algebra
          import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
          import matplotlib.pyplot as plt
          import seaborn as sns
In [182]: from pathlib import Path
          input_dir = Path('/Users/pavangedala/Documents/Self Projects /Heart Atta
          for file path in input dir.rglob('*'):
              if file path.is file():
                  print(file path)
In [183]: from sklearn.linear model import LogisticRegression
          from sklearn.preprocessing import StandardScaler
          from sklearn.model selection import train test split, GridSearchCV
          from sklearn.metrics import accuracy_score, roc_curve
In [184]: import warnings
          warnings.filterwarnings("ignore")
In [185]: import os
          file path = "/Users/pavangedala/Documents/Self Projects/Heart Attack Dat
          if os.path.exists(file path):
              df = pd.read csv(file path)
          else:
              print("File not found! Check the file path.")
          File not found! Check the file path.
In [186]: | import os
          for dirname, _, filenames in os.walk('/Users/pavangedala/Documents/Self
              for filename in filenames:
                  print(os.path.join(dirname, filename))
In [187]: #Read and Analyse Data
In [188]:
          df = pd.read csv("/content/heart.csv")
```

In [189]: df.head()

Out[189]:

	age	sex	ср	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

In [190]: df.describe()

Out[190]:

	age	sex	ср	trtbps	chol	fbs	restecg	tha
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.6
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.9
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.0
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.5
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.0
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.0
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.0

In [191]: # information about data frame df.info()

> <class 'pandas.core.frame.DataFrame'> RangeIndex: 303 entries, 0 to 302 Data columns (total 14 columns):

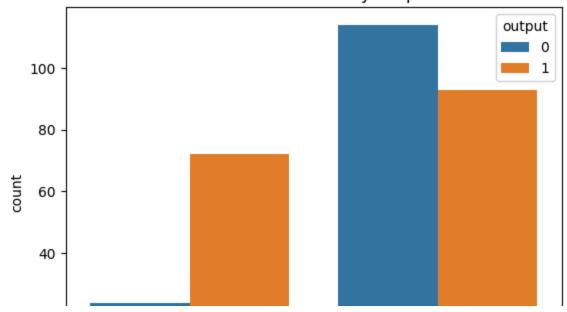
#	Column	Non-Null Count	Dtype
0	age	303 non-null	int64
1	sex	303 non-null	int64
2	ср	303 non-null	int64
3	trtbps	303 non-null	int64
4	chol	303 non-null	int64
5	fbs	303 non-null	int64
6	restecg	303 non-null	int64
7	thalachh	303 non-null	int64
8	exng	303 non-null	int64
9	oldpeak	303 non-null	float64
10	slp	303 non-null	int64
11	caa	303 non-null	int64
12	thall	303 non-null	int64
13	output	303 non-null	int64

dtypes: float64(1), int64(13)

memory usage: 33.3 KB

```
In [192]: #Missing Value Analysis¶
In [193]: | df.isnull().sum()
Out[193]:
                   0
               age
                   0
               sex 0
                cp 0
             trtbps 0
               chol 0
               fbs
                   0
            restecg 0
           thalachh 0
              exng 0
            oldpeak 0
                slp 0
               caa 0
               thall 0
             output 0
           dtype: int64
In [194]: #Unique Value Analysis¶
In [195]: for i in list(df.columns):
               print("{} -- {}".format(i, df[i].value_counts().shape[0]))
           age -- 41
           sex -- 2
           cp -- 4
           trtbps -- 49
           chol -- 152
           fbs -- 2
           restecg -- 3
           thalachh -- 91
           exng -- 2
           oldpeak -- 40
           slp -- 3
           caa -- 5
           thall -- 4
           output -- 2
```

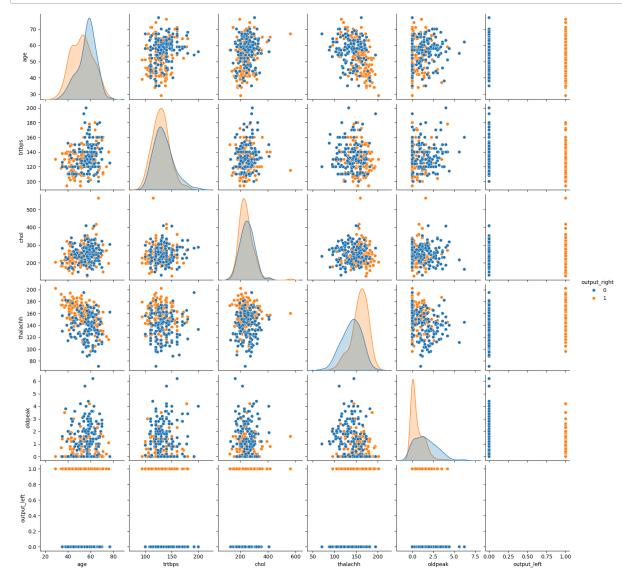
Distribution of sex by Output



In [199]: #Numeric Feature Analysis #Bivariate data analysis with scatter plot

In [200]: numeric_list = ["age", "trtbps","chol","thalachh","oldpeak","output"]

In [201]: df_numeric = df[numeric_list]
Use the merge function instead of join and specify suffixes for overla
result = pd.merge(df_numeric, df['output'], left_index=True, right_index=
Plot the result using sns.pairplot
sns.pairplot(result, hue='output_right', diag_kind='kde') # Use the corr
plt.show()



In [202]: #Standardization¶

In [203]: scaler = StandardScaler()
scaler

Out[203]: StandardScaler()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

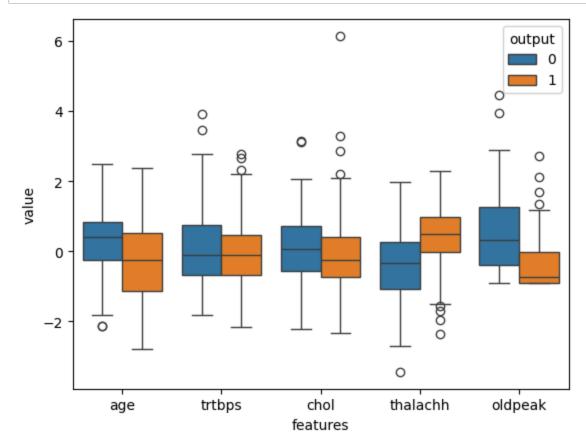
```
In [204]: | scaled_array = scaler.fit_transform(df[numeric_list[:-1]])
In [205]: scaled array
Out[205]: array([[ 0.9521966 ,  0.76395577, -0.25633371,
                                                                0.01544279,
                                                                              1.0873380
           6],
                   [-1.91531289, -0.09273778, 0.07219949,
                                                                1.63347147,
                                                                              2.1225727
           3],
                   [-1.47415758, -0.09273778, -0.81677269, 0.97751389,
                                                                              0.3109120
           6],
                   [ 1.50364073, 0.70684287, -1.029353 , -0.37813176, 2.0363031
           7],
                   [0.29046364, -0.09273778, -2.2275329, -1.51512489, 0.1383729]
           5],
                   [ 0.29046364, -0.09273778, -0.19835726, 1.0649749 , -0.8968617
           2]])
In [206]: # pd.DataFrame(scaled array).describe()
In [207]: #Box Plot Analysis¶
In [208]: df dummy = pd.DataFrame(scaled array, columns = numeric list[:-1])
           df dummy.head()
Out[208]:
                          trtbps
                                    chol thalachh
                                                  oldpeak
                   age
              0.952197
                        0.763956 -0.256334 0.015443
                                                 1.087338
            1 -1.915313 -0.092738 0.072199 1.633471
                                                 2.122573
            2 -1.474158 -0.092738 -0.816773 0.977514
                                                 0.310912
            3 0.180175 -0.663867 -0.198357 1.239897 -0.206705
            4 0.290464 -0.663867 2.082050 0.583939 -0.379244
In [209]:
           df_dummy = pd.concat([df_dummy, df.loc[:, "output"]], axis = 1)
           df dummy.head()
Out [209]:
                                                  oldpeak output
                   age
                          trtbps
                                    chol thalachh
               0.952197
                        0.763956 -0.256334
                                        0.015443
                                                 1.087338
                                                             1
            1 -1.915313 -0.092738
                                0.072199 1.633471
                                                 2.122573
                                                             1
            2 -1.474158 -0.092738 -0.816773 0.977514
                                                 0.310912
                                                             1
            3 0.180175 -0.663867 -0.198357 1.239897
                                                -0.206705
                                                             1
            4 0.290464 -0.663867 2.082050 0.583939 -0.379244
```

In [210]: data_melted = pd.melt(df_dummy, id_vars = "output", var_name = "features
data_melted.head(20)

Out[210]:

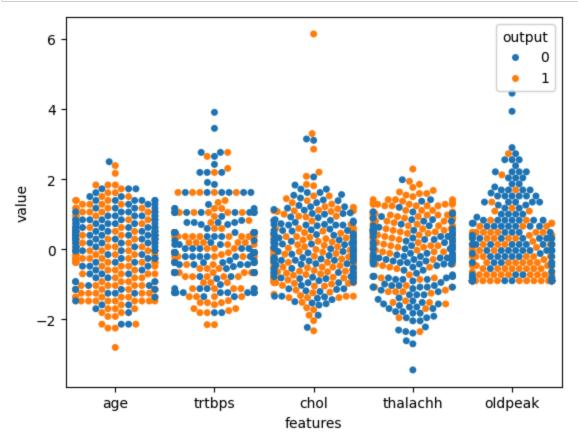
	output	features	value
0	1	age	0.952197
1	1	age	-1.915313
2	1	age	-1.474158
3	1	age	0.180175
4	1	age	0.290464
5	1	age	0.290464
6	1	age	0.180175
7	1	age	-1.143291
8	1	age	-0.260980
9	1	age	0.290464
10	1	age	-0.040403
11	1	age	-0.702136
12	1	age	-0.591847
13	1	age	1.062485
14	1	age	0.400752
15	1	age	-0.481558
16	1	age	0.400752
17	1	age	1.283063
18	1	age	-1.253580
19	1	age	1.613930

```
In [211]: # box plot
plt.figure()
sns.boxplot(x = "features", y = "value", hue = "output", data= data_melt
plt.show()
```

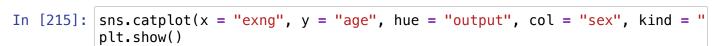


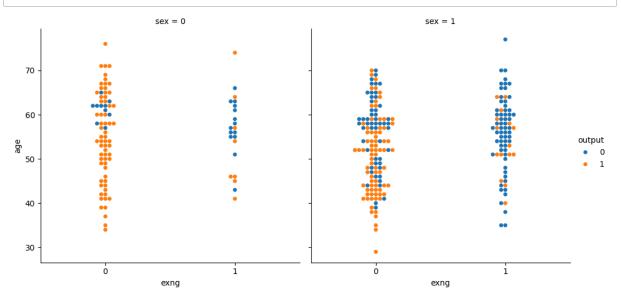
In [212]: #Swarm Plot Analysis¶

```
In [213]: # swarm plot
plt.figure()
sns.swarmplot(x = "features", y = "value", hue = "output", data= data_me
plt.show()
```



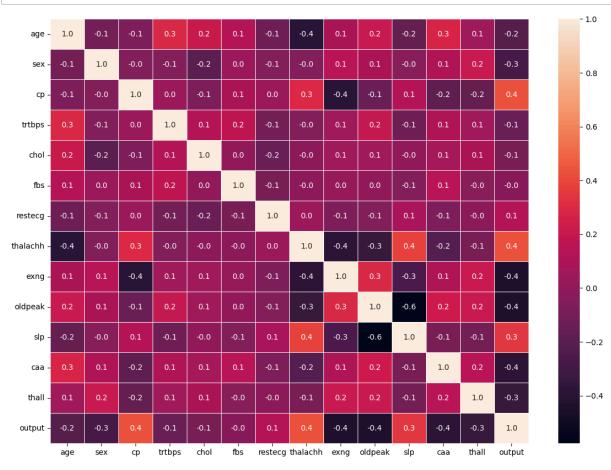






In [216]: #Correlation Analysis¶

```
In [217]: plt.figure(figsize = (14,10))
    sns.heatmap(df.corr(), annot = True, fmt = ".1f", linewidths = .7)
    plt.show()
```



In [218]: #Outlier Detection¶

```
In [219]: numeric_list = ["age", "trtbps","chol","thalachh","oldpeak"]
    df_numeric = df.loc[:, numeric_list]
    df_numeric.head()
```

Out [219]:

	age	trtbps	chol	thalachh	oldpeak
0	63	145	233	150	2.3
1	37	130	250	187	3.5
2	41	130	204	172	1.4
3	56	120	236	178	0.8
4	57	120	354	163	0.6

In [220]: df.describe()

Out[220]:

	age	sex	ср	trtbps	chol	fbs	restecg	tha
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.0
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.6
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.9
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.0
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.5
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.0
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.0
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.0

```
In [221]: # outlier detection
          for i in numeric list:
              Q1 = np.percentile(df.loc[:, i],25)
              Q3 = np.percentile(df.loc[:, i],75)
              IQR = Q3 - Q1
              print("Old shape: ", df.loc[:, i].shape)
              # upper bound
              upper = np.where(df.loc[:, i] \geq (Q3 +2.5*IQR))
              # lower bound
              lower = np.where(df.loc[:, i] \leftarrow (Q1 - 2.5*IQR))
              print("{} -- {}".format(upper, lower))
              try:
                  df.drop(upper[0], inplace = True)
              except: print("KeyError: {} not found in axis".format(upper[0]))
              trv:
                  df.drop(lower[0], inplace = True)
              except: print("KeyError: {} not found in axis".format(lower[0]))
              print("New shape: ", df.shape)
          Old shape:
                      (303,)
          (array([], dtype=int64),) -- (array([], dtype=int64),)
          New shape: (303, 14)
          Old shape: (303,)
          (array([223, 248]),) -- (array([], dtype=int64),)
          New shape: (301, 14)
          Old shape: (301,)
          (array([85]),) -- (array([], dtype=int64),)
          New shape: (300, 14)
          Old shape: (300,)
          (array([], dtype=int64),) -- (array([], dtype=int64),)
          New shape: (300, 14)
          Old shape:
                      (300,)
          (array([203, 220]),) -- (array([], dtype=int64),)
          New shape: (298, 14)
In [222]: |#Modelling¶
In [223]: df1 = df.copy()
```

Out [224]:

	age	trtbps	chol	thalachh	oldpeak	output	sex_1	cp_1	cp_2	cp_3	 exng_1	slp_1	slp
0	63	145	233	150	2.3	1	True	False	False	True	 False	False	Fal
1	37	130	250	187	3.5	1	True	False	True	False	 False	False	Fal
2	41	130	204	172	1.4	1	False	True	False	False	 False	False	Trı
3	56	120	236	178	0.8	1	True	True	False	False	 False	False	Trı
4	57	120	354	163	0.6	1	False	False	False	False	 True	False	Trı

5 rows × 23 columns

```
In [225]: X = df1.drop(["output"], axis = 1)
y = df1[["output"]]
```

In [226]: #Scaling

In [227]: scaler = StandardScaler()
scaler

Out[227]: StandardScaler()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [228]: X[numeric_list[:-1]] = scaler.fit_transform(X[numeric_list[:-1]])
X.head()

Out [228]:

	age	trtbps	chol	thalachh	oldpeak	sex_1	cp_1	cp_2	cp_3	fbs_1	 exng_
0	0.965901	0.845093	-0.236684	0.021855	2.3	True	False	False	True	True	 Fals
1	-1.902555	-0.061886	0.119326	1.639116	3.5	True	False	True	False	False	 Fals
2	-1.461254	-0.061886	-0.843995	0.983470	1.4	False	True	False	False	False	 Fals
3	0.193624	-0.666538	-0.173859	1.245729	0.8	True	True	False	False	False	 Fals
4	0.303950	-0.666538	2.297269	0.590082	0.6	False	False	False	False	False	 Tru

5 rows × 22 columns

In [229]: #Train/Test Split¶

```
In [232]: logreg = LogisticRegression()
logreg
```

Out[232]: LogisticRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [233]: # fitting = training
logreg.fit(X_train, y_train)
```

Out[233]: LogisticRegression()

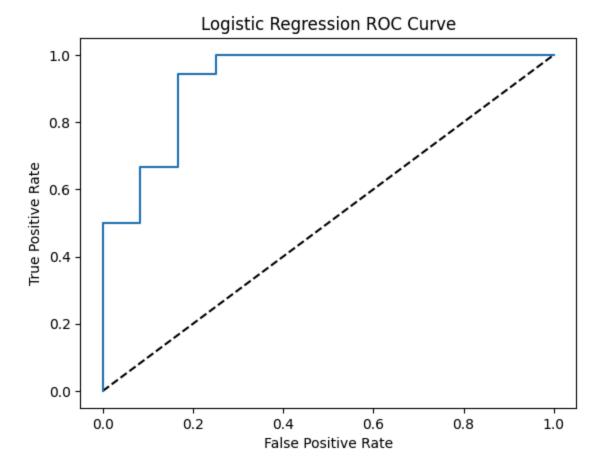
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

```
In [234]: # calculate probabilities
          y_pred_prob = logreg.predict_proba(X_test)
          y_pred_prob
Out[234]: array([[0.94268667, 0.05731333],
                  [0.06997145, 0.93002855],
                  [0.11282989, 0.88717011],
                  [0.48063308, 0.51936692],
                  [0.08770139, 0.91229861],
                  [0.01943155. 0.98056845].
                  [0.01314682, 0.98685318],
                  [0.25649952, 0.74350048],
                  [0.93057819, 0.06942181],
                  [0.04667535, 0.95332465],
                  [0.95754617, 0.04245383],
                  [0.01122815, 0.98877185],
                  [0.41901335, 0.58098665],
                  [0.60411313, 0.39588687],
                  [0.02729659, 0.97270341],
                  [0.02614833, 0.97385167],
                  [0.84042163, 0.15957837],
                  [0.03595037, 0.96404963],
                  [0.86160266, 0.13839734],
                  [0.97611122, 0.02388878],
                  [0.61984028, 0.38015972],
                  [0.31186627, 0.68813373],
                  [0.93464752, 0.06535248],
                  [0.00474577, 0.99525423],
                  [0.44456547, 0.55543453],
                  [0.3387469, 0.6612531],
                  [0.03944728, 0.96055272],
                  [0.99154986, 0.00845014],
                  [0.46893753, 0.53106247],
                  [0.69712671, 0.30287329]])
In [235]: y pred = np.argmax(y pred prob, axis = 1)
          y_pred
Out[235]: array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0,
          1,
                 0, 1, 1, 1, 1, 0, 1, 0])
In [236]: |#dummy = pd.DataFrame(y pred prob)
          \#dummy_["y_pred"] = y_pred
          #dummy_.head()
In [237]: print("Test accuracy: {}".format(accuracy_score(y_pred, y_test)))
```

Test accuracy: 0.9

```
In [238]: # ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob[:,1])
```

```
In [239]: # plot curve
plt.plot([0,1],[0,1],"k--")
plt.plot(fpr, tpr, label = "Logistic Regression")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Logistic Regression ROC Curve")
plt.show()
```



```
In [240]: #Logistic Regression Hyperparameter Tuning¶
```

Out[241]: LogisticRegression()

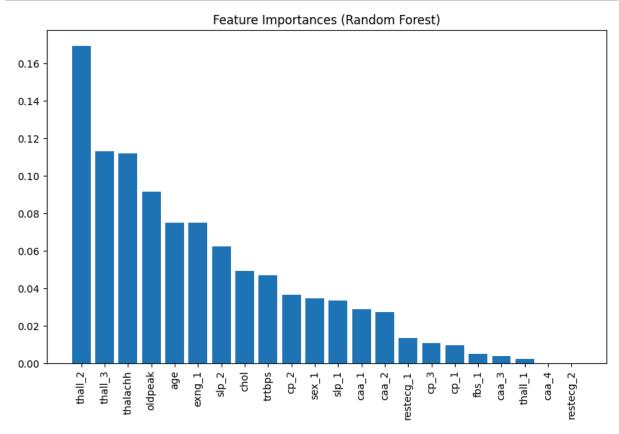
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

```
In [242]: penalty = ["l1", "l2"]
           parameters = {"penalty":penalty}
In [243]: | lr_searcher = GridSearchCV(lr, parameters)
In [244]: | lr searcher.fit(X train, y train)
Out[244]: GridSearchCV(estimator=LogisticRegression(),
                        param_grid={'penalty': ['l1', 'l2']})
           In a Jupyter environment, please rerun this cell to show the HTML representation or trust
           the notebook.
           On GitHub, the HTML representation is unable to render, please try loading this page with
           nbviewer.org.
In [245]: print("Best parameters: ", lr_searcher.best_params_)
           Best parameters: {'penalty': 'l2'}
In [246]: |y_pred = lr_searcher.predict(X_test)
In [247]: print("Test accuracy: {}".format(accuracy_score(y_pred, y_test)))
           Test accuracy: 0.9
In [248]: #Random Forest Extension
In [249]: from sklearn.ensemble import RandomForestClassifier
In [250]: # Random Forest Classifier with Hyperparameter Tuning
           rf = RandomForestClassifier(random state=42)
In [251]:
          # Define the hyperparameters grid
           param grid rf = {
               'n_estimators': [50, 100, 200],
               'max_depth': [None, 10, 20, 30],
               'min_samples_split': [2, 5, 10],
               'min samples leaf': [1, 2, 4]
```

```
In [253]: # Best Parameters and Evaluation
    print("Best Random Forest Parameters:", rf_grid_search.best_params_)
    y_pred_rf = rf_grid_search.predict(X_test)
    accuracy_rf = accuracy_score(y_test, y_pred_rf)
    print(f"Random Forest Accuracy: {accuracy_rf:.4f}")
```

```
Best Random Forest Parameters: {'max_depth': None, 'min_samples_leaf':
4, 'min_samples_split': 10, 'n_estimators': 200}
Random Forest Accuracy: 0.8000
```

```
In [254]: # Feature Importance Plot
    plt.figure(figsize=(10, 6))
    importances_rf = rf_grid_search.best_estimator_.feature_importances_
    indices_rf = np.argsort(importances_rf)[::-1]
    plt.title("Feature Importances (Random Forest)")
    plt.bar(range(X.shape[1]), importances_rf[indices_rf], align="center")
    plt.xticks(range(X.shape[1]), X.columns[indices_rf], rotation=90)
    plt.show()
```



```
In [255]: #Decision Tree Extension

In [256]: from sklearn.tree import DecisionTreeClassifier # Import DecisionTreeClassifier
In [257]: # Decision Tree Classifier with Hyperparameter Tuning
dt = DecisionTreeClassifier(random_state=42)

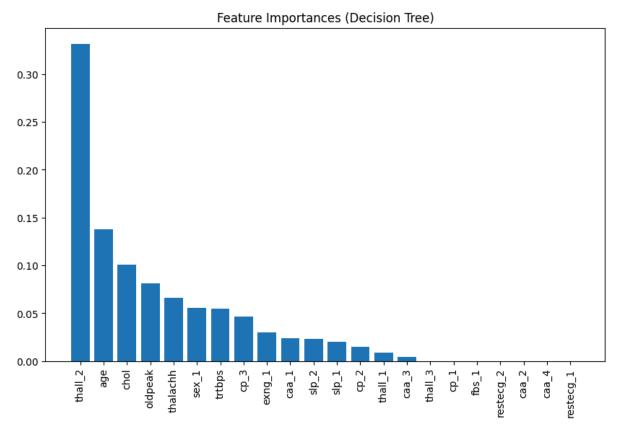
In [258]: # Define the hyperparameters grid
param_grid_dt = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
```

}

```
In [260]: # Best Parameters and Evaluation
    print("Best Decision Tree Parameters:", dt_grid_search.best_params_)
    y_pred_dt = dt_grid_search.predict(X_test)
    accuracy_dt = accuracy_score(y_test, y_pred_dt)
    print(f"Decision Tree Accuracy: {accuracy_dt:.4f}")
```

```
Best Decision Tree Parameters: {'max_depth': None, 'min_samples_leaf':
2, 'min_samples_split': 5}
Decision Tree Accuracy: 0.6000
```

```
In [261]: # Feature Importance Plot
    plt.figure(figsize=(10, 6))
    importances_dt = dt_grid_search.best_estimator_.feature_importances_
    indices_dt = np.argsort(importances_dt)[::-1]
    plt.title("Feature Importances (Decision Tree)")
    plt.bar(range(X.shape[1]), importances_dt[indices_dt], align="center")
    plt.xticks(range(X.shape[1]), X.columns[indices_dt], rotation=90)
    plt.show()
```



```
In [262]: #K-Nearest Neighbors (KNN) Extension
```

In [263]: **from** sklearn.neighbors **import** KNeighborsClassifier

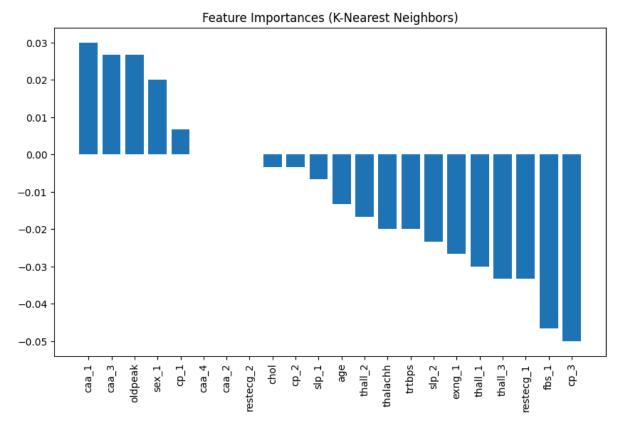
```
In [264]: # KNN Classifier with Hyperparameter Tuning
knn = KNeighborsClassifier()
```

```
In [265]: # Define the hyperparameters grid
param_grid_knn = {
    'n_neighbors': [3, 5, 7, 9],
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan', 'minkowski']
}
```

```
In [267]: # Best Parameters and Evaluation
    print("Best KNN Parameters:", knn_grid_search.best_params_)
    y_pred_knn = knn_grid_search.predict(X_test)
    accuracy_knn = accuracy_score(y_test, y_pred_knn)
    print(f"KNN Accuracy: {accuracy_knn:.4f}")

Best KNN Parameters: {'metric': 'manhattan', 'n_neighbors': 3, 'weight s': 'uniform'}
    KNN Accuracy: 0.7667
```

In [268]: # Feature Importance Plot (using permutation importance instead) from sklearn.inspection import permutation_importance plt.figure(figsize=(10, 6)) # Calculate permutation importance result = permutation_importance(knn_grid_search, X_test, y_test, n_repeatimportances_knn = result.importances_mean indices_knn = np.argsort(importances_knn)[::-1] plt.title("Feature Importances (K-Nearest Neighbors)") plt.bar(range(X.shape[1]), importances_knn[indices_knn], align="center") plt.xticks(range(X.shape[1]), X.columns[indices_knn], rotation=90) plt.show()



In [269]: #Support Vector Machine (SVM) Extension

In [270]: # Import the necessary class from the sklearn.svm module
from sklearn.svm import SVC

In [271]: # SVM Classifier with Hyperparameter Tuning
svm = SVC(probability=True)

```
In [272]: # Define the hyperparameters grid
param_grid_svm = {
    'C': [0.1, 1, 10, 100],
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'gamma': ['scale', 'auto']
}
```

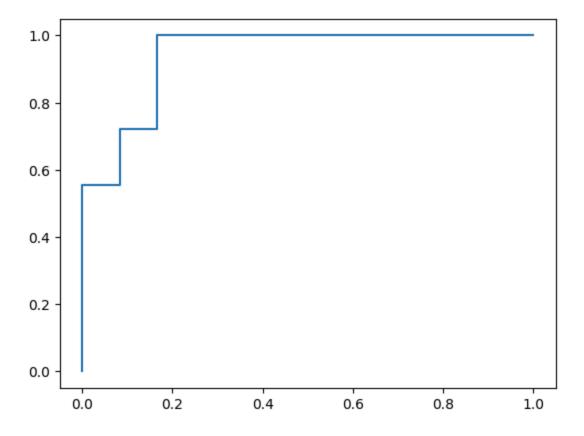
```
In [273]: # GridSearchCV for SVM
    svm_grid_search = GridSearchCV(svm, param_grid_svm, cv=5, scoring='accur
    svm_grid_search.fit(X_train, y_train)
```

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [274]:
    # Best Parameters and Evaluation
    print("Best SVM Parameters:", svm_grid_search.best_params_)
    y_pred_svm = svm_grid_search.predict(X_test)
    accuracy_svm = accuracy_score(y_test, y_pred_svm)
    print(f"SVM Accuracy: {accuracy_svm:.4f}")
```

Best SVM Parameters: {'C': 1, 'gamma': 'auto', 'kernel': 'sigmoid'}
SVM Accuracy: 0.8667

Out[275]: [<matplotlib.lines.Line2D at 0x7f9d1ccb3f40>]



```
In [276]: #Gradient Boosting Extension
```

In [277]: # Gradient Boosting Extension
from sklearn.ensemble import GradientBoostingClassifier # Import Gradient

In [278]:
Gradient Boosting Classifier with Hyperparameter Tuning
gb = GradientBoostingClassifier(random_state=42)

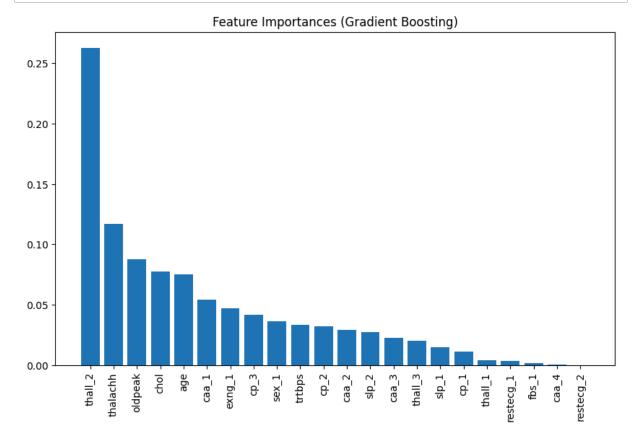
```
In [279]: # Define the hyperparameters grid
param_grid_gb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    'min_samples_split': [2, 5, 10]
}
```

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [281]: # Best Parameters and Evaluation
    print("Best Gradient Boosting Parameters:", gb_grid_search.best_params_)
    y_pred_gb = gb_grid_search.predict(X_test)
    accuracy_gb = accuracy_score(y_test, y_pred_gb)
    print(f"Gradient Boosting Accuracy: {accuracy_gb:.4f}")
```

Best Gradient Boosting Parameters: {'learning_rate': 0.2, 'max_depth':
3, 'min_samples_split': 2, 'n_estimators': 100}
Gradient Boosting Accuracy: 0.7667

In [284]: # Feature Importance Plot for Gradient Boosting
 plt.figure(figsize=(10, 6))
 importances_gb = gb_grid_search.best_estimator_.feature_importances_
 indices_gb = np.argsort(importances_gb)[::-1]
 plt.title("Feature Importances (Gradient Boosting)")
 plt.bar(range(X.shape[1]), importances_gb[indices_gb], align="center")
 plt.xticks(range(X.shape[1]), X.columns[indices_gb], rotation=90)
 plt.show()

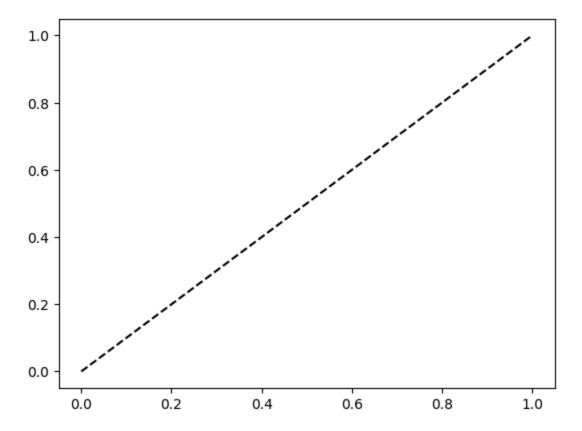


```
In [286]: #ROC Curves for All Models (Combined)
          # Plot ROC Curves for all models
          plt.plot([0, 1], [0, 1], "k--") # Reference line for random guessing
          # Plot ROC curve for each model
          # Assign a value to y pred prob rf
          y_pred_prob_rf = rf_grid_search.predict_proba(X_test)[:, 1] # Assuming
          if y_pred_prob_rf is not None:
              fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_prob_rf)
              plt.plot(fpr rf, tpr rf, label=f'Random Forest (AUC = {accuracy rf:.
          # Plot ROC curve for each model
          # Calculate and assign a value to y_pred_prob_dt
          y pred prob dt = dt grid search.predict proba(X test)[:, 1] # Assuming
          if y pred prob dt is not None:
              fpr_dt, tpr_dt, _ = roc_curve(y_test, y_pred_prob_dt)
              plt.plot(fpr_dt, tpr_dt, label=f'Decision Tree (AUC = {accuracy_dt:...})
          if y pred prob svm is not None:
              plt.plot(fpr_svm, tpr_svm, label=f'SVM (AUC = {accuracy_svm:.4f})')
          # Plot ROC curve for each model
          # Calculate and assign a value to y_pred_prob_gb
          y pred prob gb = gb grid search.predict proba(X test)[:, 1] # Assuming
          if y pred prob qb is not None:
              fpr_gb, tpr_gb, _ = roc_curve(y_test, y_pred_prob_gb)
              plt.plot(fpr_gb, tpr_gb, label=f'Gradient Boosting (AUC = {accuracy_
          plt.xlabel("False Positive Rate")
          plt.ylabel("True Positive Rate")
          plt.title("ROC Curves for All Models")
          plt.legend(loc="lower r
            File "<ipython-input-286-caac7b6e1a2a>", line 36
              plt.legend(loc="lower r
```

SyntaxError: unterminated string literal (detected at line 36)

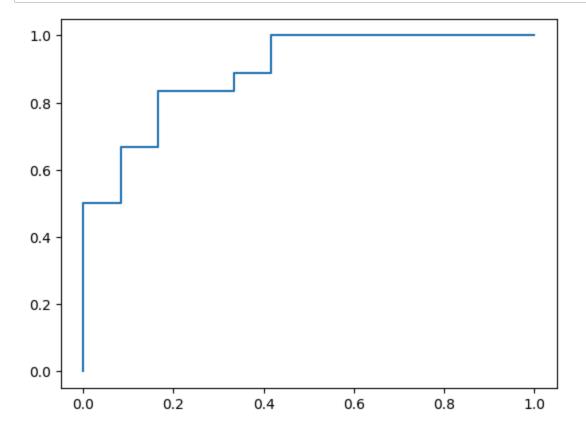
In [287]: # Plot ROC Curves for all models
plt.plot([0, 1], [0, 1], "k--") # Reference line for random guessing

Out[287]: [<matplotlib.lines.Line2D at 0x7f9d258d6410>]

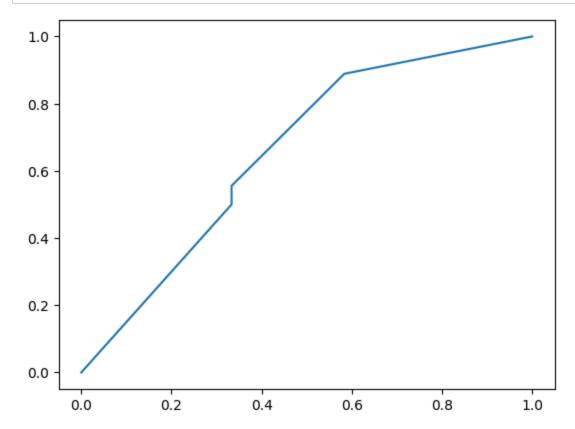


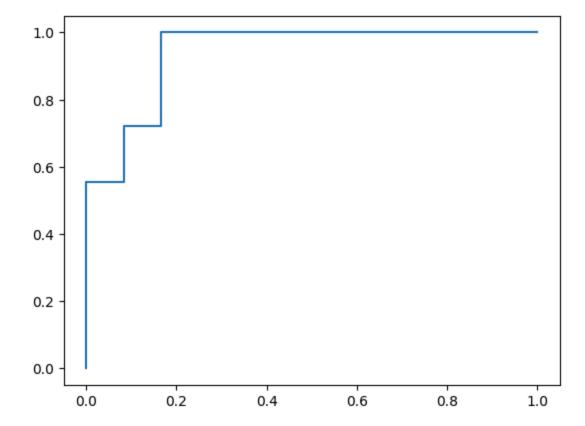
```
In [288]: # Plot ROC curve for each model
    # Assign a value to y_pred_prob_rf
    y_pred_prob_rf = rf_grid_search.predict_proba(X_test)[:, 1] # Assuming

if y_pred_prob_rf is not None:
    fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_prob_rf)
    plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {accuracy_rf:.
```

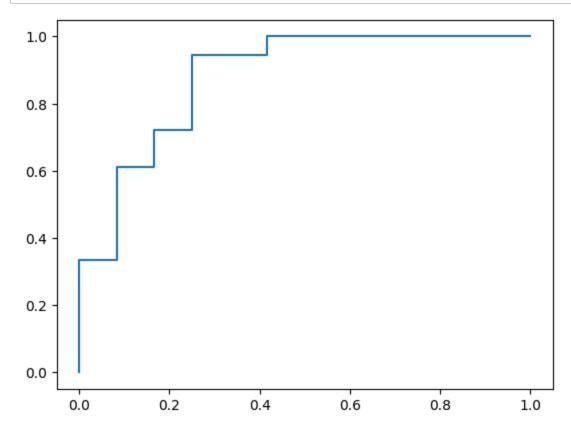


```
In [289]: # Plot ROC curve for each model
    # Calculate and assign a value to y_pred_prob_dt
    y_pred_prob_dt = dt_grid_search.predict_proba(X_test)[:, 1] # Assuming
```





```
In [292]: # Plot ROC curve for each model
# Calculate and assign a value to y_pred_prob_gb
y_pred_prob_gb = gb_grid_search.predict_proba(X_test)[:, 1] # Assuming
```

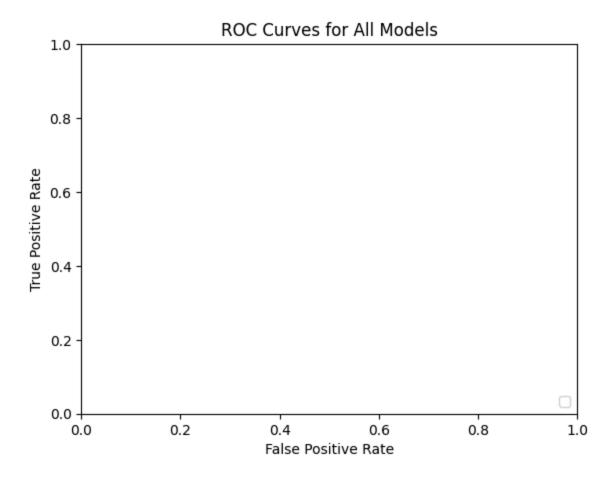


In [295]:

```
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves for All Models")
plt.legend(loc="lower right")
```

WARNING:matplotlib.legend:No artists with labels found to put in legen d. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.

Out[295]: <matplotlib.legend.Legend at 0x7f9d257e1510>



In []: