#I imported several libraries for the project: import numpy as np import pandas as pd import matplotlib.pyplot as plt from matplotlib import rcParams from matplotlib.cm import rainbow **%matplotlib** inline import warnings warnings.filterwarnings('ignore') # Other libraries from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler # Machine Learning from sklearn.neighbors import KNeighborsClassifier from sklearn.svm import SVC from sklearn.tree import DecisionTreeClassifier from sklearn.ensemble import RandomForestClassifier dataset = pd.read_csv("heart.csv") In [139... dataset age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal target Out[139]: 52 125 212 1 0 0 53 140 203 155 3.1 0 70 1 0 145 174 0 1 125 1 2.6 0 3 161 0 0.0 2 1 0 61 1 0 148 203 0 1 3 138 294 106 1.9 298 35 1 1 122 192 0 1 174 0 0.0 0 2 1 299 52 1 1 120 325 0 172 0.2 0 105 204 0.0 1 300 301 51 1 2 94 227 154 0.0 302 55 132 342 166 1.2 0 303 rows × 14 columns dataset.isnull().sum() In [140.. 0 age Out[140]: 0 sex 0 ср trestbps 0 0 chol 0 fbs 0 restecg 0 thalach 0 exang oldpeak 0 0 slope 0 thal target dtype: int64 In [141... dataset.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 303 entries, 0 to 302 Data columns (total 14 columns): Non-Null Count Dtype Column 303 non-null int64 1 303 non-null sex int64 303 non-null ср int64 3 303 non-null trestbps int64 chol 303 non-null 4 int64 5 303 non-null fbs int64 restecg 303 non-null int64 7 thalach 303 non-null int64 303 non-null int64 exang 303 non-null float64 oldpeak 303 non-null 10 slope int64 11 303 non-null int64 ca 303 non-null 12 thal int64 13 target 303 non-null int64 dtypes: float64(1), int64(13) memory usage: 33.3 KB dataset.tail() In [142.. age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal target Out[142]: 298 35 1 1 122 192 0 174 0.0 2 1 299 52 1 1 120 325 0 1 172 0.2 0 2 1 300 46 0 1 105 204 0 1 172 0 0.0 0 1 301 51 1 2 94 227 0 154 0.0 3 1 1 1 2 302 55 0 1 132 342 0 1 166 0 1.2 2 0 1 dataset.describe() In [143.. trestbps chol fbs restecg thalach oldpeak slope ca thal Out[143]: exang target age sex ср count 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 303.000000 0.732673 0.953795 131.679868 247.442244 0.165017 0.498350 151.033003 0.343234 1.066337 1.429043 0.696370 2.316832 mean 53.399340 0.534653 std 9.458638 0.443296 1.012101 18.462235 56.956145 0.371809 0.526607 23.361801 0.475574 1.229059 0.630947 1.006709 0.596858 0.499623 29.000000 0.000000 0.000000 94.000000 126.000000 0.000000 0.000000 71.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 min **25**% 46.000000 0.000000 0.000000 120.000000 208.000000 0.000000 0.000000 138.500000 0.000000 0.000000 1.000000 0.000000 2.000000 0.000000 54.000000 1.000000 1.000000 130.000000 240.000000 0.0000000.000000 154.000000 0.0000000.800000 2.000000 0.000000 2.000000 1.000000 **50**% 60.000000 1.000000 2.000000 140.000000 283.000000 0.000000 1.000000 168.500000 1.000000 1.600000 2.000000 1.000000 3.000000 1.000000 77.000000 1.000000 3.000000 200.000000 564.000000 1.000000 2.000000 202.000000 6.200000 2.000000 3.000000 1.000000 4.000000 1.000000 max rcParams['figure.figsize'] = 20, 14 In [144... plt.matshow(dataset.corr()) plt.yticks(np.arange(dataset.shape[1]), dataset.columns) plt.xticks(np.arange(dataset.shape[1]), dataset.columns) plt.colorbar() <matplotlib.colorbar.Colorbar at 0x24a3262ab00> Out[144]: 1.0 trestbps thal chol fbs restecg thalach exang oldpeak slope ca target age sex 0.8 age sex ср 0.6 trestbps chol - 0.4 fbs restecg - 0.2 thalach exang - 0.0 oldpeak slope · ca - -0.2 thal target --0.4 dataset.hist()#Let's take a look at the plots. It shows how each feature and label is distributed along different ranges, array([[<Axes: title={'center': 'age'}>, <Axes: title={'center': 'sex'}>, <Axes: title={'center': 'cp'}>, <Axes: title={'center': 'trestbps'}>], [<Axes: title={'center': 'chol'}>, <Axes: title={'center': 'fbs'}>, <Axes: title={'center': 'restecg'}>, <Axes: title={'center': 'thalach'}>], [<Axes: title={'center': 'exang'}>, <Axes: title={'center': 'oldpeak'}>, <Axes: title={'center': 'slope'}>, <Axes: title={'center': 'ca'}>], [<Axes: title={'center': 'thal'}>, <Axes: title={'center': 'target'}>, <Axes: >, <Axes: >]], dtype=object) trestbps sex 60 200 125 50 100 150 40 75 40 30 100 50 20 25 10 1.5 70 0.4 0.8 120 140 160 30 40 50 60 0.0 0.2 0.6 0.0 0.5 1.0 2.0 2.5 100 180 200 chol restecg thalach 250 150 -80 60 125 200 60 100 150 75 40 100 50 20 20 50 25 200 500 0.5 1.0 100 125 150 175 exang oldpeak slope 150 200 -150 125 150 125 150 100 100 100 75 100 75 50 50 50 25 25 0.8 0.4 0.6 0.0 0.5 1.0 1.5 0.0 2.0 thal target 150 150 125 100 100 75 50 50 25 0.0 0.5 1.0 1.5 0.2 0.6 In [146... #Bar Plot for Target Class #It's really essential that the dataset we are working on should beapproximately #balanced. An extremely imbalanced dataset can render the whole model training useless #and thus, will be of no use. Let's understand it with an example. In [147... rcParams['figure.figsize']=8,6 plt.bar(dataset['target'].unique(),dataset['target'].value_counts(),color=['red','green']) plt.xticks([0,1]) plt.xlabel('Target Classes') plt.ylabel('Count') plt.title('Count of each Target Class') Text(0.5, 1.0, 'Count of each Target Class') Out[147]: Count of each Target Class 160 140 120 100 80 60 40 20 0 Target Classes **Data Processing** To work with categorical variables, we should break each categorical column into dummy columns with 1s and 0s. In [148... dataset = pd.get_dummies(dataset, columns = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal']) standardScaler = StandardScaler() columns_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak'] dataset[columns_to_scale] = standardScaler.fit_transform(dataset[columns_to_scale]) K Neighbors Classifier y = dataset['target'] X = dataset.drop(['target'], axis = 1) X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.20,random_state=0) print('Shape of x_train = ',X_train.shape) print('Shape of y_train = ',y_train.shape) print('Shape of x_test = ',X_test.shape) print('Shape of y_train = ',y_test.shape) Shape of $x_{train} = (242, 30)$ Shape of $y_{train} = (242,)$ Shape of $x_{test} = (61, 30)$ Shape of $y_{train} = (61,)$ In [160... Classifier=KNeighborsClassifier(n_neighbors = 5) Classifier.fit(X_train, y_train) Out[160]: • KNeighborsClassifier KNeighborsClassifier() Classifier.score(X_test, y_test) In [161... 0.8032786885245902 Out[161]: In [162... import seaborn as sns from sklearn.metrics import confusion_matrix model1=Classifier.fit(X_train, y_train) prediction1=model1.predict(X_test) cm=confusion_matrix(y_test,prediction1) CM sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20}) TP=cm[0][0]TN=cm[1][1]FN=cm[1][0]FP=cm[0][1] print('Testing Accuracy for Logistic Regression:',(TP+TN)/(TP+TN+FN+FP)) print('Testing Sensitivity for Logistic Regression:',(TP/(TP+FN))) print('Testing Specificity for Logistic Regression:',(TN/(TN+FP))) print('Testing Precision for Logistic Regression:',(TP/(TP+FP))) Testing Accuracy for Logistic Regression: 0.8032786885245902 Testing Sensitivity for Logistic Regression: 0.7777777777778 Testing Specificity for Logistic Regression: 0.8235294117647058 Testing Precision for Logistic Regression: 0.7777777777778 - 27.5 - 25.0 6 0 - 22.5 - 20.0 - 17.5 - 15.0 - 12.5 6 - 10.0 0 1 #DecisionTreeClassifier In [166... classifier_entropy=DecisionTreeClassifier(criterion="entropy") classifier_entropy.fit(X_train,y_train) Out[166]: ▼ DecisionTreeClassifier DecisionTreeClassifier(criterion='entropy') classifier_entropy.score(X_test,y_test) In [167... 0.8524590163934426 Out[167]: random forest from sklearn.ensemble import RandomForestClassifier In [156...

classifier=RandomForestClassifier(n_estimators=100, criterion='gini')

classifier.fit(X_train,y_train)

classifier.score(X_test,y_test)

0.9180327868852459

Out[156]:

In []: