import numpy as np import pandas as pd import matplotlib.pyplot as plt from sklearn.metrics import classification\_report from sklearn.metrics import confusion\_matrix from sklearn.metrics import accuracy\_score from sklearn.model\_selection import train\_test\_split from sklearn.model\_selection import cross\_val\_score from sklearn.model\_selection import KFold from sklearn.tree import DecisionTreeClassifier from sklearn.neighbors import KNeighborsClassifier from sklearn.naive\_bayes import GaussianNB from sklearn.pipeline import Pipeline from sklearn.preprocessing import StandardScaler from sklearn.model\_selection import GridSearchCV from sklearn.svm import SVC import time **Exploratory analysis** data = pd.read\_csv("C:/Users/Mounika/Downloads/data.csv") In [4]: data.head(5) Out[4]: id diagnosis radius\_mean texture\_mean perimeter\_mean area\_mean smoothness\_mean compactness\_mean concavity\_mean texture\_worst perimeter\_worst area\_worst points\_mean 842302 M 17.99 10.38 122.80 1001.0 0.11840 0.27760 0.3001 0.14710 ... 17.33 184.60 2019.0 842517 M 20.57 132.90 1326.0 0.08474 0.07864 0.0869 0.07017 23.41 158.80 1956.0 17.77 2 84300903 19.69 21.25 130.00 1203.0 0.10960 0.15990 0.1974 0.12790 ... 25.53 152.50 1709.0 M 3 84348301 77.58 386.1 0.14250 0.28390 0.2414 0.10520 ... 26.50 98.87 M 11.42 20.38 567.7 4 84358402 20.29 14.34 135.10 1297.0 0.10030 0.13280 0.1980 0.10430 ... 16.67 152.20 1575.0 5 rows × 33 columns print(data.shape) In [5]: (569, 33)data.describe() Out[6]: texture worst perimeter wo id radius\_mean texture\_mean perimeter\_mean area\_mean smoothness\_mean compactness\_mean concavity\_mean symmetry\_mean ... points\_mean 569.000000 569.000000 569.000000 count 5.690000e+02 569.000000 569.000000 569.000000 569.000000 569.000000 569.000000 569.000000 569.000 mean 3.037183e+07 14.127292 19.289649 91.969033 654.889104 0.096360 0.104341 0.088799 0.048919 0.181162 ... 107.261 25.677223 0.038803 std 1.250206e+08 3.524049 4.301036 24.298981 351.914129 0.014064 0.052813 0.079720 0.027414 ... 6.146258 33.602 min 8.670000e+03 6.981000 9.710000 43.790000 143.500000 0.052630 0.019380 0.000000 0.000000 0.106000 ... 12.020000 50.410 8.692180e+05 11.700000 16.170000 75.170000 420.300000 0.086370 0.064920 0.029560 0.020310 0.161900 ... 21.080000 84.110 25% 0.061540 0.033500 **50**% 9.060240e+05 13.370000 18.840000 86.240000 551.100000 0.095870 0.092630 0.179200 ... 25.410000 97.660 0.105300 0.130400 0.130700 75% 8.813129e+06 15.780000 21.800000 104.100000 782.700000 0.074000 0.195700 ... 29.720000 125.400 max 9.113205e+08 28.110000 39.280000 188.500000 2501.000000 0.163400 0.345400 0.426800 0.201200 0.304000 ... 49.540000 251.200 8 rows × 32 columns Data visualisation and pre-processing data['diagnosis'] = data['diagnosis'].apply(lambda x: '1' if x == 'M' else '0') data = data.set\_index('id') del data['Unnamed: 32'] print(data.groupby('diagnosis').size()) diagnosis 0 357 212 dtype: int64 data.plot(kind='density', subplots=True, layout=(5,7), sharex=False, legend=False, fontsize=1) plt.show() In [10]: from matplotlib import cm as cm fig = plt.figure()  $ax1 = fig.add_subplot(111)$  $cmap = cm.get\_cmap('jet', 30)$ cax = ax1.imshow(data.corr(), interpolation="none", cmap=cmap) ax1.grid(True) plt.title('Breast Cancer Attributes Correlation') # Add colorbar, make sure to specify tick locations to match desired ticklabels fig.colorbar(cax, ticks=[.75,.8,.85,.90,.95,1]) plt.show() Breast Cancer Attributes Correlation 10 15 20 Y = data['diagnosis'].values X = data.drop('diagnosis', axis=1).values X\_train, X\_test, Y\_train, Y\_test = train\_test\_split (X, Y, test\_size = 0.20, random\_state=21) Baseline algorithm checking models\_list = [] In [15]: models\_list.append(('CART', DecisionTreeClassifier())) models\_list.append(('SVM', SVC())) models\_list.append(('NB', GaussianNB())) models\_list.append(('KNN', KNeighborsClassifier()))  $num_folds = 10$ results = [] names = []for name, model in models\_list: kfold = KFold(n\_splits=num\_folds, random\_state=123) start = time.time() cv\_results = cross\_val\_score(model, X\_train, Y\_train, cv=kfold, scoring='accuracy') end = time.time() results.append(cv\_results) names.append(name) print( "%s: %f (%f) (run time: %f)" % (name, cv\_results.mean(), cv\_results.std(), end-start)) C:\Users\Mounika\anaconda\lib\site-packages\sklearn\model\_selection\\_split.py:293: FutureWarning: Setting a random\_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random\_state to its default (None), or set shuffle=True. C:\Users\Mounika\anaconda\lib\site-packages\sklearn\model\_selection\\_split.py:293: FutureWarning: Setting a random\_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random\_state to its default (None), or set shuffle=True. warnings.warn( C:\Users\Mounika\anaconda\lib\site-packages\sklearn\model\_selection\\_split.py:293: FutureWarning: Setting a random\_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random\_state to its default (None), or set shuffle=True. CART: 0.921063 (0.039453) (run time: 0.108120) SVM: 0.907681 (0.054723) (run time: 0.060003) NB: 0.940773 (0.033921) (run time: 0.036790) KNN: 0.927729 (0.055250) (run time: 0.076570) C:\Users\Mounika\anaconda\lib\site-packages\sklearn\model\_selection\\_split.py:293: FutureWarning: Setting a random\_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random\_state to its default (None), or set shuffle=True. warnings.warn( In [16]: fig = plt.figure() fig.suptitle('Performance Comparison') ax = fig.add\_subplot(111) plt.boxplot(results) ax.set\_xticklabels(names) plt.show() Performance Comparison 1.000 0.975 0.950 0.925 0.900 0.875 0.850 0.825 0.800 NB KŃN Evaluation of algorithm on Standardised Data In [17]: import warnings # Standardize the dataset pipelines = [] pipelines.append(('ScaledCART', Pipeline([('Scaler', StandardScaler()),('CART', DecisionTreeClassifier())]))) pipelines.append(('ScaledSVM', Pipeline([('Scaler', StandardScaler()),('SVM', SVC())]))) pipelines.append(('ScaledNB', Pipeline([('Scaler', StandardScaler()),('NB', GaussianNB())]))) pipelines.append(('ScaledKNN', Pipeline([('Scaler', StandardScaler()),('KNN', KNeighborsClassifier())]))) results = [] names = []with warnings.catch\_warnings(): warnings.simplefilter("ignore") kfold = KFold(n\_splits=num\_folds, random\_state=123) for name, model in pipelines: start = time.time() cv\_results = cross\_val\_score(model, X\_train, Y\_train, cv=kfold, scoring='accuracy') end = time.time() results.append(cv\_results) names.append(name) print( "%s: %f (%f) (run time: %f)" % (name, cv\_results.mean(), cv\_results.std(), end-start)) ScaledCART: 0.916473 (0.035364) (run time: 0.165091) ScaledSVM: 0.964879 (0.038621) (run time: 0.093325) ScaledNB: 0.931932 (0.038625) (run time: 0.043218) ScaledKNN: 0.958357 (0.038595) (run time: 0.125401) fig = plt.figure() In [18]: fig.suptitle('Performance Comparison') ax = fig.add\_subplot(111) plt.boxplot(results) ax.set\_xticklabels(names) plt.show() Performance Comparison 1.00 0.98 0.96 0.94 0.92 0.90 0.88 0.86 0.84 ScaledCART ScaledSVM ScaledNB ScaledKNN Algorithm Tuning - Tuning SVM scaler = StandardScaler().fit(X\_train) In [19]: rescaledX = scaler.transform(X\_train) c\_values = [0.1, 0.3, 0.5, 0.7, 0.9, 1.0, 1.3, 1.5, 1.7, 2.0] kernel\_values = ['linear', 'poly', 'rbf', 'sigmoid'] param\_grid = dict(C=c\_values, kernel=kernel\_values) model = SVC() kfold = KFold(n\_splits=num\_folds, random\_state=21) grid = GridSearchCV(estimator=model, param\_grid=param\_grid, scoring='accuracy', cv=kfold) grid\_result = grid.fit(rescaledX, Y\_train) print("Best: %f using %s" % (grid\_result.best\_score\_, grid\_result.best\_params\_)) means = grid\_result.cv\_results\_['mean\_test\_score'] stds = grid\_result.cv\_results\_['std\_test\_score'] params = grid\_result.cv\_results\_['params'] for mean, stdev, param in zip(means, stds, params): print("%f (%f) with: %r" % (mean, stdev, param)) C:\Users\Mounika\anaconda\lib\site-packages\sklearn\model\_selection\\_split.py:293: FutureWarning: Setting a random\_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random\_state to its default (None), or set shuffle=True. warnings.warn( Best: 0.969324 using {'C': 2.0, 'kernel': 'rbf'} 0.964976 (0.026211) with: {'C': 0.1, 'kernel': 'linear'} 0.828551 (0.054707) with: {'C': 0.1, 'kernel': 'poly'} 0.940725 (0.038380) with: {'C': 0.1, 'kernel': 'rbf'} 0.949469 (0.032899) with: {'C': 0.1, 'kernel': 'sigmoid'} 0.962754 (0.029531) with: {'C': 0.3, 'kernel': 'linear'} 'kernel': 'poly'} 0.863720 (0.050997) with: {'C': 0.3, 'kernel': 'rbf'} 0.956039 (0.032900) with: {'C': 0.3, 'kernel': 'sigmoid'} 0.960386 (0.029499) with: {'C': 0.3, 0.956184 (0.030988) with: {'C': 0.5, 'kernel': 'linear'} 0.879034 (0.053507) with: {'C': 0.5, 'kernel': 'polv'} 0.964879 (0.030054) with: {'C': 0.5, 'kernel': 'rbf'} 0.956087 (0.027848) with:  $\{'C': 0.5,$ 'kernel': 'sigmoid'} 0.954010 (0.031644) with: {'C': 0.7, 'kernel': 'linear'} 0.885604 (0.038275) with: {'C': 0.7, 'kernel': 'poly'} 'kernel': 'rbf'} 0.967053 (0.037461) with: {'C': 0.7, 0.949565 (0.027831) with: {'C': 0.7, 'kernel': 'sigmoid'} 0.951836 (0.028830) with: {'C': 0.9, 'kernel': 'linear'} 0.887826 (0.039039) with: {'C': 0.9, 'kernel': 'poly'} 0.967053 (0.037461) with: {'C': 0.9, 'kernel': 'rbf'} 0.947391 (0.032846) with: {'C': 0.9, 'kernel': 'sigmoid'} 0.954010 (0.026552) with: {'C': 1.0, 'kernel': 'linear'} 0.890048 (0.038398) with: {'C': 1.0, 'kernel': 'poly'} 0.967101 (0.033160) with: {'C': 1.0, 'kernel': 'rbf'} 0.947391 (0.032846) with:  $\{'C': 1.0,$ 'kernel': 'sigmoid'} 0.956184 (0.025767) with: {'C': 1.3, 'kernel': 'linear'} 0.894396 (0.039509) with: {'C': 1.3, 'kernel': 'polv'} 0.967150 (0.028285) with: {'C': 1.3, 'kernel': 'rbf'} 0.947391 (0.029759) with: {'C': 1.3, 'kernel': 'sigmoid'} 0.958357 (0.024768) with: {'C': 1.5, 'kernel': 'linear'} 0.898792 (0.033329) with: {'C': 1.5, 'kernel': 'poly'} 'kernel': 'rbf'} 0.967150 (0.028285) with: {'C': 1.5, 0.940821 (0.039361) with: {'C': 1.5, 'kernel': 'sigmoid'} 0.956135 (0.021744) with:  $\{'C': 1.7,$ 'kernel': 'linear'} 0.900966 (0.034861) with: {'C': 1.7, 'kernel': 'poly'} 'kernel': 'rbf'} 0.967150 (0.024547) with: {'C': 1.7, 'kernel': 'sigmoid'} 0.940918 (0.037900) with: {'C': 1.7, 0.956135 (0.021744) with: {'C': 2.0, 'kernel': 'linear'} 'kernel': 'poly'} 0.907536 (0.034327) with: {'C': 2.0, 0.969324 (0.022458) with: {'C': 2.0, 'kernel': 'rbf'} 0.932029 (0.028300) with: {'C': 2.0, 'kernel': 'sigmoid'} Application of SVC on dataset In [20]: # prepare the model with warnings.catch\_warnings(): warnings.simplefilter("ignore") scaler = StandardScaler().fit(X\_train) X\_train\_scaled = scaler.transform(X\_train) model = SVC(C=2.0, kernel='rbf') start = time.time() model.fit(X\_train\_scaled, Y\_train) end = time.time() print( "Run Time: %f" % (end-start)) Run Time: 0.006001 # estimate accuracy on test dataset In [21]: with warnings.catch\_warnings(): warnings.simplefilter("ignore") X\_test\_scaled = scaler.transform(X\_test) predictions = model.predict(X\_test\_scaled) print("Accuracy score %f" % accuracy\_score(Y\_test, predictions)) In [22]: print(classification\_report(Y\_test, predictions)) Accuracy score 0.991228 recall f1-score support precision 1.00 0.99 0.99 75 0.97 1.00 0.99 39 0.99 114 accuracy 0.99 0.99 0.99 macro avg 114 weighted avg 0.99 0.99 0.99 114 print(confusion\_matrix(Y\_test, predictions)) [[74 1] [ 0 39]]