In [87]: import numpy as np import pandas as pd from sklearn.model_selection import train test split from sklearn.metrics import confusion matrix, classification report from sklearn.metrics import precision score, recall score Reading excel file In [88]: data file = pd.read csv("Data for UCI named.csv") # read csv file In [89]: data file Out[89]: p2 tau1 tau2 tau3 tau4 р1 p3 g4 sta g2 g3 $0 \quad 2.959060 \quad 3.079885 \quad 8.381025 \quad 9.780754 \quad 3.763085 \quad -0.782604 \quad -1.257395 \quad -1.723086 \quad 0.650456 \quad 0.859578 \quad 0.887445$ $1 \quad 9.304097 \quad 4.902524 \quad 3.047541 \quad 1.369357 \quad 5.067812 \quad -1.940058 \quad -1.872742 \quad -1.255012 \quad 0.413441 \quad 0.862414 \quad 0.562139 \quad 0.781760$ -0.00595 2 8.971707 8.848428 3.046479 1.214518 3.405158 -1.207456 -1.277210 -0.920492 0.163041 0.766689 0.839444 0.109853 3 0.716415 7.669600 4.486641 2.340563 3.963791 -1.027473 -1.938944 -0.997374 0.446209 0.976744 0.929381 0.362718 0.02887 3.134112 7.608772 4.943759 9.857573 3.525811 -1.125531 -1.845975 -0.554305 0.797110 0.455450 0.656947 0.04986 2.930406 9.487627 2.376524 6.187797 3.343416 -0.658054 -1.449106 -1.236256 0.601709 0.779642 0.813512 0.608385 0.02389 3.392299 1.274827 2.954947 6.894759 4.349512 -1.663661 -0.952437 -1.733414 0.502079 0.567242 0.285880 0.366120 -0.02580 9997 2.364034 2.842030 8.776391 1.008906 4.299976 -1.380719 -0.943884 -1.975373 0.487838 0.986505 0.149286 0.145984 -0.03181 9.631511 3.994398 2.757071 7.821347 2.514755 -0.966330 -0.649915 -0.898510 0.365246 0.587558 0.889118 0.818391 9998 0.03778 9999 6.530527 6.781790 4.349695 8.673138 3.492807 -1.390285 -1.532193 -0.570329 0.073056 0.505441 0.378761 0.942631 10000 rows × 14 columns data file.columns In [90]: Out[90]: Index(['tau1', 'tau2', 'tau3', 'tau4', 'p1', 'p2', 'p3', 'p4', 'g1', 'g2', 'g3', 'g4', 'stab', 'stabf'], dtype='object') In [91]: data_file.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 10000 entries, 0 to 9999 Data columns (total 14 columns): 10000 non-null float64 10000 non-null float64 tau2 10000 non-null float64 tau3 10000 non-null float64 tau4 10000 non-null float64 р1 p2 10000 non-null float64 рЗ 10000 non-null float64 p4 10000 non-null float64 10000 non-null float64 g1 10000 non-null float64 g2 10000 non-null float64 g3 10000 non-null float64 g4 10000 non-null float64 stab 10000 non-null object stabf dtypes: float64(13), object(1) memory usage: 1.1+ MB import seaborn as sns In [92]: import matplotlib.pyplot as plt %matplotlib inline In [93]: figure = plt.figure(figsize = (10,10)) column_list =list(data_file.columns[:-2]) for i, v in enumerate(column_list): figure.add_subplot(3, 4, i+1) sns.distplot(data_file[v], hist = False) #plotting all the values 0.10 **d**10 0.10 0.10 0.08 0.08 0.08 0.08 0.06 d.06 0.06 0.06 0.04 0.04 0.04 0.04 0.02 ¢02 0.02 0.02 0.00 9.00 9.00 10 tau1 0.5 0.6 0.6 0.6 0.4 0.3 0.4 0.4 0.4 0.2 0.2 0.2 0.2 0.1 -1 -1 1.0 1.0 1.0 1.0 0.8 0.8 0.8 0.8 0.6 0.6 0.6 0.6 0.4 0.4 0.4 0.4 0.2 0.2 0.2 0.5 0.5 1.0 0.5 g1 In [95]: # Seperated the target and data from each other # target = stabf and data is all the data except stabf and stab def preprocess_inputs(df, task='classification'): df = df.copy()if task == 'classification': df = df.drop('stab', axis=1) y = df['stabf'].copy()X = df.drop('stabf', axis=1).copy() elif task == 'regression': df = df.drop('stabf', axis=1) y = df['stab'].copy()X = df.drop('stab', axis=1).copy() X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.8, shuffle=True, random_stat e = 1) return X train, X test, y train, y test **CLASSIFICATION** In [96]: # Train test splitting X train, X test, y train, y test = preprocess inputs(data file, task='classification') In [97]: X train Out [97]: tau1 tau2 tau3 tau4 р1 p2 p3 p4 g1 g2 g3 g4 6.255995 -0.688228 -1.616780 2694 2.542401 7.024714 9.476518 3.529888 -1.224881 0.568221 0.618403 0.685739 0.660088 5.490253 0.761075 4.220888 5140 5.070581 8.075688 -1.280596 -1.902185 -1.038107 0.443515 0.097244 0.916955 2568 1.220072 8.804028 3.874283 8.433949 3.614027 -1.039236 -0.953566 -1.621224 0.908353 0.923594 0.238881 0.660156 3671 7.498402 6.697603 8.798626 2.126236 3.134585 -1.581906 -0.589386 -0.963293 0.260826 0.899003 0.964752 0.600598 1.337511 7.759156 0.716082 0.165162 7427 7.074006 6.100756 2.526922 -0.922540 -0.632600 -0.971782 0.984580 0.836928 9.504984 5.265415 2.029617 -0.922754 -1.000696 0.191864 2895 8.026334 3.449756 -1.526305 0.611297 0.080008 0.350312 -1.568218 7813 8.035818 4.632548 1.177810 1.204950 4.093208 -0.819966 -1.705024 0.223384 0.317770 0.726623 3.264057 -0.629026 0.100591 905 7.052560 1.405949 4.497549 3.741358 -1.407945 -1.704387 0.868306 0.605566 3.159670 -0.892898 5192 5.085242 1.790031 2.486392 2.848192 -1.025461 -1.241311 0.473917 0.418512 0.326253 0.982488 5.930860 235 1.205354 6.995045 2.523856 5.230127 -1.755047 -1.567927 8000 rows × 12 columns In [98]: y train Out[98]: 2694 unstable 5140 unstable unstable 2568 3671 unstable 7427 unstable 2895 stable 7813 stable 905 unstable 5192 unstable 235 stable Name: stabf, Length: 8000, dtype: object **Stochastic Gradient Descent** In [99]: from sklearn.linear_model import SGDClassifier sgd clf = SGDClassifier() sgd_clf.fit(X_train, y_train) # fitting data Out[99]: SGDClassifier(alpha=0.0001, average=False, class weight=None, early stopping=False, epsilon=0.1, eta0=0.0, fit intercept=True, 11_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='12', power t=0.5, random state=None, shuffle=True, tol=0.001, validation fraction=0.1, verbose=0, warm start=False) In [100]: X test[:5] # Checking for first 5 test data Out[100]: tau1 tau2 tau3 tau4 p1 p2 p3 p4 g1 g2 g3 g4 9953 6.877876 4.113820 9.356768 8.299753 4.056779 -1.897470 -1.590581 -0.568728 0.276567 0.845536 0.112440 0.822562 5.802841 6.271371 4.731540 3.819867 3.579569 -1.709480 -1.067511 -0.802579 0.077527 0.416478 0.912846 3850 4962 2.286998 4.385142 2.830232 5.293880 3.035814 -1.202764 -0.902011 -0.931039 0.924216 0.130186 0.703887 0.063811 3886 5.019920 2.209962 6.266080 0.578901 4.322584 -1.960207 -1.074561 -1.287815 0.546910 0.065992 0.427349 0.814648 5437 7.646145 9.187896 5.484219 9.934313 3.634226 -1.254541 -1.335366 -1.044319 0.561528 0.121611 0.787318 0.300314 In [101]: y_test # Checking for first 5 test data labels Out[101]: 9953 unstable 3850 unstable stable 4962 stable 3886 5437 unstable stable 3919 162 stable 7903 stable unstable 2242 2745 unstable Name: stabf, Length: 2000, dtype: object In [102]: sgd_clf.predict(X_test) # Predicting first 5 test data labels Out[102]: array(['unstable', 'unstable', 'stable', ..., 'unstable', 'stable', 'unstable'], dtype='<U8')</pre> In [103]: from sklearn.model_selection import cross_val_score score = cross_val_score(sgd_clf, X_train,y_train, scoring ='roc_auc', cv=4) score.mean() Out[103]: 0.881347713758724 In [104]: y_pred = sgd_clf.predict(X_test) # confusion matrix values In [105]: confusion_matrix(y_test,y_pred) Out[105]: array([[539, 173], [252, 1036]], dtype=int64) In [106]: # precision score and recall score precision_score(y_test,y_pred, pos_label="stable"), recall_score(y_test,y_pred, pos_label="stable") Out[106]: (0.6814159292035398, 0.7570224719101124) In [107]: print(classification_report(y_test, y_pred)) precision recall f1-score support 0.68 0.76 0.72 712 stable unstable 0.86 0.80 0.83 1288 0.79 2000 accuracy macro avg 0.77 2000 0.78 0.77 0.79 weighted avg 0.79 0.79 2000 **Support Vector Machines** In [108]: from sklearn import svm svm clf = svm.SVC()svm_clf.fit(X_train, y_train) C:\Users\17328\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: FutureWarning: The default value of gamma will change from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or 'scale' to avoid this warning. "avoid this warning.", FutureWarning) Out[108]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0, decision_function_shape='ovr', degree=3, gamma='auto_deprecated', kernel='rbf', max iter=-1, probability=False, random state=None, shrinking=True, tol=0.001, verbose=False) In [109]: | X_test[:5] # Checking for first 5 test data Out[109]: p2 g1 g2 g3 g4 4.113820 9.356768 8.299753 4.056779 -1.897470 -1.590581 -0.568728 0.276567 0.845536 0.112440 0.822562 9953 6.877876 3850 5.802841 6.271371 4.731540 3.819867 3.579569 -1.709480 -1.067511 -0.802579 0.077527 0.416478 4962 2.286998 4.385142 2.830232 5.293880 3.035814 -1.202764 -0.902011 3886 5.019920 2.209962 6.266080 0.578901 4.322584 -1.960207 -1.074561 -1.287815 0.546910 0.065992 0.427349 7.646145 9.187896 5.484219 9.934313 3.634226 -1.254541 -1.335366 -1.044319 0.561528 0.121611 0.787318 0.300314 In [110]: y_test[:5] # Checking for first 5 test data Out[110]: 9953 unstable 3850 unstable 4962 stable 3886 stable 5437 unstable Name: stabf, dtype: object # Predicting first 5 test data In [111]: | svm_clf.predict(X_test[:5]) Out[111]: array(['unstable', 'unstable', 'stable', 'stable', 'unstable'], dtype=object) In [112]: y pred svm = svm clf.predict(X test) # predicting all test data In [113]: confusion_matrix(y_test, y_pred_svm) Out[113]: array([[602, 110], [61, 1227]], dtype=int64) In [114]: precision_score(y_test, y_pred_svm, pos_label = "stable"), recall_score(y_test, y_pred_svm, pos_label = "stable") Out[114]: (0.9079939668174962, 0.8455056179775281) In [115]: print(classification report(y test, y pred svm)) precision recall f1-score support 0.91 0.85 0.88 712 stable unstable 0.92 0.95 0.93 1288 accuracy 0.91 2000 0.91 0.90 0.91 2000 macro avg 0.91 0.91 0.91 2000 weighted avg **Naive Bayes** In [116]: from sklearn.naive_bayes import GaussianNB In [117]: gnb = GaussianNB() In [118]: | gnb.fit(X_train, y_train) Out[118]: GaussianNB(priors=None, var smoothing=1e-09) In [119]: X test[:5] # Checking for first 5 test data Out[119]: tau1 tau2 tau3 tau4 р1 p2 p3 p4 g1 g2 g3 g4 9953 6.877876 4.113820 9.356768 8.299753 4.056779 -1.897470 -1.590581 -0.568728 0.276567 0.845536 0.112440 0.822562 3850 5.802841 6.271371 4.731540 3.819867 3.579569 -1.709480 -1.067511 -0.802579 0.077527 0.416478 0.912846 0.861306 4962 2.286998 4.385142 2.830232 5.293880 3.035814 -1.202764 -0.902011 -0.931039 0.924216 0.130186 0.703887 0.063811 3886 5.019920 2.209962 6.266080 0.578901 4.322584 -1.960207 -1.074561 -1.287815 0.546910 0.065992 0.427349 0.814648 5437 7.646145 9.187896 5.484219 9.934313 3.634226 -1.254541 -1.335366 -1.044319 0.561528 0.121611 0.787318 0.300314 In [120]: y_test[:5] # Checking for first 5 test data Out[120]: 9953 unstable 3850 unstable 4962 stable 3886 stable 5437 unstable Name: stabf, dtype: object In [121]: gnb.predict(X test[:5]) # Predicting first 5 test data Out[121]: array(['unstable', 'unstable', 'stable', 'stable', 'unstable'], dtype='<U8') In [122]: y pred gnb = gnb.predict(X test) # Predicting all test data In [123]: confusion_matrix(y_test, y_pred_gnb) Out[123]: array([[476, 236], [106, 1182]], dtype=int64) In [124]: precision_score(y_test, y_pred_gnb, pos_label = "stable"), recall_score(y_test, y_pred_gnb, pos_label = "stable") Out[124]: (0.8178694158075601, 0.6685393258426966) In [125]: print(classification report(y test, y pred gnb)) precision recall f1-score support stable 0.82 0.67 0.74 712 0.83 0.92 1288 unstable 0.87 0.83 2000 accuracy macro avg 0.83 0.79 0.80 2000 0.83 weighted avg 0.83 0.82 2000 **Decision Trees** In [126]: **from sklearn import** tree tree clf = tree.DecisionTreeClassifier() tree_clf.fit(X_train, y_train) Out[126]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None, max_features=None, max_leaf_nodes=None, min impurity decrease=0.0, min impurity split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort=False, random_state=None, splitter='best') In [127]: X test[:5] # Checking for first 5 test data Out [127]: tau1 tau2 tau4 р1 p2 p3 p4 g1 9953 6.877876 4.113820 9.356768 8.299753 4.056779 -1.897470 -1.590581 -0.568728 0.276567 0.845536 0.112440 0.822562 3850 5.802841 6.271371 4.731540 3.819867 3.579569 -1.709480 -1.067511 -0.802579 0.077527 0.416478 0.912846 0.861306 4962 2.286998 4.385142 2.830232 5.293880 3.035814 -1.202764 -0.902011 -0.931039 0.924216 0.130186 0.703887 0.063811 3886 5.019920 2.209962 6.266080 0.578901 4.322584 -1.960207 -1.074561 -1.287815 0.546910 0.065992 0.427349 5437 7.646145 9.187896 5.484219 9.934313 3.634226 -1.254541 -1.335366 -1.044319 0.561528 0.121611 0.787318 0.300314 In [128]: y_test[:5] # Checking for first 5 test data Out[128]: 9953 unstable 3850 unstable 4962 stable 3886 stable 5437 unstable Name: stabf, dtype: object In [129]: | tree_clf.predict(X_test[:5]) # Predicting first 5 test data Out[129]: array(['unstable', 'unstable', 'stable', 'stable', 'unstable'], dtype=object) In [130]: | y_pred_tree = tree_clf.predict(X_test) # Predicting all test data In [131]: | confusion_matrix(y_test, y_pred_tree) Out[131]: array([[576, 136], [144, 1144]], dtype=int64) In [132]: precision_score(y_test, y_pred_tree, pos_label = "stable"), recall_score(y_test, y_pred_tree, pos_labe 1 = "stable") Out[132]: (0.8, 0.8089887640449438) In [133]: | print(classification_report(y_test, y_pred_tree)) precision recall f1-score support stable 0.80 0.81 0.80 712 unstable 0.89 0.89 0.89 1288 accuracy 0.86 2000 0.85 0.85 0.85 2000 macro avg weighted avg 0.86 0.86 0.86 2000 **K Nearest Neighbors** In [134]: from sklearn.neighbors import KNeighborsClassifier In [135]: classifier = KNeighborsClassifier(n_neighbors=5) classifier.fit(X_train, y_train) Out[135]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=None, n_neighbors=5, p=2, weights='uniform') # Checking for first 5 test data In [136]: X test[:5] Out[136]: р1 **p2** g2 g4 tau1 tau2 p3 p4 g1 tau3 tau4 g3 9953 6.877876 4.113820 9.356768 8.299753 4.056779 -1.897470 -1.590581 -0.568728 0.276567 0.845536 0.112440 0.822562 3850 5.802841 6.271371 4.731540 3.819867 3.579569 -1.709480 -1.067511 -0.802579 0.077527 0.416478 0.912846 0.861306 4962 2.286998 4.385142 2.830232 5.293880 3.035814 -1.202764 -0.902011 -0.931039 0.924216 0.130186 0.703887 0.063811 3886 5.019920 2.209962 6.266080 0.578901 4.322584 -1.960207 -1.074561 -1.287815 0.546910 0.065992 0.427349 0.814648 5437 7.646145 9.187896 5.484219 9.934313 3.634226 -1.254541 -1.335366 -1.044319 0.561528 0.121611 0.787318 0.300314 In [137]: y test[:5] # Checking for first 5 test data Out[137]: 9953 unstable 3850 unstable stable 4962 3886 stable 5437 unstable Name: stabf, dtype: object In [138]: | classifier.predict(X test[:5]) # Predicting first 5 test data Out[138]: array(['unstable', 'unstable', 'unstable', 'stable', 'unstable'], dtype=object) In [139]: y pred knn = classifier.predict(X test) # Predicting all test data In [140]: confusion matrix(y test, y pred knn) Out[140]: array([[488, 224], [189, 1099]], dtype=int64) In [141]: precision score(y test, y pred knn, pos label = "stable"), recall score(y test, y pred knn, pos label = "stable") Out[141]: (0.7208271787296898, 0.6853932584269663) In [142]: print(classification report(y test, y pred knn)) precision recall f1-score support 0.72 stable 0.69 0.70 712 unstable 0.83 0.85 0.84 1288 0.79 2000 accuracy macro avg 0.78 0.77 weighted avg 0.79 0.79 0.77 2000 0.79 2000 In conclusion, it can be seen through the 5 predictive models that Decision tree is performing better than others due to overfitting Attributes and Distributions are evaluated Confusion matrix, precision and recall score are calculated for all 5 models 1. Stochastic Gradient Descent 2. Support vector machines 3. Naive Bayes 4. Decision trees 5. Knn