	<pre>#load data from csv file tennis = pd.read_csv('play_tennis.csv')  #transform label for tennis le = preprocessing.LabelEncoder()  tennis = tennis.drop('day', axis = 1) tennis['outlook'] = le.fit_transform(tennis['outlook']) tennis['temp'] = le.fit_transform(tennis['temp']) tennis['humidity'] = le.fit_transform(tennis['windity']) tennis['wind'] = le.fit_transform(tennis['wind']) tennis['play'] = le.fit_transform(tennis['play'])  X_cancer = cancer.data y_cancer = cancer.data y_cancer = cancer.target  X_tennis = tennis.drop('play', axis = 1) y tennis = tennis.play</pre>					
[108	<pre>#Set training data to 80% and test data to 20% for cancer X_train_cancer, X_test_cancer, y_train_cancer, y_test_cancer = model_selection.train_test_split(X_cancer,y_cancer,y_cancer) #Set training data to 80% and test data to 20% for tennis X_train_tennis, X_test_tennis, y_train_tennis, y_test_tennis = model_selection.train_test_split(X_tennis,y_test)  Decision Tree Classifier  decision_tree = tree.DecisionTreeClassifier(criterion='entropy', max_depth=20)  #decision_tree for tennis</pre>					
[110	<pre>decision_tree_tennis = decision_tree.fit(X_train_tennis, y_train_tennis) r_tennis = tree.export_text(decision_tree_tennis, feature_names=tennis.columns[:-1].tolist()) print("Play Tennis") print(r_tennis)  Play Tennis   wind &lt;= 0.50     outlook &lt;= 0.50       class: 1     outlook &gt; 0.50       outlook &lt;= 1.50       outlook &lt;= 1.50       class: 0       outlook &gt; 1.50</pre>					
[111	<pre>            humidity &lt;= 0.50               class: 0             humidity &gt; 0.50               class: 1   wind &gt; 0.50       class: 1</pre> prediction_tennis_decisionTreeClassifier = decision_tree_tennis.predict(X_test_tennis) print("Decision Tree Classifier: Tennis") print("Accuracy:", metrics.accuracy_score(y_test_tennis, prediction_tennis_decisionTreeClassifier)) print("F1 Macro avg:", metrics.f1_score(y_test_tennis, prediction_tennis_decisionTreeClassifier, average="mappint("F1 Weighted avg:", metrics.f1_score(y_test_tennis, prediction_tennis_decisionTreeClassifier,					
[112	Decision Tree Classifier: Tennis Accuracy: 0.333333333333333333333333333333333333					
	worst concave points <= 0.14					
	mean concavity <= 0.09             fractal dimension error <= 0.00               class: 0             fractal dimension error > 0.00               class: 1         mean concavity > 0.09             class: 0   worst radius > 16.80     mean texture <= 14.99         mean concavity <= 0.16         class: 1       mean concavity > 0.16         class: 0					
[113	<pre>    mean texture &gt; 14.99       worst concavity &lt;= 0.20         mean concavity &lt;= 0.05           class: 0         class: 1       class: 1       class: 0</pre>         class: 1       class: 0 prediction_cancer_decisionTreeClassifier = decision_tree_cancer.predict(X_test_cancer) print("Decision Tree Classifier: Cancer") print("Accuracy:", metrics.accuracy_score(y_test_cancer, prediction_cancer_decisionTreeClassifier))					
[114	<pre>print("F1 Macro avg:", metrics.f1_score(y_test_cancer, prediction_cancer_decisionTreeClassifier, average="ma print("F1 Weighted avg:", metrics.f1_score(y_test_cancer, prediction_cancer_decisionTreeClassifier, average= Decision Tree Classifier: Cancer Accuracy: 0.9385964912280702 F1 Macro avg: 0.9246814535158093 F1 Weighted avg: 0.9377445501436461  Id3Estimator  estimator = Id3Estimator()</pre>					
	<pre>estimator_tennis = estimator.fit(X_train_tennis, y_train_tennis)  prediction_tennis_Id3 = estimator_tennis.predict(X_test_tennis)  print("Id3Estimator: Tennis")  print("Accuracy:", metrics.accuracy_score(y_test_tennis, prediction_tennis_Id3))  print("F1 Macro avg:", metrics.f1_score(y_test_tennis, prediction_tennis_Id3, average="macro"))  print("F1 Weighted avg:", metrics.f1_score(y_test_tennis, prediction_tennis_Id3, average="weighted"))  Id3Estimator: Tennis  Accuracy: 0.333333333333333333333333333333333333</pre>					
[117	<pre>estimator_tennis_tree = export_text(estimator_tennis.tree_, feature_names=tennis.columns[:-1].tolist()) print("Play Tennis") print(estimator_tennis_tree)  Play Tennis  wind &lt;=0.50</pre>					
	<pre>wind &gt;0.50: 1 (5)  estimator_cancer = estimator.fit(X_train_cancer, y_train_cancer)  estimator_cancer_tree = export_text(estimator_cancer.tree_, cancer['feature_names']) print("Breast Cancer") print(estimator_cancer_tree)  Breast Cancer  worst radius &lt;=16.80   worst concave points &lt;=0.14</pre>					
	mean texture <=21.43: 1 (215)   mean texture >21.43     worst area <=643.25: 1 (30)     worst area >643.25       mean smoothness <=0.09       mean radius <=13.45       mean perimeter <=86.26: 0 (2)       mean perimeter >86.26: 1 (1)     mean radius >13.45: 1 (10)     mean smoothness >0.09: 0 (2)   worst concave points >0.14   worst texture <=25.67     concave points error <=0.01					
	mean texture <=16.98: 0 (2)     mean texture >16.98: 1 (2)     concave points error >0.01: 1 (10)   worst texture >25.67   mean concavity <=0.09   mean radius <=13.34: 0 (1)   mean radius >13.34: 1 (2)   mean concavity >0.09: 0 (22)   mean texture <=14.99   mean compactness <=0.13: 1 (5)   mean compactness >0.13: 0 (2)   mean texture >14.99					
[120	<pre>  worst concavity &lt;=0.20   mean compactness &lt;=0.07: 0 (3)   mean compactness &gt;0.07: 1 (2)   worst concavity &gt;0.20: 0 (144)  prediction_cancer_Id3 = estimator_cancer.predict(X_test_cancer) print("Id3Estimator: Cancer") print("Accuracy:", metrics.accuracy_score(y_test_cancer, prediction_cancer_Id3)) print("F1 Macro avg:", metrics.f1_score(y_test_cancer, prediction_cancer_Id3, average="macro")) print("F1 Weighted avg:", metrics.f1_score(y_test_cancer, prediction_cancer_Id3, average="weighted"))  Id3Estimator: Cancer Accuracy: 0.9122807017543859</pre>					
[122	F1 Macro avg: 0.8952205882352942 F1 Weighted avg: 0.9122807017543859  K-Means  kmeans = cluster.KMeans(n_clusters=2)  kmeans_tennis = kmeans.fit(X_train_tennis, y_train_tennis)  kmeans_tennis_centroid = pd.DataFrame(kmeans_tennis.cluster_centerstranspose())					
[124	<pre>kmeans_tennis_centroid.index = tennis.columns[:-1].tolist() kmeans_tennis_centroid.columns = ["Centroid 1", "Centroid 2"] print(kmeans_tennis_centroid)</pre>					
	<pre>print("F1 Macro avg:", metrics.f1_score(y_test_tennis, prediction_tennis_kmeans, average="macro")) print("F1 Weighted avg:", metrics.f1_score(y_test_tennis, prediction_tennis_kmeans, average="weighted"))  K-Means: Tennis Accuracy: 0.66666666666666 F1 Macro avg: 0.4 F1 Weighted avg: 0.5333333333333333333333333333333333333</pre>					
	Centroid 1 Centroid 2 mean radius 12.630837 19.587429 mean texture 18.618429 21.724476 mean perimeter 81.683886 129.484762 mean area 501.985429 1206.572381 mean smoothness 0.094825 0.101158 mean compactness 0.092810 0.146516 mean concavity 0.064946 0.175317 mean concave points 0.034320 0.101167 mean symmetry 0.178605 0.190745 mean fractal dimension 0.063443 0.060226 radius error 0.302593 0.725070 texture error 1.196623 1.239931					
	texture error 1.196623 1.239931 perimeter error 2.166278 5.121648 area error 24.009317 92.783714 smoothness error 0.007092 0.006614 compactness error 0.023842 0.031844 concavity error 0.029107 0.042084 concave points error 0.010629 0.015767 symmetry error 0.020467 0.020688 fractal dimension error 0.003699 0.003944 worst radius 14.162960 23.785714 worst texture 24.897171 28.994000 worst perimeter 92.894286 158.588571 worst area 630.333714 1757.771429 worst smoothness 0.130538 0.139894					
	<pre>worst compactness</pre>					
[129	Accuracy: 0.10526315789473684 F1 Macro avg: 0.09832506203473944 F1 Weighted avg: 0.06640982107875146  Logistic Regression  lr = linear_model.LogisticRegression(class_weight='balanced', max_iter=2500, random_state=0)  lr_tennis = lr.fit(X_train_tennis, y_train_tennis)  prediction_tennis_lr = lr_tennis.predict(X_test_tennis)  print("Logistic Regression: Tennis")					
	<pre>print("Logistic Regression: Tennis") print("Accuracy:", metrics.accuracy_score(y_test_tennis, prediction_tennis_lr)) print("Fl Macro avg:", metrics.fl_score(y_test_tennis, prediction_tennis_lr, average="macro")) print("Fl Weighted avg:", metrics.fl_score(y_test_tennis, prediction_tennis_lr, average="weighted"))  Logistic Regression: Tennis Accuracy: 0.666666666666666666666666666666666666</pre>					
[132	<pre>print("") print(lr_tennis_coefficient)  Play Tennis</pre>					
	<pre>prediction_cancer_lr = lr_cancer.predict(X_test_cancer) print("Logistic Regression: Cancer") print("Accuracy:", metrics.accuracy_score(y_test_cancer, prediction_cancer_lr)) print("F1 Macro avg:", metrics.f1_score(y_test_cancer, prediction_cancer_lr, average="macro")) print("F1 Weighted avg:", metrics.f1_score(y_test_cancer, prediction_cancer_lr, average="weighted"))  Logistic Regression: Cancer Accuracy: 0.956140350877193 F1 Macro avg: 0.9480448455017774 F1 Weighted avg: 0.9563202509966466  lr_cancer_coefficient = pd.DataFrame(lr_cancer.coeftranspose()) lr_cancer_coefficient.index = cancer.feature_names.tolist() lr_cancer_coefficient.sidex = cancer.feature_names.tolist()</pre>					
	<pre>lr_cancer_coefficient.columns = ["Coefficient"] print("Breast Cancer") print(lr") print(lr_cancer_coefficient)  Breast Cancer</pre>					
	mean concavity       -0.453349         mean concave points       -0.250831         mean symmetry       -0.272578         mean fractal dimension       -0.035377         radius error       -0.018472         texture error       1.699444         perimeter error       0.163954         area error       -0.115496         smoothness error       -0.022168         compactness error       0.057191         concavity error       -0.028179         concave points error       -0.031378         symmetry error       -0.044235					
	fractal dimension error 0.013249  worst radius 0.228848  worst texture -0.516900  worst perimeter -0.084322  worst area -0.015815  worst smoothness -0.321128  worst compactness -0.805459  worst concavity -1.333088  worst concave points -0.552800  worst symmetry -0.782240  worst fractal dimension -0.113955					
[136	<pre>Neural Network  neural = neural_network.MLPClassifier(max_iter=1000)  neural_tennis = neural.fit(X_train_tennis,y_train_tennis)  prediction_tennis_neural = neural_tennis.predict(X_test_tennis)  print("Neural Network: Tennis")  print("Accuracy:", metrics.accuracy_score(y_test_tennis, prediction_tennis_neural))  print("F1 Macro avg:", metrics.f1_score(y_test_tennis, prediction_tennis_neural, average="macro"))  print("F1 Weighted:", metrics.f1 score(y test_tennis, prediction_tennis_neural, average="weighted"))</pre>					
[138	<pre>Neural Network: Tennis Accuracy: 0.333333333333333333333333333333333333</pre>					
	-9.06265515e-02, -2.21376682e-01, -1.20596133e-01, 1.88444635e-01, -3.54340810e-01, 6.61429659e-15, -5.28094546e-02, -3.81503808e-01, 4.49444827e-01, -1.95213540e-02, 1.37185919e-01, 1.20672159e-12, 5.86934673e-17, -1.02676464e-01, 2.66385365e-01, -4.51563274e-01, 2.10394437e-01, -1.80523375e-01, -3.11013355e-01, -4.47417100e-01, -2.03966360e-01, -2.81119334e-01, 3.11124510e-01, 3.41082278e-01, -1.44133846e-01, 1.57995447e-01, 2.80851474e-01, -7.71803262e-15, -2.49291742e-01, 2.74176017e-01, 5.13885296e-01, 2.69944061e-01, -1.26441045e-02, 3.11645708e-01, -5.18790618e-01, 1.19110390e-01, 1.57711164e-01, 3.39626225e-01, -7.42221896e-03,					
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In [143 In [144 In [145	<pre>svc_tennis = svc.fit(X_tr  prediction_tennis_svm = s print("SVM: Tennis") print("Accuracy:", metric print("F1 Macro avg:", me print("F1 Weighted avg:",  SVM: Tennis Accuracy: 0.333333333333333333333333333333333333</pre>	svc_tennis.predict cs.accuracy_score( etrics.f1_score(y_ metrics.f1_score	<pre>c(X_test_tennis)  (y_test_tennis, predictest_tennis, predicte(y_test_tennis, predicte(y_test_tentis, predicte(y_test_tent</pre>	tion_tennis_svm, a	verage="macro"))	3"))
		rain_cancer, y_trainsvc_cancer.predictsvc_cancer.predictsvs.accuracy_score (etrics.f1_score (y_metrics.f1_score) 25950681 26950681 26950681 2702 25950681 2702 2702 2702 2702 2702 2702 2702 270	core dari masing- a algoritma di atas, nilai ression yaitu sebesar 0.0 on sebesar 0.66 untuk mengan keempat algoritm 0.167 untuk F1 Macro / core dari masing- a algoritma di atas, dida uk Accuracy, 0.948 untuajaran KMeans dengan i pembelajaran berbagai besar daripada untuk di aset breast cancer mem	tion_cancer_svm, a diction_cancer_svm  -masing Algoritr  tertinggi untuk Accura 66. Untuk untuk F1 Schacro average F1 dan valainnya yaitu Decisio Weighted average.  -masing Algoritr  patkan nilai tertinggi duk F1 Macro avg, dan (0.105 untuk Accuracy, dan (1.105 un	ma pada dataseh  acy diperoleh dengan  are, nilai tertinggi diperenghted average F1. Sin Tree, Neural Network  ma pada dataseh  engan menggunakan la 0.956 untuk F1 Weight  0.098 untuk F1 Macro  at pola di mana skor yini kami asumsikan di banyak sedangkan dar	roleh edangkan k, ID3, dan  Breast Neural ed avg. avg, dan

Breast Cancer Coefficient