me me ma	QR 0 kew 0 urt 0 p.ent 0 fm 0 ode 0 entroid 0 eanfun 0 infun 0 axfun 0 eandom 0
ma d1 mc la d1 la	
QZ QZ SI SI SI MC CC MC MC MC	Float64 Floa
di mo la di N	axdom float64 frange float64 odindx float64 abel object type: object Ote ere, we found that one of the data named 'label' has datatype of object so it is necessary to change its datatype print(df['label'].value_counts()) ale 1584
fe Na	demale 1584 ame: label, dtype: int64 from sklearn.preprocessing import LabelEncoder lb = LabelEncoder() df['label'] = lb.fit_transform(df['label']) print(df['label'].value_counts()) 1584
me so me Q2 Q7 IO sk	1584 ame: label, dtype: int64 df.dtypes eanfreq float64 d float64 edian float64 25 float64 75 float64 QR float64 kew float64 kew float64 p.ent float64
ma ma ma ma da da da	fm float64 ode float64 entroid float64 eanfun float64 infun float64 axfun float64 eandom float64 indom float64 indom float64 indom float64 axdom float64 intoff frange float64 odindx float64 abel int32 type: object
c 1	Depicting the percentage distribution of 'label' on a piechart data =[1584, 1584] label = ['Male', 'Female'] plt.pie(data, labels= label) plt.show() Male
×	Considering all values as independent and 'label' as dependent value and splitting the data into training and test data with test size = 20% X = df.iloc[:,:-1]
<pre></pre>	<pre>print(type(y)) print(x.shape) print(y.shape) class 'pandas.core.frame.DataFrame'> class 'pandas.core.series.Series'> 3168, 20) 3168,) from sklearn.model_selection import train_test_split x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.20) print(x_train.shape)</pre>
(2) (4) (2) (4)	print(x_test.shape) print(y_train.shape) print(y_test.shape) 2534, 20) 634, 20) 2534,) 634,) 634,) x_train.head() meanfreq sd median Q25 Q75 IQR skew kurt sp.ent sfm mode centroid meanfun minfun maxfun meandom mindom maxdom dfrange modindx
15 8 27 23 23 24 26 15 15 15 15 15 15 15 15 15 15 15 15 15	615 0.235271 0.029317 0.236563 0.223198 0.251933 0.028735 2.141051 7.623588 0.83982 0.124648 0.232554 0.235271 0.185272 0.048780 0.279070 1.992188 0.023438 10.242188 10.218750 0.151448 547 0.165113 0.060920 0.133009 0.117278 0.227391 0.110112 2.806798 13.195741 0.910558 0.408569 0.121473 0.165113 0.114636 0.026882 0.270270 0.537109 0.004883 0.952148 0.947266 0.384255 804 0.173483 0.058914 0.183241 0.119797 0.227899 0.108101 1.280841 4.269679 0.926355 0.443394 0.121215 0.173483 0.095161 0.015717 0.163265 0.597470 0.007812 3.468750 3.460938 0.287246 792 0.186230 0.032530 0.178776 0.170204 0.208571 0.038367 3.761459 22.198601 0.833996 0.214438 0.173061 0.186230 0.160490 0.050633 0.277457 1.940805 0.023438 9.937500 9.914062 0.164085 351 0.234232 0.031842 0.238263 0.221650 0.252851 0.031201 2.062098 6.785469 0.826263 0.153974 0.246773 0.234232 0.175598 0.049587 0.279070 1.271365 0.023438 9.796875 9.773438 0.066294 9_train.head() 615 0 547 1 04 1
23 Na 4) a.	792 0 351 0 ame: label, dtype: int32 Different Classifier Models Decsion Tree Classifier from sklearn.tree import DecisionTreeClassifier st = DecisionTreeClassifier(criterion = 'gini', max_depth = 18) st.fit(x_train,y_train)
ре р Тте	ecisionTreeClassifier(max_depth=18) print('Training Score', s1.score(x_train,y_train)) print('Testing Score', s1.score(x_test,y_test)) raining Score 1.0 esting Score 0.9763406940063092 . Random Forest Classifier from sklearn.ensemble import RandomForestClassifier
Ra p p	s2 = RandomForestClassifier(n_estimators = 80, criterion = 'gini', max_depth = 18) s2.fit(x_train,y_train) andomForestClassifier(max_depth=18, n_estimators=80) print('Training Score', s2.score(x_train,y_train)) print('Testing Score', s2.score(x_test,y_test)) raining Score 1.0 esting Score 0.9858044164037855
f s s	KNN Classifier from sklearn.neighbors import KNeighborsClassifier s3 = KNeighborsClassifier(n_neighbors = 15) s3.fit(x_train,y_train) NeighborsClassifier(n_neighbors=15) print('Training Score', s3.score(x_train,y_train))
d.	raining Score 0.7415153906866614 esting Score 0.7113564668769716 LOgistic Regression from sklearn.linear_model import LogisticRegression s4 = LogisticRegression(solver = 'liblinear') s4.fit(x_train,y_train) ogisticRegression(solver='liblinear')
r Ti Te	print('Training Score', s4.score(x_train,y_train)) print('Testing Score', s4.score(x_test,y_test)) raining Score 0.9116022099447514 esting Score 0.916403785488959 . SVM Classifier from sklearn.svm import SVC
S\S\THE	s5 = SVC(kernel = 'linear', C=1) s5.fit(x_train,y_train) VC(C=1, kernel='linear') print('Training Score', s5.score(x_train,y_train)) print('Testing Score', s5.score(x_test,y_test)) raining Score 0.9210734017363852 esting Score 0.9227129337539433) Generating Confusion Matrix and Classification Report for all the Models
	<pre>def each_model(model, x_train,x_test,y_train,y_test): model.fit(x_train,y_train) ypredict = model.predict(x_test) conf_m = confusion_matrix(y_test,ypredict) print('Training Score', model.score(x_train,y_train)) print('Testing Score', model.score(x_test,y_test)) print('Predicted Values\n',ypredict) print('Confusion_Matrix\n',conf_m) print('Classification_Report\n',classification_report(y_test,ypredict))</pre>
ti e Ti Te Pi	Lt = DecisionTreeClassifier(criterion='gini', max_depth= 18) each_model(t1,x_train,x_test,y_train,y_test) raining Score 1.0 esting Score 0.9779179810725552 redicted Values [0 0 1 1 1 0 1 1 0 1 0 1 1 1 1 1 0 0 1 0 0 1 0 1 1 1 1 1 1 1 0 1 1 0 0 0 0
() () () () () () ()	0 0 1 0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0
web.	[8 308]] lassification_Report
	t2 = RandomForestClassifier(n_estimators=80,criterion='gini',max_depth=18) each_model(t2,x_train,x_test,y_train,y_test) raining Score 1.0 esting Score 0.9842271293375394 redicted Values [0 0 1 1 0 1 0 1 0 1 0 1 1 1 1 0 0 1 0 0 0 1 0 1 1 1 1 1 1 1 1 0 1 1 1 0 0 0 0
Co	1 0 0 0 1 1 0 1 0 0 1 0 0 1 0 1 0 0 0 0
C.	0 0.98 0.99 0.98 318 1 0.99 0.97 0.98 316 accuracy 0.98 634 macro avg 0.98 0.98 0.98 634 eighted avg 0.98 0.98 0.98 634 KNN Regression t3 = KNeighborsClassifier(n_neighbors=15) each_model(t3,x_train,x_test,y_train,y_test) raining Score 0.7415153906866614
Pi () () () () () () () () () () () () ()	redicted Values [1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
C C C	1 1 1 1 1 1 0 0 0 1 1 1 0 0 0 0 1 1 1 0 1 0 1 1 1 0 0 0 1 0 0 1 0 0 1
d.	macro avg 0.72 0.71 0.71 634 eighted avg 0.72 0.71 0.71 634 LOgistic Regression t4 = LogisticRegression(solver='liblinear') each_model(t4, x_train, x_test, y_train, y_test) raining Score 0.9116022099447514 esting Score 0.916403785488959 redicted Values [0 0 1 1 1 0 1 1 0 1 1 1 1 1 1 1 0 0 1 0 0 0 1 0 1 1 1 1 1 1 1 0 1 1 1 1 0 0 0 1 0 0 1 1 1 1
	1 0 1 0 0 0 0 0 1 1 0 1 0 1 0 1 0 1 1 0 1 0 0 1 1 1 1 1 0 0 0 1 1 1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1 0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1 1 0 0 0 1 1 0 0 0 1 1 1 0 0 0 1 1 0 0 0 1 1 1 0 0 0 1 1 0 0 0 1 1 1 1 1 0 0 0 1 1 1 1 1 0 0 0 0 1 1 1 1 1 1 0 1 1 1 1 0 1 1 1 1 0 1 0 1 1 1 1 0 1 0 1 1 1 1 0 1 0 1 1 0 1 0 1 0 1 0 1 0
CC C	1 1 0 1] onfusion_Matrix [[275 43] [10 306]] lassification_Report
ti e	LS = SVC(kernel='linear',C= 1) each_model(t5,x_train,x_test,y_train,y_test) raining Score 0.9210734017363852 esting Score 0.9227129337539433 redicted Values [0 0 1 1 0 0 1 1 0 1 1 1 1 1 1 1 1 0 1 0
() () () () () ()	0 0 1 0 0 0 1 1 1 1 1 1 1 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0 0 0 1 1 0 1 0 1 0
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