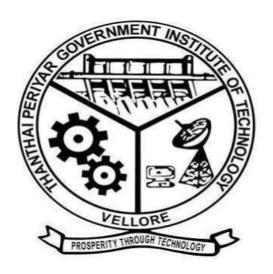
ANNA UNIVERSITY THANTHAI PERIYAR GOVERNMENT INSTITUTE OF TECHNOLOGY

VELLORE-632 002



MASTER OF COMPUTER APPLICATIONS MC4311- MACHINE LEARNING

Name:			
Reg. No:			

THANTHAI PERIYAR GOVERNMENT INSTITUTE OF TECHNOLOGY

VELLORE-632 002



MASTER OF COMPUTER APPLICATIONS MC4311 –MACHINE LEARNING LABORATORY

2023 - 2025

	Certified that	this is a	bonafide	record of	work done by
	•••••				with
Reg. no				in t	his department
during the academic year of 2024	1 - 2025.				
Staff Incharge				Head of t	the Department
Date:					
Submitted for M.C.A Degree I	Practical Exam	nination (l	II Semeste	er) held on	
at T	PGIT Bagaya	m, Vellor	e-2.		

Internal Examiner

External Examiner

INDEX

Ex.No	Date	Title	Pg.No	Signature
1		STRUCTURE DATA		
2		DATA PREPROCESSING		
3		FEATURE SUBSET SELECTION		
4		PERFORMANCE MATRIX		
5		NAVIE BAYES CLASSIFICATION - GAUSSIANNB		
6		NAVIE BAYES CLASSIFICATION - MULTINOMIALNB		
7		BAYESIAN NETWORK		
8		EM ALGORITHM		
9		LOGISTIC REGRESSION - SPAM DETECTION		
10		LOGISTIC REGRESSION - DIABETES		
11		ANN BACK PROPOGATION		
12		K-NEAREST NEIGHBOUR		
13		DECISION TREE		
14		SUPPORT VECTOR CLASSIFICATION		

STRUCTURE DATA

PROGRAM:

```
In [1]: | import pandas as pd
In [8]:
      s1=pd.Series([2201,2202,2203,2204,2205,2206,2207,2208,2209,2210])
      s2=pd.Series(["Shibu","Vicky","Akash","Surya","Nandhu","Vinzz","Lechu","Preethi",
                        "Raghul", "Mathesh"])
      s3=pd.Series(["MCA","CSC","IT","MCA","IT","CSC","BCA","AI","BCA","BSC"])
s4=pd.Series["02/09/2001","12/08/2002","23/04/2001","28/05/2000","30/02/2002",
"26/07/2000","20/05/2002","19/08/2001","28/01/2001","01/09/2000"])
       s5=pd.Series([23,22,23,24,22,24,22,23,23,24])
      s6=pd.Series(["Male","Male","Male","Male","Female","Female",
                        "Female", "Male", "Male"])
      s7=pd.Series(["shibu@gmail.com","vicky7@gmail.com","akash12@gmail.com","surya7@gmail.com,
                       "nandhu19@gmail.com", "vinzz11@gmail.com", "lechu05@gmail.com",
                       "preethi8@gmail.com", "raghul@gmail.com", "mathesh20@gmail.com"])
      s8=pd.Series([8479782752,92378451052,8752305137,9462357103,8967453210,9087635812,
                       9845671230,8765423912,8654320852,9543267539])
      Student=pd.DataFrame({"REGNO":s1,"NAME":s2,"DEPT":s3,"DOB":s4,"AGE":s5,"GENDER":s6,
                                 "EMAIL-ID":s7, "PH.NO":s8})
```

In [9]: Student

OUTPUT:

Out[9]:

R	EGNO	NAME	DEPT	DOB	AGE	GENDER	EMAIL-ID	PH.NO
0	1890	Shibu	MCA	02/09/2001	23	Male	shibu@gmail.com	8479782752
1	1891	Vicky	CSC	12/08/2002	22	Male	vicky7@gmail.com	92378451052
2	1892	Akash	IT	23/04/2001	23	Male	akash12@gmail.com	8752305137
3	1893	Surya	MCA	28/05/2000	24	Male	surya7@gmail.com	9462357103
4	1894	Nandhu	IT	30/02/2002	22	Male	nandhu19@gmail.co	8967453210
							<u>m</u>	
5	1895	Vinzz	CSC	26/07/2000	24	Female	vinzz11@gmail.com	9087635812
6	1896	Lechu	BCA	20/05/2002	22	Female	lechu05@gmail.com	9845671230
7	1897	Preethi	AI	19/08/2001	23	Female	preethi8@gmail.com	8765423912
8	1898	Raghul	BCA	28/01/2001	23	Male	raghul@gmail.com	8654320852
9	1899	Mathesh	BSC	01/09/2000	24	Male	mathesh20@gmail.c om	9543267539

DATA PRE-PROCESSING

```
In [62]:
           Import numpy as nm
           Import pandas as pd
 In [63]:
          dataset=pd.read_csv('Data1.csv')
 In [64]: Dataset
 Out[64]:
               Country Age
                              Salary Purchased
            0
                             72000.0
                France
                       23.0
                                           No
            1
                 Spain
                       14.0
                             48000.0
                                           Yes
            2 Germany
                       30.0
                             54000.0
                                           No
            3
                       38.0
                            61000.0
                 Spain
                                           No
            4 Germany
                       40.0
                               NaN
                                           Yes
            5
                       35.0
                             58000.0
                France
                                           Yes
            6
                 Spain
                       NaN
                             52000.0
                                           No
                       48.0
                            79000.0
            7
                France
                                           Yes
            8
                       50.0
                            83000.0
              Germany
                                           No
            9
                France
                       37.0 67000.0
                                           Yes
In[65]:
           x=dataset.iloc[:,:-1].values
In[66]:
           Х
               array([['France',23.0,72000.0],
Out[66]:
                      ['Spain',14.0,48000.0],
                   ['Germany',30.0,54000.0],
                   ['Spain',38.0,61000.0],
                   ['Germany',40.0,nan],
                   ['France',35.0,58000.0],
                   ['Spain',nan,52000.0],
                   ['France',48.0,79000.0],
                   ['Germany',50.0,83000.0],
                   ['France',37.0,67000.0]],dtype=object)
In[67]:
           y=dataset.iloc[:,3].values
In[68]:
           array(['No','Yes','No','Yes','Yes','No','Yes'], dtype=object)
Out[68]:
In[69]:
           From sklearn.impute import SimpleImputer
In[70]:
           imputer=SimpleImputer(missing_values=nm.nan,strategy='mean')
In[71]:
           imputer1=imputer.fit(x[:,1:3])
In[72]:
           x[:,1:3]=imputer.transform(x[:,1:3])
           Х
```

```
array([['France',23.0,72000.0],
Out[73]:
                      ['Spain',14.0,48000.0],
                  ['Germany',30.0,54000.0],
                  ['Spain',38.0,61000.0],
                  ['Germany',40.0,63777.777777778],
                  ['France',35.0,58000.0],
                  ['Spain',35.0,52000.0],
                  ['France',48.0,79000.0],
                  ['Germany',50.0,83000.0],
                  ['France',37.0,67000.0]],dtype=object)
In[74]:
           From sklearn.preprocessing import LabelEncoder
In[75]:
           labelencoder_x=LabelEncoder()
In[76]:
           x[:,0]=labelencoder x.fit transform(x[:,0])
In[77]:
           Х
           array([[0, 23.0, 72000.0],
Out[77]:
                   [2, 14.0, 48000.0],
                   [1, 30.0, 54000.0],
                   [2, 38.0, 61000.0],
                   [1, 40.0, 63777.7777777778],
                   [0, 35.0, 58000.0],
                   [2, 35.0, 52000.0],
                   [0, 48.0, 79000.0],
                   [1, 50.0, 83000.0],
                   [0, 37.0, 67000.0]],dtype=object)
In[78]:
           From sklearn.compose import ColumnTransformer
In[79]:
           From sklearn.preprocessing import OneHotEncoder
          ct=ColumnTransformer([("Country",OneHotEncoder(),[0])],remainder="passthrough")
In[82]:
In[83]:
           ct=ColumnTransformer([("Country",OneHotEncoder(),[0])],remainder="passthrough")
In[84]:
           x=ct.fit_transform(x)
In[85]:
           x=x[:,0:]
In[86]:
           Х
           array([[1.0, 0.0, 0.0, 23.0, 72000.0],
Out[86]:
                   [0.0, 0.0, 1.0, 14.0, 48000.0],
                   [0.0, 1.0, 0.0, 30.0, 54000.0],
                   [0.0, 0.0, 1.0, 38.0, 61000.0],
                   [0.0, 1.0, 0.0, 40.0, 63777.777777778],
                   [1.0, 0.0, 0.0, 35.0, 58000.0],
                   [0.0, 0.0, 1.0, 35.0, 52000.0],
                   [1.0, 0.0, 0.0, 48.0, 79000.0],
                   [0.0, 1.0, 0.0, 50.0, 83000.0],
                   [1.0, 0.0, 0.0, 37.0, 67000.0]],dtype=object)
In[87]:
           label_encoder_y=LabelEncoder()
In[88]:
           y=label_encoder_y.fit_transform(y)
```

```
In[89]:
           From sklearn.model_selection import train_test_split
In[90]:
           x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
In[91]:
           x_train
           array([[0.0, 1.0, 0.0, 40.0, 63777.777777778],
Out[91]:
                   [1.0, 0.0, 0.0, 37.0, 67000.0],
                   [0.0, 0.0, 1.0, 14.0, 48000.0],
                   [0.0, 0.0, 1.0, 35.0, 52000.0],
                   [1.0, 0.0, 0.0, 48.0, 79000.0],
                   [0.0, 0.0, 1.0, 38.0, 61000.0],
                   [1.0, 0.0, 0.0, 23.0, 72000.0],
                   [1.0, 0.0, 0.0, 35.0, 58000.0]],dtype=object)
In[92]:
           x_test
           array([[0.0, 1.0, 0.0, 30.0, 54000.0], [0.0, 1.0, 0.0, 50.0, 83000.0]],dtype=object)
Out[92]:
In[93]:
           y_train
           array([1,1,1,0,1,0,0,1])
Out[93]:
In[94]:
           y_test
           array([0,0])
Out[94]:
In[97]:
           From sklearn.preprocessing import StandardScaler
In[98]:
           st_x=StandardScaler()
In[99]:
           x_train=st_x.fit_transform(x_train)
           x=test=st_x.transform(x_test)
In[100]:
In[103]:
           print("Feature Scaling")
           print("x_train \n",x_train)
           print("x_test \n",x_test)
OUTPUT:
           FeatureScaling
           x_train
            [[-1.
                          2.64575131-0.774596670.633165070.12381479]
                           -0.37796447 -0.77459667 0.32924584 0.46175632]
             [1.
            [-1.
                          -0.37796447 1.29099445 -2.00080164 -1.53093341]
            [-1.
                          -0.37796447 1.29099445 0.12663301 -1.11141978]
                          -0.37796447 -0.77459667 1.44361637 1.7202972]
             [1.
                          -0.37796447 1.29099445 0.43055225 -0.16751412]
            [-1.
             [1.
                          -0.37796447 -0.77459667 -1.08904393 0.98614835]
             [1.
                          -0.37796447 -0.77459667 0.12663301 -0.48214934]]
```

x_test

[[0.01.00.030.054000.0] [0.01.00.050.083000.0]]

FEATURE SUBSET SELECTION

```
In [1]:
         import pandas as pd
         import numpy as np
         data="https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-d
In [3]:
         features=['preg','plas','pres','skin','test','mass','pedi','age','class']
         df=pd.read csv(data,names=features)
In [5]:
         df.head()
 Out[5]:
             preg plas
                        Pres skin test mass
                                               pedi age
                                                           class
          0
                   148
                          72
                                35
                                          33.6 0.627
                                                              1
                6
                                      0
                                                       50
                    85
                                          26.6 0.351
                1
                          66
                                29
                                      0
                                                       31
                                                              0
          2
                   183
                                      0
                                          23.3 0.672
                                                       32
                8
                          64
                               0
                                                              1
                    89
                                23
                                     94
                                          28.1 0.167
                                                       21
                                                              0
                          66
                0
                   137
                          40
                                35
                                   168
                                          43.1 2.288
                                                       33
                                                              1
In [7]:
        df.shape
Out[7]: (768, 9)
In [9]: data=df.values
         x=data[:,0:8]
         y=data[:,8]
In [11]: from sklearn.feature_selection import SelectKBest
         from sklearn.feature_selection import chi2
In [13]: chi_best=SelectKBest(score_func=chi2,k=4)
         k_best=chi_best.fit(x,y)
         np.set_printoptions(precision=3)
         print(k_best.scores_)
         k_features=k_best.transform(x)
         print(k_features[0:5,:])
        [ 111.52 1411.887
                                       53.108 2175.565 127.669
                              17.605
                                                                    5.393 181.304]
                              50. ]
        [[148.
                   0.
                        33.6
         [ 85.
                   0.
                        26.6
                              31. ]
         [183.
                   0.
                        23.3 32.]
         [ 89.
                  94.
                        28.1 21. ]
         [137.
                168.
                        43.1
In [15]: from sklearn.feature_selection import RFE
         from sklearn.linear_model import LogisticRegression
```

```
In [17]:
         import warnings
         warnings.filterwarnings('ignore')
In [19]: model_lr=LogisticRegression()
         recur fe=RFE(model lr)
         Feature=recur_fe.fit(x,y)
print("Number of Features: %d" % (Feature.n_features_))
         print("Selected Features are: %s" % (Feature.support ))
         print("Feature Ranking is as follows: %s" % (Feature.ranking ))
        Number of Features: 4
        Selected Features are: [ True True False False True True False]
        Feature Ranking is as follows: [1 1 3 4 5 1 1 2]
In [21]: from sklearn.linear_model import Ridge
         ridge_reg=Ridge(alpha=1.0)
         ridge reg.fit(x,y)
Out[21]:
              Ridge
         Ridge()
In [23]: def print_coefs(coef,names=None,sort=False):
              if names==None:
                  names=["x%s" % x for x in range(len(coef))]
              lst=zip(coef,names)
              if sort:
                  lst =sorted(lst,key=lambda x:-np.abs(x[0]))
              return " + ".join("%s * %s" %(round(coefs,3),name) for coefs,name in lst)
In [25]:
         print("Ridge model:",print_coefs(ridge_reg.coef_))
```

OUTPUT:

```
Ridge model: 0.021 * x0 + 0.006 * x1 + -0.002 * x2 + 0.0 * x3 + -0.0 * x4 + 0.013 * x5 + 0.145 * x6 + 0.003 * x7
```

PERFORMANCE MATRIX

```
import pandas as pd
In [3]:
         from sklearn import model_selection
         from sklearn.linear_model import LogisticRegression
         url = "pima-indians-diabetes.data.csv"
         names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
In [4]:
         'class']dataframe = pd.read csv(url, names=names)
         array = dataframe.values
         X = array[:,0:8]
         Y = array[:,8]
In [5]:
         kfold = model selection.KFold(n splits=10,random state=7,shuffle=True) model =
         LogisticRegression(solver='liblinear')
         print("Classification Accuracy")
 In [6]:
         results =
         model_selection.cross_val_score(model,X,Y,cv=kfold,scoring='accuracy')
        print("Accuracy: %.3f (%.3f)" % (results.mean(), results.std()))
        Classification
        Accuracy: 0.771 (0.051)
         print("Log Loss")
                     model_selection.cross_val_score(model,X,Y,cv=kfold,scoring='neg_log_loss')
 In [7]:
         print("Logloss: %.3f (%.3f)" % (results.mean(), results.std()))
        Logloss: -0.494 (0.042)
        print('Area Under ROC Drive')
In [8]:
        results = model_selection.cross_val_score(model,X,Y,cv=kfold,scoring='roc_auc')
        print("AUC: %.3f (%.3f)" % (results.mean(), results.std()))
       Area Under ROC Drive
       AUC: 0.826 (0.050)
        from sklearn import model_selection
In [9]:
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import confusion_matrix
        X = array[:,0:8]
In [10]:
        Y = array[:,8]
        X_train,X_test,Y_train,Y_test=model_selection.train_test_split(X,Y,test_siz
        =0.33, random state=7)
        model =
In [11]:
        LogisticRegression(solver='liblinear')
        model.fit(X train, Y train)
        predicted = model.predict(X_test)
```

OUTPUT:

Classification	Report			
	Precision	recall	f1-score	support
0.0 1.0	0.77 0.71	0.87 0.55	0.82 0.62	162 92
accuracy macro avg weighted avg	0.74 0.75	0.71 0.76	0.76 0.72 0.75	254 254 254

NAVIE BAYES CLASSIFICATION - GAUSSIANNB

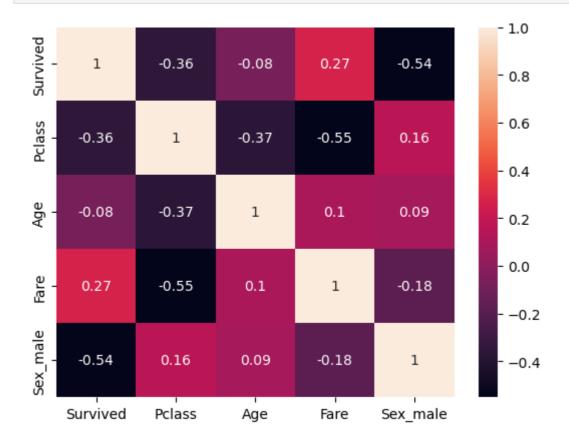
```
In [1]: import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
In [2]: from sklearn.model_selection import train_test_split
          from sklearn.naive bayes import GaussianNB
          from sklearn.metrics import accuracy score, confusion matrix, classification report
In [4]: raw_data=pd.read_csv("titanic.csv")
          raw data.head()
Out[4]:
          Passengerld Survived Pclass
                                                                    Sex Age SibSp Parch
                                                                                               Ticket
                                                            Name
                                                                                                       Fare Cabin Embarked
        0
                                                                                             A/5 21171 7.2500
                 1
                              3
                                                 Braund, Mr. Owen Harris
                                                                   male 22.0
                                                                                                            NaN
                                                                                                                       S
                               1 Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0
                                                                                             PC 17599 71.2833
                                                                                                             C85
                                                  Heikkinen, Miss. Laina female 26.0
                                                                               0
                                                                                     0 STON/O2. 3101282
                                                                                                     7.9250
                                                                                                            NaN
       3
                                     Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0
                                                                                               113803 53.1000
                                                 Allen, Mr. William Henry male 35.0
                                                                                               373450 8.0500
                                                                                                                       S
In [5]: raw_data.describe(include='all')
 Out[5]:
                          Survived
                                     Pclass
                                                                             SibSp
                                                                                           Ticket
                                                                                                            Cabin Embarked
               Passengerld
                                                                     Age
                                                                                      Parch
                                                                                                      Fare
                                                      Name
                                                            Sex
               891.000000 891.000000 891.000000
                                                        891
                                                             891 714.000000 891.000000 891.000000
                                                                                              891 891.000000
                                                                                                             204
                                                                                                                      889
         count
                             NaN
                                                        891
                                                                                              681
                                                                                                                       3
                                                                     NaN
                                      NaN Braund, Mr. Owen Harris male
                                                                                       NaN 347082
                                                                                                           B96 B98
                             NaN
                                                                              NaN
                                                                                                      NaN
                                                                                                                        S
          freq
                    NaN
                             NaN
                                      NaN
                                                            577
                                                                     NaN
                                                                              NaN
                                                                                       NaN
                                                                                                      NaN
                                                                                                                      644
          mean
               446.000000
                          0.383838
                                  2.308642
                                                       NaN NaN
                                                                 29.699118
                                                                          0.523008
                                                                                    0.381594
                                                                                             NaN 32,204208
                                                                                                             NaN
                                                                                                                     NaN
               257.353842
                          0.486592
                                   0.836071
                                                                 14.526497
                                                                           1.102743
                                                                                    0.806057
                                                                                             NaN 49.693429
                                                                                                             NaN
                                                                                                                     NaN
                                                       NaN NaN
                 1.000000
                          0.000000
                                   1.000000
                                                                  0.420000
                                                                           0.000000
                                                                                    0.000000
                                                                                                   0.000000
                                                                                                             NaN
                                                                                                                     NaN
           min
                                                       NaN NaN
                                                                                             NaN
          25%
               223.500000
                                   2.000000
                                                       NaN NaN
                                                                 20.125000
                                                                           0.000000
                                                                                    0.000000
                                                                                             NaN 7.910400
                                                                                                             NaN
                                                                                                                     NaN
          50%
               446.000000
                          0.000000
                                   3.000000
                                                       NaN NaN
                                                                 28.000000
                                                                           0.000000
                                                                                    0.000000
                                                                                             NaN 14.454200
                                                                                                             NaN
                                                                                                                     NaN
          75%
               668.500000
                          1.000000
                                   3.000000
                                                       NaN NaN
                                                                 38.000000
                                                                           1.000000
                                                                                    0.000000
                                                                                             NaN 31.000000
                                                                                                             NaN
                                                                                                                     NaN
               891.000000
                          1.000000
                                   3.000000
                                                                                             NaN 512,329200
                                                       NaN NaN 80.000000
                                                                           8.000000
                                                                                   6.000000
                                                                                                             NaN
                                                                                                                     NaN
In [9]: print(raw_data.columns)
             Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age',
                       'SibSp', 'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
                     dtype='object')
In [10] raw_data.columns = raw_data.columns.str.strip()
         columns to drop = ['PassengerId', 'Name', 'SibSp', 'Parch', 'Ticket',
In [11
          ('Cabin', 'Embmbarked']
          missing_columns = [col for col in columns_to_drop if col not in raw_data.columns]
          print("Missing columns:", missing_columns)
```

```
In [12]: data = raw_data.drop(columns=['PassengerId', 'Name', 'SibSp', 'Parch', 'Ticket',
          'Cabin', 'Embarked'], errors='ignore')
In [13]: data.head()
Out[13]:
              Survived
                           Pclass
                                      Sex Age
                                                      Fare
           0
                       0
                                3
                                      male
                                            22.0
                                                    7.2500
                                   female 38.0
                                                  71.2833
           1
           2
                       1
                                   female 26.0
                                                    7.9250
           3
                                   female
                                            35.0
                                                   53.1000
           4
                       0
                                      male 35.0
                                                    8.0500
In [15]: mv=data.isnull()
Out [15]:
              Survived
                             0
              Pclass
              Sex
                             0
                           177
              Age
              Fare
              dtype: int64
In [16]: data_no_mv=data.dropna(axis=0)
In [17]:
          data_no_mv.describe(include='all')
Out[17]:
                  Survived
                              Pclass Sex
                                              Age
                                                        Fare
          count 714.000000 714.000000
                                     714 714.000000 714.000000
          unique
                     NaN
                               NaN
                                      2
                                              NaN
                                                        NaN
            top
                     NaN
                               NaN male
                                              NaN
                                                        NaN
            freq
                     NaN
                               NaN
                                     453
                                              NaN
                                                        NaN
                                                    34.694514
                  0.406162
                            2.236695 NaN
                                          29.699118
           mean
                  0.491460
                            0.838250 NaN
                                          14.526497
                                                   52.918930
                  0.000000
                            1.000000 NaN
                                           0.420000 0.000000
            min
            25%
                  0.000000
                           1.000000 NaN
                                          20.125000 8.050000
           50%
                  0.000000
                            2.000000 NaN
                                          28.000000 15.741700
           75%
                  1.000000
                            3.000000 NaN
                                          38.000000 33.375000
                                          80.000000 512.329200
           max
                  1.000000
                            3.000000 NaN
In [18]:
          data_with_dummies=pd.get_dummies(data_no_mv,drop_first=True)
In [19]:
          data_with_dummies.head()
```

Out[19]: Survived Pclass Age **Fare** Sex_male 0 0 22.0 7.2500 True 3 1 38.0 71.2833 False 2 3 26.0 False 1 7.9250 3 35.0 53.1000 False 4 0 3 35.0 8.0500 True

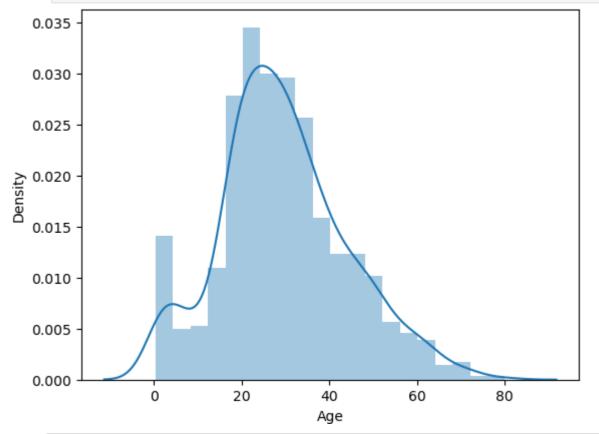
In [20]: corr_matrix=data_with_dummies.corr().round(2)

In [21]: sns.heatmap(data=corr_matrix,annot=True)
 plt.show()



Out[22]:		Survived	Pclass	Age	Sex_male
	0	0	3	22.0	True
	1	1	1	38.0	False
	2	1	3	26.0	False
	3	1	1	35.0	False
	4	0	3	35.0	True

```
In [23]: sns.distplot(data_no_multicollinearity['Age'])
    plt.show()
```



In [24]: features=data_no_multicollinearity.drop('Survived',axis=1)
 label=data_no_multicollinearity['Survived']

In [26]: X_train,X_test,y_train,y_test=train_test_split(features,label,test_size=0.2,random_

In [27]: clf=GaussianNB()
 clf.fit(X_train,y_train)

Out[27]: GaussianNB GaussianNB()

In [30]: matrix=pd.DataFrame(confusion_matrix(y_test,pred),columns=['Predicted 0', 'Predicted
1'])

In [31]: matrix

OUTPUT:

Out [31]:

_	Predicted 0	Predicted 1
0	73	14
1	19	37

In [32]: print(classification_report(y_test,pred))

	precision	recall	f1-score	support
0	0.79	0.84	0.82	87
1	0.73	0.66	0.69	56
accuracy			0.77	143
macro avg	0.76	0.75	0.75	143
weighted avg	0.77	0.77	0.77	143

NAVIE BAYES CLASSIFICATION- MULTINOMINALNB

```
In [1]: import pandas as pd
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.model selection import train test split
         from sklearn.naive_bayes import MultinomialNB
         from sklearn.metrics import accuracy_score
In [2]: data = {
         'text': [
         'Free money now',
         'Call me now',
         'Win a lottery',
         'Important information regarding your account',
         'Meeting at noon',
         'Your invoice is attached',
         'Lowest price in the market',
         'Can you send me the report?'
         ],
         'label': [
         'spam',
         'spam',
         'spam',
         'ham',
         'ham',
         'ham',
         'spam',
         'ham'
In [3]: df = pd.DataFrame(data)
In [4]: X = df['text']
         y = df['label']
In [5]: vectorizer = CountVectorizer()
         X_vectorized = vectorizer.fit_transform(X)
In [6]: X_train, X_test, y_train, y_test = train_test_split(X_vectorized, y, test_size=0.3,
In [7]: model = MultinomialNB()
         model.fit(X_train, y_train)
In [8]: y_pred = model.predict(X_test)
In [9]: accuracy = accuracy_score(y_test, y_pred)
         print(f'Accuracy of the Naïve Bayes classifier: {accuracy * 100:.2f}%')
        Accuracy of the Naïve Bayes classifier: 66.67%
```

```
In [10]:
    test_data = [
        "Congratulations! You have won a gift card",
        "Can we reschedule our meeting?",
        "Get paid for taking surveys",
        "Your appointment is confirmed",
        "you have won a lottery",
        "Congratulations! You've unlocked access to an exclusive AI course!",
        "Can we schedule a call to discuss your AI project?",
        "Get paid to test machine learning models—sign up now!",
        "Your AI consultation is confirmed—see you soon!",
        "You've been selected for a free machine learning webinar!",
        ]
```

OUTPUT:

Text: "Congratulations! You have won a gift card" | Prediction: ham

Text: "Can we reschedule our meeting?" | Prediction: ham

Text: "Get paid for taking surveys" | Prediction: ham

Text: "Your appointment is confirmed" | Prediction:
ham Text: "you have won a lottery" | Prediction: ham

Text: "Congratulations! You've unlocked access to an exclusive AI course!" | Prediction: ham

Text: "Can we schedule a call to discuss your AI project?" | Prediction: ham

Text: "Get paid to test machine learning models—sign up now!" | Prediction:
ham Text: "Your AI consultation is confirmed—see you soon!" | Prediction: ham

Text: "You've been selected for a free machine learning webinar!" | Prediction:
ham

BAYESIAN NETWORK

```
In [3]: import numpy as np
         import csv
         import pandas as pd
         #python -m pip install pgmpy in jupyter terminal or anaconda terminal
         from pgmpy.models import BayesianNetwork
         from pgmpy.estimators import MaximumLikelihoodEstimator
         from pgmpy.inference import VariableElimination
 In [5]: #read Cleveland Heart Disease data
         heartDisease = pd.read csv('heart.csv')
         heartDisease = heartDisease.replace('?',np.nan)
 In [7]: #display the data
         print('Few examples from the dataset are given below')
         print(heartDisease.head())
       Few examples from the dataset are given below
          age sex cp trestbps chol fbs restecg thalach exang oldpeak slope \
                    3
                             145
                                                                   0
       а
           63
                 1
                                   233
                                          1
                                                   a
                                                          150
                                                                          2.3
           37
                 1 2
                             130
                                   250
                                                   1
                                                          187
                                                                   0
                                                                          3.5
                                                                                   0
       1
                 0 1
       2
           41
                             130
                                   204
                                          0
                                                  0
                                                          172
                                                                   0
                                                                          1.4
                                                                                   2
           56
                 1
                    1
                             120
                                   236 0
                                                   1
                                                          178
                                                                   0
                                                                          0.8
                                                                                   2
                             120 354 0
                                                 1
                                                          163
                                                                          0.6
           57
                 0 0
                                                                   1
           ca thal target
       a
           a
                 1
                         1
       1
           0
                 2
                         1
       2
          0
                 2
                         1
        3
           0
                 2
                         1
                 2
                         1
           0
In [21]: #Model Bayesian Network
         Model=BayesianNetwork([('age','trestbps'),('age','fbs'), ('sex','trestbps'),
         ('exang','trestbps'),('trestbps','target'),('fbs','target'),
         ('target','restecg'), ('target','thalach'),('target','chol')])
In [23]: #Learning CPDs using Maximum Likelihood Estimators
         print('\n Learning CPD using Maximum likelihood estimators')
         Model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)
         Learning CPD using Maximum likelihood estimators
In [25]: # Inferencing with Bayesian Network
         print('\n Inferencing with Bayesian Network:')
         HeartDisease infer = VariableElimination(Model)
         Inferencing with Bayesian Network:
In [29]:
         #computing the Probability of HeartDisease given Age
         print('\n 1. Probability of HeartDisease given Age=29')
         q=HeartDisease_infer.query(variables=['target'],evidence ={'age':29})
         print(q)
```

1. Probability of HeartDisease given Age=29

```
+-----+
| target | phi(target) |
+-----+
| target(0) | 0.3872 |
+-----+
| target(1) | 0.6128 |
+------+
```

In [31]: #computing the Probability of HeartDisease given cholesterol
 print('\n 2. Probability of HeartDisease given cholesterol=160')
 q=HeartDisease_infer.query(variables=['target'],evidence ={'chol':160})
 print(q)

2. Probability of HeartDisease given cholesterol=160

```
+-----+
| target | phi(target) |
+-----+
| target(0) | 0.0000 |
+-----+
| target(1) | 1.0000 |
+------+
```

EM ALGORITHM

PROGRAM:

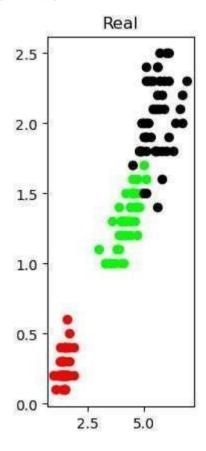
```
In [3]: names = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width', 'Class']
    dataset = pd.read_csv("8-dataset.csv", names=names)
    X = dataset.iloc[:, :-1]
    label = {'Iris-setosa': 0,'Iris-versicolor': 1, 'Iris-virginica': 2}
    y = [label[c] for c in dataset.iloc[:, -1]]

In [5]: plt.figure(figsize=(14,7))
    colormap=np.array(['red','lime','black'])

<Figure size 1400x700 with 0 Axes>
```

```
In [7]: # REAL PLOT
plt.subplot(1,3,1)
plt.title('Real')
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y])
```

Out[7]: <matplotlib.collections.PathCollection at 0x24ae3703f50>



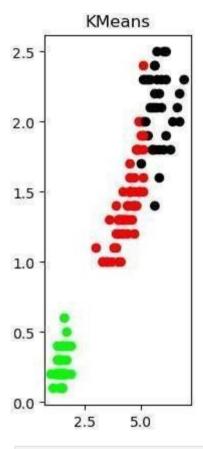
```
In [11]: # K-PLOT
model=KMeans(n_clusters=3, random_state=0).fit(X)
plt.subplot(1,3,2)
```

```
plt.title('KMeans')
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[model.labels_])
```

C:\Users\surya\anaconda3\Lib\site-packages\sklearn\cluster_kmeans.py:1429: UserWarn ing: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.

warnings.warn(

Out[11]: <matplotlib.collections.PathCollection at 0x24ae87b1fd0>



```
In [13]: print('The accuracy score of K-Mean: ',metrics.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean:\n',metrics.confusion_matrix(y, model.labels_)
```

```
The accuracy score of K-Mean: 0.24
The Confusion matrixof K-Mean:
[[ 0 50  0]
[47  0  3]
[14  0  36]]
```

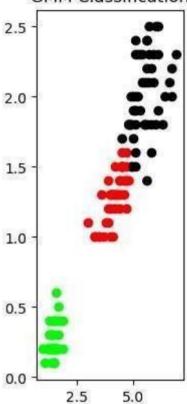
```
In [15]: # GMM PLOT
    gmm=GaussianMixture(n_components=3, random_state=0).fit(X)
    y_cluster_gmm=gmm.predict(X)
    plt.subplot(1,3,3)
    plt.title('GMM Classification')
    plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y_cluster_gmm])
```

C:\Users\surya\anaconda3\Lib\site-packages\sklearn\cluster_kmeans.py:1429: UserWarn ing: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.

warnings.warn(

Out[15]: <matplotlib.collections.PathCollection at 0x24ae88eb110>

GMM Classification



In [17]: print('The accuracy score of EM: ',metrics.accuracy_score(y, y_cluster_gmm))
print('The Confusion matrix of EM:\n ',metrics.confusion_matrix(y, y_cluster_gmm))

LOGISTIC REGRESSION – SPAM DETECTION

```
In [2]:
                  import pandas as pd
                  from sklearn.model selection import train test split
                  from sklearn.feature extraction.text import CountVectorizer
                  from sklearn.linear_model import LogisticRegression
                  from sklearn.metrics import confusion matrix,
                  accuracy_score,classification_report
                  # Load the dataset
                  data = pd.read_csv('spam.csv',
                  encoding='latin-1') # Display the first few
                  rows of the dataset print(data.head())
                  # Data preprocessing
                  # The dataset has columns 'v1' for labels and 'v2' for messages
                  data = data[['v1', 'v2']]
                  data.columns = ['label',
                  'message']
                  # Convert labels to binary: spam=1, ham=0
                  data['label'] = data['label'].map({'spam': 1, 'ham': 0})
                  # Split the dataset into features and target variable
                  X = data['message'] # Features
                  y = data['label'] # Target variable
                  # Split the dataset into training and testing sets
                  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                  random state=20)
                  # Convert text data to numerical data using CountVectorizer
                  vectorizer = CountVectorizer()
                  X_train_vectorized = vectorizer.fit_transform(X_train)
                  X_test_vectorized = vectorizer.transform(X_test)
                  # Create a Logistic Regression model
                  model = LogisticRegression()
                  # Train the model
                  model.fit(X_train_vectorized,
                  y_train) # Make predictions
                  y_pred = model.predict(X_test_vectorized)
                  # Evaluate the model
                  accuracy = accuracy_score(y_test, y_pred)
                  conf_matrix = confusion_matrix(y_test,
                  y_pred) class_report =
                  classification_report(y_test, y_pred)
                  print(f'Accuracy: {accuracy:.2f}')
                  print('Confusion Matrix:')
                  print(conf matrix)
                  print('Classification
                  Report:') print(class_report)
```

OUTPUT

	v1	v2 Unnamed: 2 \	
0	ham	Go until jurong point, crazy Available only	NaN
1	ham	Ok lar Joking wif u oni	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina	NaN
3		U dun say so early hor U c already then say	NaN
4	ham	Nah I don't think he goes to usf, he lives aro	NaN

Accuracy: 0.98

Confusion Matrix: [[968 2] [21 124]]

Classi

	precision	recall	f1-score	support
0	0.98	1.00	0.99	970
1	0.98	0.86	0.92	145
accuracy			0.98	1115
macro avg	0.98	0.93	0.95	1115
weighted avg	0.98	0.98	0.98	1115

LOGISTIC REGRESSION - DIABETES

```
In [6]: import pandas as pd
        from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
         # Load the dataset
        data = pd.read_csv('diabetes.csv')
         # Display the first few rows of the dataset
        print(data.head())
        # Features and target variable
        X = data.drop('Outcome', axis=1) # Features
        y = data['Outcome'] # Target variable
         # Split the dataset into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
        # Standardize the features
        scaler = StandardScaler()
        X_train = scaler.fit_transform(X_train)
        X_test = scaler.transform(X_test)
         # Create a Logistic Regression model
        model = LogisticRegression()
         # Train the model
        model.fit(X_train, y_train)
         # Make predictions
        y_pred = model.predict(X_test)
         # Evaluate the model
        accuracy = accuracy_score(y_test, y_pred)
        conf_matrix = confusion_matrix(y_test, y_pred)
         class_report = classification_report(y_test, y_pred)
         print(f'Accuracy: {accuracy:.2f}')
         print('Confusion Matrix:')
         print(conf_matrix)
         print('Classification Report:')
         print(class_report)
```

$\underline{\mathbf{OUTPUT}}$

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	

	DiabetesPedigreeFunction	Age	Outcome	
0	0.627	50	1	
1	0.351	31	0	
2	0.672	32	1	
3	0.167	21	0	
4	2.288	33	1	

Accuracy: 0.75

Confusion Matrix:

[[87 14] [24 29]]

Classification Report:

	precision	recall	f1-score	support
0	0.78	0.86	0.82	101
1	0.67	0.55	0.60	53
accuracy			0.75	154
macro avg	0.73	0.70	0.71	154
weighted avg	0.75	0.75	0.75	154

```
In [ ]:
```

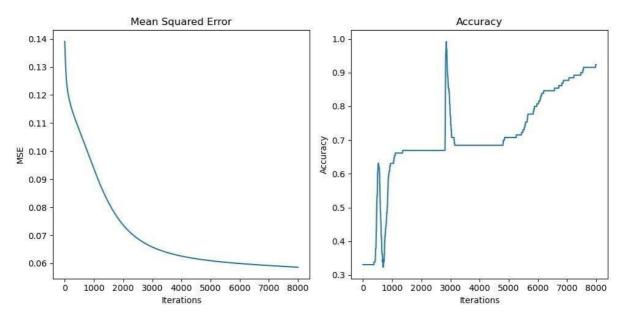
ANN BACK PROPAGATION

```
import numpy as np
           import pandas as pd
           from sklearn.datasets import load_iris
           from sklearn.model_selection import train_test_split
In [11]:
           import matplotlib.pyplot as plt
           # Load dataset
           data = load_iris()
           # Get features and target
           X = data.datay
           Y= data.target
           # Prepare Dataset: Create dummy variables for class labels using get_dummies()
           y = pd.get_dummies(y).values
           # Split data into train and test data
           x_train,x_test,y_train,y_test=train_test_split(X, y,test_size=20,random_state=4)
           # Initialize variables
           learning_rate = 0.1
           iterations=8000
           N = y_{train.size}
           # Number of input features
           input\_size = 4
           # Number of hidden layers neurons
           hidden_size = 2
           # Number of neurons at the output layer
           output\_size = 3
           results = pd.DataFrame(columns=["mse", "accuracy"])
           # Initialize weights
           np.random.seed(10)
           # Initializing weight for the hidden layer
           W1 = np<sub>*</sub>random<sub>*</sub>normal(scale=0.5, size=(input_size, hidden_size))
           # Initializing weight for the output layer
           W2 = np.random.normal(scale=0.5, size=(hidden_size, output_size))
```

```
# Helper functions
def sigmoid(x):
     return 1/(1 + np.exp(-x))
def mean_squared_error(y_pred,y_true):
     return((y_pred-y_true)**2).sum()/(2*y_pred.size)
def accuracy(y_pred,y_true):
    acc=y_pred.argmax(axis=1)==y_true.argmax(axis=1)
     return acc.mean()
#Back propagation Neural Network
mse_list=[]
accuracy_list=[]
for itr in range(iterations):
    #Feed forward propagation
    #Hidden layer
    Z1=np.dot(x_train,W1)
    A1 = sigmoid(Z1)
    #Outputlayer
    Z2=np.dot(A1,2)
    A2 = sigmoid(Z2)
    #Calculating error
     Mse=mean_squared_error(A2,y_train)
     acc = accuracy(A2, y_train)
     mse_list.append(mse)
     accuracy_list.append(acc)
    #Error calculation
    error_output=A2-y_train
    dZ2 = error\_output * A2 * (1-A2)
    error\_hidden = np.dot(dZ2, W2.T)
    dZ1=error_hidden*A1*(1-A1)
    #Weight updates
    W2\_update=np.dot(A1.T,dZ2)/NW1\_update =
    np.dot(x_train.T,dZ1)/ N
     W2 = W2 - learning_rate * W2_update
    W1=W1-learning_rate*W1_update
```

```
\#Plotting Mean Squared Error and Accuracy
plt.figure(figsize=(10,5)) plt.subplot(1, 2,
1) plt.plot(mse_list)
plt.title('Mean Squared Error')
plt.xlabel('Iterations')
plt.ylabel('MSE') plt.subplot(1,2,2)
plt.plot(accuracy_list)
plt.title('Accuracy')
plt.xlabel('Iterations')
plt.ylabel('Accuracy')
plt.tight_layout()
plt.show()
Z1 = np.dot(x_test, W1)
A1 = sigmoid(Z1)
Z2=np.dot(A1,W2)
A2=sigmoid(Z2)
test_acc=accuracy(A2,y_test)
print("TestAccuracy:{}".format(test_acc))
```

OUTPUT:



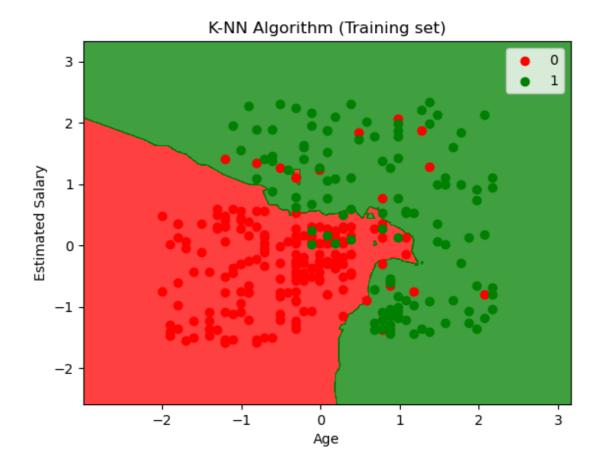
Test Accuracy: 0.9

K-NEAREST NEIGHBOR

```
import numpy as nm
   Tn
 [1]:
         import matplotlib.pyplot as mtp
         import pandas as pd
   In
         data set= pd.read csv('user data.csv')
 [3]:
         x= data set.iloc[:,
   In
 [5]:
         [2,3]].values y=
         data set.iloc[:, 4].values
   In
         from sklearn.model selection import train test split
 [7]:
         x train, x test, y train, y test= train test split(x, y,test size=0.25,
         random state-0
         from sklearn.preprocessing import StandardScaler
   In
         st x= StandardScaler()
 [9]:
         x_train= st_x.fit_transform(x train)
         x test= st x.transform(x test)
         from sklearn.neighbors import KNeighborsClassifier
   In
[11]:
         classifier = KNeighborsClassifier(n neighbors=5, metric='minkowski', p=2)
         classifier.fit(x train, y train)
Out[11
             KNeighborsClassifier
   ]:
         KNeighborsClassifier()
         y pred= classifier.predict(x test)
   In
[13]:
         from sklearn.metrics import
   In
[25]:
         confusion matrix cm=
         confusion_matrix(y_test,y_pred)
         print(cm)
     [[64 4]
      [ 3 29]]
```

```
In [21]: from
                  matplotlib.colors
                                          import
       ListedColormap x_set, y_set = x_train,
       y train
       x1, x2 = nm.meshgrid(nm.arange(start = x set[:, 0].min() - 1, stop =
       x set[:, 0].max()+1, step=0.01),
       nm.arange(start=x_set[:,1].min()-1,stop=x_set[:,1].max()+1,step=0.01)
       mtp.contourf(x1,x2,classifier.predict(nm.array([x1.ravel(),x2.ravel()]).T).
       reshape(x1.shape),
       alpha = 0.75, cmap = ListedColormap(('red', 'green')))
       mtp.xlim(x1.min(),x1.max())
       mtp.ylim(x2.min(),x2.max())
       for i, j in enumerate(nm.unique(y_set)):
       mtp.scatter(x_set[y_set==j,0],x_set[y_set==j,1],
       c = ListedColormap(('red', 'green'))(i), label = j)
       mtp.title('K-NN Algorithm (Training set)')
       mtp.xlabel('Age')
       mtp.ylabel('Estimated Salary')
       mtp.legend()
       mtp.show()
```

OUTPUT:



DECISION TREE

PROGRAM:

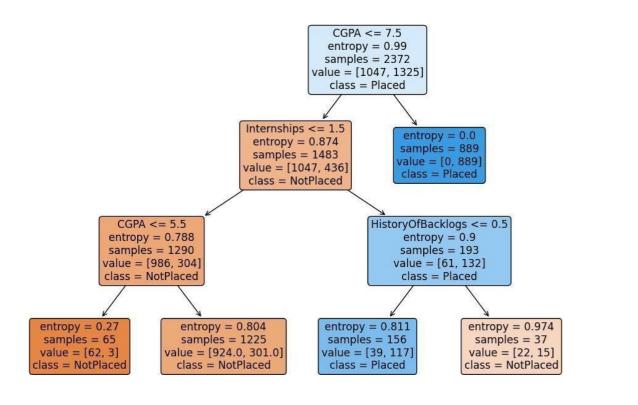
In [1]:

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import tree
import matplotlib.pyplot as plt
data_set = pd.read_csv('collegePlace.csv') print("Data Set")
print(data set.head())
# Features and target variable
#x = data_set.iloc[:, [3, 4, 6]].values
#y = data_set.iloc[:, 7].values
X = data_set[['Internships', 'CGPA', 'HistoryOfBacklogs']] # Feature columns
y = data_set['PlacedOrNot'] # Target column
# Split dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
# Initialize and train the decision tree classifier
clf = DecisionTreeClassifier(criterion='entropy', max depth=3, random state=42)
clf.fit(X_train, y_train)
# Predict on the test set
y_pred = clf.predict(X_test)
# Print test predictions and tree accuracy
print("Predictions on the test set:", y_pred)
print("Decision Tree Accuracy on the test set:", clf.score(X test, y test))
# Visualize the decision tree
plt.figure(figsize=(12, 8))
tree.plot tree(clf, feature names=X.columns, class names=['NotPlaced','Placed'], fi
rounded=True)
#tree.plot_tree(clf, filled=True)
plt.show()
```

OUTPUT:

```
Data Set
Age Gender Stream Internships CGPA Hostel \
0 22
  Male
     ECE
         1
             8
               1
  Female CSE
             7
1 21
         0
               1
               0
2 22
  Female IT
         1
             6
3 21
             8
               0
  Male
     IT
         0
4 22
  Male
     Mech
         0
             8
               1
HistoryOfBacklogs PlacedOrNot
0
    1
        1
1
    1
        1
2
    0
        1
3
    1
        1
4
        1
111100
0100100010100000011000101001
                     1 1 1 1 0 1
01101000001000101000011
                 10001
                     110000
0\;1\;0\;0\;1\;0\;1\;0\;1\;1\;0\;1\;1\;0\;1\;0\;0\;0\;0\;1\;0\;0\;1\;0\;1\;1\;0\;1\;0\;0\;0\;0\;0\;0\;0
0100110000100
          011110101000100011000010
1\ 1\ 1\ 1\ 1\ 0\ 1\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 0
1 0]
```

Decision Tree Accuracy on the test set: 0.8451178451178452



SUPPORT VECTOR CLASSIFICATION

```
In [1]:
             from sklearn.datasets import load breast cancer
            import matplotlib.pyplot as plt
            from sklearn.inspection import DecisionBoundaryDisplay
             from sklearn.svm import SVC
In [2]:
           #Load the dataset
            cancer=load breast canser()
            X=cancer.data[:, :2]
            Y=cancer.targer
In [3]:
            #Build the model
            svm = SVC(kernel="rbf", gamma=0.5, C=1.0)
            #Trained the model
             svm.fit(X, y)
                SVC
Out[3]:
          SVC(gamma=0.5)
            # Plot Decision Boundary
In [4]:
             DecisionBoundaryDisplay.from estimator(svm, X,
            response_method="predict",
             cmap=plt.cm.Spectral,
            alpha=0.8,
            xlabel=cancer.feature names[0],
            ylabel=cancer.feature names[1],)
             # Scatter plot
            plt.scatter(X[:, 0], X[:, 1], c=y, s=20, edgecolors="k")
            plt.show()
```

OUTPUT;

