```
RMP.py > ...
  1 v dict_gn = dict(
              Arad = dict(Zerind=75, Timisoara=118, Sibiu=140),
  2
              Bucharest = dict(Urziceni=85, Giurgiu=90, Pitesti=101, Fagaras=211),
  3
  4
               Craiova = dict(Drobeta=120,Pitesti=138,Rimnicu=146),
              Drobeta = dict(Mehadia=75, Craiova=120),
  5
               Eforie = dict(Hirsova=86),
  6
  7
               Fagaras = dict(Sibiu=99, Bucharest=211),
              Giurgiu = dict(Bucharest=90),
  8
  9
              Hirsova = dict(Eforie=86, Urziceni=98),
 10
               Iasi = dict(Neamt=87, Vaslui=92),
               Lugoj = dict(Mehadia=70, Timisoara=111),
 11
 12
              Mehadia = dict(Lugoj=70, Drobeta=75),
              Neamt = dict(Iasi=87),
 13
              Oradea = dict(Zerind=71,Sibiu=151),
 14
              Pitesti = dict(Rimnicu=97, Bucharest=101, Craiova=138),
 15
 16
              Rimnicu = dict(Sibiu=80,Pitesti=97,Craiova=146),
 17
              Sibiu = dict(Rimnicu=80, Fagaras=99, Arad=140, Oradea=151),
              Timisoara = dict(Lugoj=111, Arad=118),
 18
              Urziceni = dict(Bucharest=85, Hirsova=98, Vaslui=142),
 19
 20
              Vaslui = dict(Iasi=92,Urziceni=142),
 21
               Zerind = dict(Oradea=71,Arad=75)
 22
practical_1.py > ...
     import queue as Q
  1
  2
     from RMP import dict_gn
     start = 'Arad'
  3
      goal = "Bucharest"
  4
  5
      result="
  6
      def BFS(city,cityq,visitedq):
  7
          global result
  8
          if city==start:
               result = result + "" + city
  9
           for eachcity in dict_gn[city].keys():
 10
               if eachcity==goal:
 11
                   result = result + " " + eachcity
 12
 13
                   return
               if eachcity not in cityq.queue and eachcity not in visitedq.queue:
 14
 15
                   cityq.put(eachcity)
                   result = result + " " + eachcity
 16
 17
          visitedq.put(city)
 18
          BFS(cityq.get(),cityq,visitedq)
 19
      def main():
 20
          cityq = Q.Queue()
 21
          visitedq = Q.Queue()
 22
          BFS(start,cityq,visitedq)
          print("BFS Traversal From ", start," to " , goal, "is :")
 23
          print(result)
 24
 25
      main()
     pwsh D:\College\TYCS\AI
```

python -u "d:\College\TYCS\AI\practical\_1.py" BFS Traversal From Arad to Bucharest is:

Arad Zerind Timisoara Sibiu Oradea Lugoj Rimnicu Fagaras Mehadia Pitesti Craiova Bucharest

### Practical 1 B: Iterative Depth First Search

```
practical_1B.py > ...
     import queue as Q
     from RMP import dict gn
  2
      start = "Arad"
  3
      goal = "Bucharest"
  4
  5
      result = ""
  6
      def DLS(city, visitedstack, startlimit, endlimit):
 7
          global result
 8
          found = 0
 9
          result = result + city + " "
 10
          visitedstack.append(city)
 11
12
          if city == goal:
13
              return 1
14
          if startlimit == endlimit:
15
              return 0
16
          for eachcity in dict_gn[city].keys():
              if eachcity not in visitedstack:
17
                  found = DLS(eachcity, visitedstack, startlimit+1, endlimit)
18
19
              if found:
20
                  return found
21
      def IDDFS(city, visitedstack, endlimit):
 22
          global result
23
 24
          for i in range(0,endlimit):
              print("Seaching at Limit:", i)
25
              found = DLS(city, visitedstack, 0 , i)
26
              if found:
27
                  print("Found")
 28
 29
                  break
30
               else:
                  print("Not Found!")
 31
32
                  print(result)
                  print(" ")
33
                  result=""
34
35
                  visitedstack = []
 36
37
      def main():
          visitedstack = []
38
          IDDFS(start, visitedstack, 9)
39
          print("IDDFS Traversal from ", start, " to ",goal," is:")
40
          print(result)
41
      main()
42
```

### pwsh D:\College\TYCS\AI

python -u "d:\College\TYCS\AI\practical\_1B.py"

Seaching at Limit: 0

Not Found!

Arad

Seaching at Limit: 1

Not Found!

Arad Zerind Timisoara Sibiu

Seaching at Limit: 2

Not Found!

Arad Zerind Oradea Timisoara Lugoj Sibiu Rimnicu Fagaras

Seaching at Limit: 3

Not Found!

Arad Zerind Oradea Sibiu Timisoara Lugoj Mehadia

Seaching at Limit: 4

Not Found!

Arad Zerind Oradea Sibiu Rimnicu Fagaras Timisoara Lugoj Mehadia Drobeta

Seaching at Limit: 5

Found

IDDFS Traversal from Arad to Bucharest is:

Arad Zerind Oradea Sibiu Rimnicu Pitesti Craiova Fagaras Bucharest

### Practical 2 A: A\* Search

```
RMP.py > ...
  1
      dict_hn={
               'Arad':336, 'Bucharest':0, 'Craiova':160, 'Drobeta':242, 'Eforie':161,
  2
               'Fagaras':176, 'Giurgiu':77, 'Hirsova':151, 'Iasi':226, 'Lugoj':244,
  3
               'Mehadia':241, 'Neamt':234, 'Oradea':380, 'Pitesti':100, 'Rimnicu':193,
  4
  5
               'Sibiu':253, 'Timisoara':329, 'Urziceni':80, 'Vaslui':199, 'Zerind':374
  6
  7
      dict gn = dict(
  8
               Arad = dict(Zerind=75, Timisoara=118, Sibiu=140),
  9
               Bucharest = dict(Urziceni=85, Giurgiu=90, Pitesti=101, Fagaras=211),
 10
               Craiova = dict(Drobeta=120, Pitesti=138, Rimnicu=146),
 11
               Drobeta = dict(Mehadia=75, Craiova=120),
 12
               Eforie = dict(Hirsova=86),
 13
               Fagaras = dict(Sibiu=99, Bucharest=211),
 14
               Giurgiu = dict(Bucharest=90),
 15
               Hirsova = dict(Eforie=86, Urziceni=98),
 16
               Iasi = dict(Neamt=87, Vaslui=92),
 17
               Lugoj = dict(Mehadia=70, Timisoara=111),
 18
               Mehadia = dict(Lugoj=70, Drobeta=75),
 19
 20
               Neamt = dict(Iasi=87),
               Oradea = dict(Zerind=71, Sibiu=151),
 21
 22
               Pitesti = dict(Rimnicu=97, Bucharest=101, Craiova=138),
 23
               Rimnicu = dict(Sibiu=80, Pitesti=97, Craiova=146),
               Sibiu = dict(Rimnicu=80, Fagaras=99, Arad=140, Oradea=151),
 24
               Timisoara = dict(Lugoj=111, Arad=118),
 25
               Urziceni = dict(Bucharest=85, Hirsova=98, Vaslui=142),
 26
               Vaslui = dict(Iasi=92, Urziceni=142),
 27
               Zerind = dict(Oradea=71,Arad=75)
 28
 29
```

```
practical_2.py > ...
      import queue as O
  1
  2
      from RMP import dict gn
      from RMP import dict_hn
  3
  4
  5
      start = 'Arad'
  6
      goal = 'Bucharest'
      result = ''
  7
  8
      def get fn(citystr):
  9
           cities=citystr.split(",")
 10
 11
          hn=gn=0
 12
          for ctr in range(0, len(cities)-1):
 13
               gn=gn+dict gn[cities[ctr]][cities[ctr+1]]
           hn=dict hn[cities[len(cities)-1]]
 14
 15
           return(hn+gn)
 16
      def expand(cityq):
 17
 18
          global result
          tot, citystr, thiscity=cityq.get()
 19
 20
          if thiscity==goal:
               result=citystr+"::"+str(tot)
 21
 22
               return
          for cty in dict_gn[thiscity]:
 23
               cityq.put((get_fn(citystr+","+cty),citystr+","+cty,cty))
 24
 25
          expand(cityq)
 26
 27
      def main():
 28
          cityq=Q.PriorityQueue()
 29
          thiscity=start
 30
          cityq.put((get_fn(start), start, thiscity))
 31
          expand(cityq)
          print("The A* path with the total is: ")
 32
          print(result)
 33
 34
 35
      main()
```

# pwsh D:\College\TYCS\AI python -u "d:\College\TYCS\AI\practical\_2.py" The A\* path with the total is: Arad,Sibiu,Rimnicu,Pitesti,Bucharest::418

```
practical_2B.py > ...
 1 ∨ import queue as Q
      from RMP import dict_gn
 2
 3
      from RMP import dict hn
 4
      start = 'Arad'
 5
      goal = 'Bucharest'
 6
      result = ''
 7
 8
     def get fn(citystr):
10
           cities=citystr.split(",")
11
          hn=gn=0
           for ctr in range(0, len(cities)-1):
12
               gn=gn+dict_gn[cities[ctr]][cities[ctr+1]]
13
           hn=dict_hn[cities[len(cities)-1]]
14
15
           return(hn+gn)
16
17
     def printout(cityq):
18
          for i in range(0, cityq.qsize()):
19
               print(cityq.queue[i])
20
21
      def expand(cityq):
22
          global result
           tot, citystr, thiscity = cityq.get()
23
24
          nexttot = 999
          if not cityq.empty():
25
26
               nexttot, nextcitystr, nextthiscity=cityq.queue[0]
           if thiscity== goal and tot < nexttot:
27
              result = citystr + "::" + str(tot)
28
29
               return
           print("Expaded city -----", thiscity)
30
          print("second best f(n)-----", nexttot)
31
32
          tempq = Q.PriorityQueue()
           for cty in dict_gn[thiscity]:
33
34
               tempq.put((get fn(citystr+','+cty), citystr+','+cty, cty))
           for ctr in range(1,3):
35
               ctrtot, ctrcitystr ,ctrthiscity = tempq.get()
36
37
               if ctrtot < nexttot:</pre>
                   cityq.put((ctrtot, ctrcitystr,ctrthiscity))
38
39
               else:
                   cityq.put((ctrtot, citystr, thiscity))
40
41
                   break
42
          printout(cityq)
43
          expand(cityq)
44
     def main():
          cityq=Q.PriorityQueue()
45
          thiscity=start
46
          cityq.put((999, "NA", "NA"))
47
48
           cityq.put((get_fn(start), start, thiscity))
49
           expand(cityq)
50
           print(result)
51
52
      main()
```

```
pwsh D:\College\TYCS\AI
python -u "d:\College\TYCS\AI\practical_2B.py"
Expaded city ----- Arad
second best f(n)----- 999
(393, 'Arad, Sibiu', 'Sibiu')
(999, 'NA', 'NA')
(447, 'Arad, Timisoara', 'Timisoara')
Expaded city ----- Sibiu
second best f(n)----- 447
(413, 'Arad, Sibiu, Rimnicu', 'Rimnicu')
(415, 'Arad, Sibiu, Fagaras', 'Fagaras')
(447, 'Arad, Timisoara', 'Timisoara')
(999, 'NA', 'NA')
Expaded city ----- Rimnicu
second best f(n)----- 415
(415, 'Arad,Sibiu,Fagaras', 'Fagaras')
(417, 'Arad,Sibiu,Rimnicu', 'Rimnicu')
     'Arad,Timisoara', 'Timisoara')
(999) 'NA', 'NA')
Expaded city ----- Fagaras
second best f(n)----- 417
(417, 'Arad, Sibiu, Rimnicu', 'Rimnicu')
(450, 'Arad, Sibiu, Fagaras', 'Fagaras')
(447, 'Arad, Timisoara', 'Timisoara')
(999, 'NA', 'NA')
Expaded city ----- Rimnicu
second best f(n)---- 447
(417, 'Arad, Sibiu, Rimnicu, Pitesti', 'Pitesti')
(447, 'Arad, Timisoara', 'Timisoara')
(999, 'NA', 'NA')
(450, 'Arad,Sibiu,Fagaras', 'Fagaras')
(526, 'Arad, Sibiu, Rimnicu', 'Rimnicu')
Expaded city ----- Pitesti
second best f(n)----- 447
(418, 'Arad, Sibiu, Rimnicu, Pitesti, Bucharest', 'Bucharest')
(447, 'Arad, Timisoara', 'Timisoara')
(607, 'Arad, Sibiu, Rimnicu, Pitesti', 'Pitesti')
(526, 'Arad, Sibiu, Rimnicu', 'Rimnicu')
(450, 'Arad, Sibiu, Fagaras', 'Fagaras')
(999, 'NA', 'NA')
Arad, Sibiu, Rimnicu, Pitesti, Bucharest::418
```

### **Practical 3: Decision Tree Learning**

```
[1]: import numpy as np
import pandas as pd

[2]: PlayTennis = pd.read_csv("C:/Users/dines/Downloads/jupyter_download_files/playTennis/playTennis.csv")

[3]: PlayTennis
```

[3]:		Outlook	Temperature	Humidity	Wind	Play Tennis
	0	Sunny	Hot	High	Weak	No
	1	Sunny	Hot	High	Strong	No
	2	Overcast	Hot	High	Weak	Yes
	3	Rain	Mild	High	Weak	Yes
	4	Rain	Cool	Normal	Weak	Yes
	5	Rain	Cool	Normal	Strong	No
	6	Overcast	Cool	Normal	Strong	Yes
	7	Sunny	Mild	High	Weak	No
	8	Sunny	Cool	Normal	Weak	Yes
	9	Rain	Mild	Normal	Weak	Yes
	10	Sunny	Mild	Normal	Strong	Yes
	11	Overcast	Mild	High	Strong	Yes
	12	Overcast	Hot	Normal	Weak	Yes
	13	Rain	Mild	High	Strong	No

```
[4]: from sklearn.preprocessing import LabelEncoder
Le = LabelEncoder()

PlayTennis['Outlook'] = Le.fit_transform(PlayTennis['Outlook'])
PlayTennis['Temperature'] = Le.fit_transform(PlayTennis['Temperature'])
PlayTennis['Humidity'] = Le.fit_transform(PlayTennis['Humidity'])
PlayTennis['Wind'] = Le.fit_transform(PlayTennis['Wind'])
PlayTennis['Play Tennis'] = Le.fit_transform(PlayTennis['Play Tennis'])
```

```
[4]: from sklearn.preprocessing import LabelEncoder
Le = LabelEncoder()

PlayTennis['Outlook'] = Le.fit_transform(PlayTennis['Outlook'])
PlayTennis['Temperature'] = Le.fit_transform(PlayTennis['Temperature'])
PlayTennis['Humidity'] = Le.fit_transform(PlayTennis['Humidity'])
PlayTennis['Wind'] = Le.fit_transform(PlayTennis['Wind'])
PlayTennis['Play Tennis'] = Le.fit_transform(PlayTennis['Play Tennis'])
```

[5]: PlayTennis

[5]:		Outlook	Temperature	Humidity	Wind	Play Tennis
	0	2	1	0	1	0
	1	2	1	0	0	0
	2	0	1	0	1	1
	3	1	2	0	1	1
	4	1	0	1	1	1
	5	1	0	1	0	0
	6	0	0	1	0	1
	7	2	2	0	1	0
	8	2	0	1	1	1
	9	1	2	1	1	1
	10	2	2	1	0	1
	11	0	2	0	0	1
	12	0	1	1	1	1
	13	1	2	0	0	0

```
[6]: y = PlayTennis['Play Tennis']
x = PlayTennis.drop(['Play Tennis'],axis=1)

[7]: from sklearn import tree
clf = tree.DecisionTreeClassifier(criterion = 'entropy')
clf = clf.fit(x, y)
```

```
tree.plot tree(clf)
[8]: [Text(0.444444444444444, 0.9, 'x[0] <= 0.5\nentropy = 0.94\nsamples = 14\nvalue = [5, 9]'),
                Text(0.333333333333333, 0.7, 'entropy = 0.0\nsamples = 4\nvalue = [0, 4]'),
                 Text(0.5555555555556, 0.7, x[2] \le 0.5 \le 1.0 \le 
                 Text(0.11111111111111, 0.1, 'entropy = 0.0\nsamples = 1\nvalue = [1, 0]'),
                 Text(0.7777777777778, 0.5, x[3] \le 0.5 = 0.722 = 5 = 5 = 1, 4]
                 Text(0.55555555555556, 0.1, 'entropy = 0.0\nsamples = 1\nvalue = [1, 0]'), Text(0.7777777777778, 0.1, 'entropy = 0.0\nsamples = 1\nvalue = [0, 1]'),
                 Text(0.888888888888888, 0.3, 'entropy = 0.0\nsamples = 3\nvalue = [0, 3]')]
                                                                               x[0] \le 0.5
                                                                             entropy = 0.94
                                                                              samples = 14
                                                                              value = [5, 9]
                                                                                                   x[2] \le 0.5
                                                           entropy = 0.0
                                                                                                 entropy = 1.0
                                                            samples = 4
                                                                                                 samples = 10
                                                           value = [0, 4]
                                                                                                 value = [5, 5]
                                                            x[0] <= 1.5
                                                                                                                                         x[3] \le 0.5
                                                        entropy = 0.722
                                                                                                                                     entropy = 0.722
                                                            samples = 5
                                                                                                                                        samples = 5
                                                           value = [4, 1]
                                                                                                                                       value = [1, 4]
                                         x[3] <= 0.5
                                                                                                                      x[0] <= 1.5
                                                                              entropy = 0.0
                                                                                                                                                           entropy = 0.0
                                        entropy = 1.0
                                                                                                                    entropy = 1.0
                                                                               samples = 3
                                                                                                                                                           samples = 3
                                         samples = 2
                                                                                                                     samples = 2
                                                                              value = [3, 0]
                                                                                                                                                          value = [0, 3]
                                        value = [1, 1]
                                                                                                                    value = [1, 1]
                                          V
                     entropy = 0.0
                                                                                                 entropy = 0.0
                                                           entropy = 0.0
                                                                                                                                       entropv = 0.0
                      samples = 1
                                                            samples = 1
                                                                                                  samples = 1
                                                                                                                                        samples = 1
                     value = [1, 0]
                                                           value = [0, 1]
                                                                                                 value = [1, 0]
                                                                                                                                        value = [0, 1]
```

```
[9]:
     import graphviz
     dot_data = tree.export_graphviz(clf, out_file=None)
     graph = graphviz.Source(dot_data)
     graph
[9]:
                                          x[0] \le 0.5
                                        entropy = 0.94
                                        samples = 14
                                        value = [5, 9]
                                                    False
                                    True,
                                                    x[2] \le 0.5
                               entropy = 0.0
                                                   entropy = 1.0
                               samples = 4
                                                  samples = 10
                               value = [0, 4]
                                                   value = [5, 5]
                                        x[0] \le 1.5
                                                               x[3] \le 0.5
                                      entropy = 0.722
                                                            entropy = 0.722
                                        samples = 5
                                                              samples = 5
                                       value = [4, 1]
                                                              value = [1, 4]
                      x[3] \le 0.5
                                                              x[0] \le 1.5
                                        entropy = 0.0
                                                                                 entropy = 0.0
                    entropy = 1.0
                                                             entropy = 1.0
                                        samples = 3
                                                                                 samples = 3
                     samples = 2
                                                              samples = 2
                                        value = [3, 0]
                                                                                 value = [0, 3]
                     value = [1, 1]
                                                             value = [1, 1]
                                                                           entropy = 0.0
      entropy = 0.0
                          entropy = 0.0
                                                        entropy = 0.0
       samples = 1
                           samples = 1
                                                        samples = 1
                                                                            samples = 1
       value = [1, 0]
                          value = [0, 1]
                                                        value = [1, 0]
                                                                            value = [0, 1]
[10]: X_pred = clf.predict(x)
[11]: X_pred == y
[11]: 0
           True
      1
           True
      2
           True
      3
           True
      4
           True
      5
           True
      6
           True
      7
           True
           True
      9
           True
      10
          True
      11
         True
      12
         True
      13
           True
      Name: Play Tennis, dtype: bool
```

```
practical_4B.py > ...
  1
      from doctest import OutputChecker
  2
      import numpy as np
  3
  4
      class NeuralNetwork():
  5
        def __init__(self):
  6
          np.random.seed()
  7
          self.synaptic weights=2*np.random.random((3,1))-1
  8
  9
        def sigmoid(self,x):
 10
          return 1/(1+np.exp(-x))
 11
 12
        def sigmoid_derivative(self,x):
 13
           return x*(1-x)
 14
 15
        def train(self,training_inputs,training_outputs,training_iterations):
           for iteration in range(training_iterations):
 16
               output=self.think(training_inputs)
 17
               error = training outputs-output
 18
               adjustments=np.dot(training_inputs.T,error*self.sigmoid_derivative(output))
 19
 20
               self.synaptic_weights +=adjustments
 21
        def think(self,inputs):
 22
 23
           inputs=inputs.astype(float)
           output=self.sigmoid(np.dot(inputs,self.synaptic_weights))
 24
 25
           return output
 26
      if __name__ == "__main__":
 27
        neural network = NeuralNetwork()
 28
 29
        print("Beginning Randomly Generated Weights: ")
 30
        print(neural_network.synaptic_weights)
 31
 32
        training_inputs = np.array([[0,0,1],
 33
                      [1,1,1],
 34
                      [1,0,1],
 35
                      [0,1,1]])
 36
 37
        training_outputs = np.array([[0,1,1,0]]).T
 38
        neural network.train(training inputs, training outputs, 15000)
 39
 40
        print("Ending Weights After Training: ")
 41
        print(neural_network.synaptic_weights)
        user_input_one = str(input("User Input One: "))
 42
        user_input_two = str(input("User Input Two: "))
 43
        user_input_three = str(input("User Input Three: "))
 44
        print("Considering New Situation: ", user_input_one, user_input_two, user_input_three)
 45
        print("New Output data: ")
 46
 47
        print(neural_network.think(np.array([user_input_one, user_input_two, user_input_three])))
```

```
pwsh D:\College\TYCS\AI\practical_4B.py"

Beginning Randomly Generated Weights:
[[-0.79779341]
[-0.76420848]
[ 0.83210476]]

Ending Weights After Training:
[[10.0870228]
[-0.20772497]
[-4.83692503]]

User Input One: 2
User Input Two: 3
User Input Three: 2
Considering New Situation: 2 3 2
New Output data:
```

[0.99994866]

### **Practical 5: Support Vector Machine**

```
[1]: # from warnings import filterwarnings
     # pip install skompiler
[3]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     import statsmodels.api as sm
     import statsmodels.formula.api as smf
     from sklearn.linear_model import LogisticRegression , LogisticRegressionCV
     from sklearn.metrics import mean squared error , r2 score
     from sklearn.model_selection import train_test_split , cross_val_score , cross_val_predict, GridSearchCV
     from sklearn.decomposition import PCA
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.preprocessing import scale
     from sklearn import model_selection
     from sklearn.metrics import roc_auc_score , roc_curve
     from sklearn.metrics import classification_report
     from sklearn.metrics import confusion_matrix , accuracy_score
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.ensemble import RandomForestClassifier , BaseEnsemble, GradientBoostingClassifier
     from sklearn.svm import SVC, LinearSVC
     import time
     from matplotlib.colors import ListedColormap
     from xgboost import XGBRegressor
     from skompiler import skompile
     from lightgbm import LGBMRegressor
[4]: pd.set_option('display.max_rows',1000)
     pd.set_option('display.max_columns',1000)
     pd.set_option('display.width',1000)
```

[5]: df = pd.read\_csv('D:\AI\_Datasets\diabetes.csv')
 df.head()

]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	${\bf Diabetes Pedigree Function}$	Age	Outcome
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1

[6]: df.shape

[6]: (768, 9)

[7]: df.describe()

[7]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
	count	768.000000	768.000000	768.000000	768,000000	768.000000	768.000000	768,000000	768.000000	768.000000
	Count	708.000000	708.000000	708.000000	700.000000	708.000000	708.000000	708.000000	708.000000	708.000000
	mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
	std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
	min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
	25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
	50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
	75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
	max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

```
[8]: x = df.drop("Outcome",axis=1)
      y = df["Outcome"]
 [9]: x_train = x.iloc[:600]
      x_test = x.iloc[600:]
      y_train = y[:600]
      y_test = y[600:]
      print("x_train shape : ", x_train.shape)
      print("x_test shape : ", x_test.shape)
      print("y_train shape : ", y_train.shape)
      print("y_test shape : ", y_test.shape)
      x_train shape: (600, 8)
      x_test shape : (168, 8)
      y_train shape: (600,)
      y_test shape: (168,)
[10]: support_vector_classifier = SVC(kernel = "linear").fit(x_train , y_train)
[11]: support_vector_classifier
[11]: •
             SVC
      SVC(kernel='linear')
[12]: support_vector_classifier.C
[12]: 1.0
[13]: support_vector_classifier
[13]: •
              SVC
      SVC(kernel='linear')
[14]: y_pred = support_vector_classifier.predict(x_test)
[15]: cm = confusion_matrix(y_test, y_pred)
[16]: cm
[16]: array([[96, 12],
             [27, 33]], dtype=int64)
 [17]: print("Our Auucracy is : ", (cm[0][0]+cm[1][1]/(cm[0][0]+cm[1][1]+cm[0][1]+cm[1][0])))
        Our Auucracy is: 96.19642857142857
 [18]: accuracy_score(y_test,y_pred)
  [18]: 0.7678571428571429
  [19]: print(classification_report(y_test , y_pred))
                    precision recall f1-score support
                                0.89
                  0
                         0.78
                                           0.83
                                                      108
                        0.73
                                           0.63
                                                       60
                                            0.77
                                                      168
           accuracy
                                0.72
0.77
                     0.76
0.76
                                                      168
          macro avg
                                            0.73
        weighted avg
                                            0.76
                                                      168
  [20]: support_vector_classifier
  [20]: •
              SVC
       SVC(kernel='linear')
  [21]: accuracies = cross_val_score(estimator = support_vector_classifier ,
                                  X = x_train, y=y_train,
                                   CV=10)
        print("Average Accuracy : {:.2f} %".format(accuracies.mean()*100))
        print("Standart Deviation of Accuracies : {:.2f} %".format(accuracies.std()*100))
        Average Accuracy : 77.33 %
        Standart Deviation of Accuracies : 4.90 %
```

```
[22]: support_vector_classifier.predict(x_test)[:10]
[22]: array([0, 0, 0, 1, 1, 0, 1, 0, 1, 0], dtype=int64)
[23]: svm_params = {"C" : np.arange(1,20)}
[24]: svm = SVC(kernel="linear")
      svm_cv = GridSearchCV(svm, svm_params,cv=8)
[25]: start_time = time.time()
      svm_cv.fit(x_train, y_train)
      elapsed_time = time.time() - start_time
      print(f"Elapsed\ time\ for\ support\ vector\ regression\ cross\ validation\ :"\ f"{elapsed\_time:.3f}}\ seconds")
      Elapsed time for support vector regression cross validation :3729.608 seconds
[26]: svm_cv.best_score_
[26]: 0.771666666666667
[27]: svm_cv.best_params_
[27]: {'C': 2}
[30]: svm_tuned = SVC(kernel = "linear", C=2).fit(x_train,y_train)
[31]: svm_tuned
[31]: 🔻
     SVC(C=2, kernel='linear')
[32]: y_pred = svm_tuned.predict(x_test)
[33]: cm = confusion_matrix(y_test, y_pred)
[34]: cm
[34]: array([[96, 12],
            [27, 33]], dtype=int64)
[36]: print("our Accuracy is : ",(cm[0][0]+cm[1][1])/(cm[0][0]+cm[1][1]+cm[0][1]+cm[1][0]))
      our Accuracy is: 0.7678571428571429
[37]: accuracy_score(y_test,y_pred)
[37]: 0.7678571428571429
[39]: print(classification_report(y_test,y_pred))
                   precision recall f1-score support
                0
                        0.78
                                0.89
                                         0.83
                                                      108
                       0.73
                                0.55
                                         0.63
                1
                                                      60
                                           0.77
                                                     168
         accuracy
                                                     168
                      0.76
                                0.72
         macro avg
                                          0.73
      weighted avg
                                         0.76
                      0.76 0.77
                                                     168
```

### **Practical 6: Adaboost Ensemble Learning**

```
[1]: # Load Libraries
     from sklearn.ensemble import AdaBoostClassifier
     from sklearn import datasets
     # Import train_test_split function
     from sklearn.model_selection import train_test_split
     #Import scikit-learn metrics module for accuracy calculation
     from sklearn import metrics
[2]: # Load data
     iris = datasets.load_iris()
     X = iris.data
     y = iris.target
[3]: # Split dataset into training set and test set
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # 70% training and 30% test
[4]: # Create adaboost classifer object
     abc = AdaBoostClassifier(n_estimators=50,
                              learning_rate=1)
     # Train Adaboost Classifer
     model = abc.fit(X_train, y_train)
     #Predict the response for test dataset
     y_pred = model.predict(X_test)
[5]: # Model Accuracy, how often is the classifier correct?
     print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
     Accuracy: 0.9111111111111111
[6]: # Load Libraries
     from sklearn.ensemble import AdaBoostClassifier
     # Import Support Vector Classifier
     from sklearn.svm import SVC
     #Import scikit-Learn metrics module for accuracy calculation
     from sklearn import metrics
     svc=SVC(probability=True, kernel='linear')
     # Create adaboost classifer object
     abc =AdaBoostClassifier(n_estimators=50, estimator=svc,learning_rate=1)
     # Train Adaboost Classifer
     model = abc.fit(X_train, y_train)
     #Predict the response for test dataset
     y_pred = model.predict(X_test)
     # Model Accuracy, how often is the classifier correct?
     print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
     Accuracy: 0.95555555555556
```

```
[7]: import pandas
     from sklearn import model_selection
     from sklearn.ensemble import AdaBoostClassifier
     url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
     names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
     dataframe = pandas.read_csv(url, names=names)
     array = dataframe.values
     X = array[:,0:8]
     Y = array[:,8]
     seed = 7
     num_trees = 30
     #kfold makes trees with split number.
     #kfold = model_selection.KFold(n_splits=10, random_state=seed)
     #n_estimators : This is the number of trees you want to build before predictions.
     #Higher number of trees give you better voting options and perfomance performance
     model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
     #cross_val_score method is used to calculate the accuracy of model sliced into x, y
     #cross validator cv is optional cv=kfold
     results = model_selection.cross_val_score(model, X, Y)
     print(results.mean())
```

0.7617774382480265

### **Practical 7: Naïve Bayes Classifiers**

```
[1]: import pandas as pd
  import matplotlib.pyplot as plt
  from sklearn.model_selection import train_test_split
  from sklearn.naive_bayes import MultinomialNB , CategoricalNB , GaussianNB
  from sklearn.metrics import accuracy_score
  import seaborn as sns
[2]: df = pd.read_csv("D:\TYCS Dinesh\AI Practical\Diesases.csv")
```

[2]: dr = pd.read\_csv( D:\ircs Dinesn\Al Practical\Diesases.csv

[3]: df.head(11)

[3]:		Sore Throat	Fever	Swollen Glands	Congestion	Headache	Diagnosis
	0	Yes	Yes	Yes	Yes	Yes	Strep thoat
	1	No	No	No	Yes	Yes	Allergy
	2	Yes	Yes	No	Yes	No	Cold
	3	Yes	No	Yes	No	No	Strep thoat
	4	No	Yes	No	Yes	No	Cold
	5	No	No	No	Yes	No	Allergy
	6	No	No	Yes	No	No	Strep thoat
	7	Yes	No	No	Yes	Yes	Allergy
	8	No	Yes	No	Yes	Yes	Cold
	9	Yes	Yes	No	Yes	Yes	Cold

[4]: df.tail()

[4]:	Sore Throat Feve		Fever	Swollen Glands	Congestion	Headache	Diagnosis	
	5	No	No	No	Yes	No	Allergy	
	6	No	No	Yes	No	No	Strep thoat	
	7	Yes	No	No	Yes	Yes	Allergy	
	8	No	Yes	No	Yes	Yes	Cold	
	0	Voc	Voc	No	Vor	Vos	Cold	

```
[5]: df.info()
      <class 'pandas.core.frame.DataFrame'>
      RangeIndex: 10 entries, 0 to 9
      Data columns (total 6 columns):
                   Non-Null Count Dtype
       #
          Column
          -----
                           -----
      ---
          Sore Throat 10 non-null object
Fever 10 non-null object
       0
       1 Fever
      2 Swollen Glands 10 non-null object
3 Congestion 10 non-null object
4 Headache 10 non-null object
5 Diagnosis 10 non-null object
      dtypes: object(6)
      memory usage: 608.0+ bytes
[6]: from sklearn.preprocessing import LabelEncoder
      le = LabelEncoder()
      df['Sore Throat'] = le.fit_transform(df['Sore Throat'])
      df['Fever'] = le.fit_transform(df['Fever'])
      df['Swollen Glands'] = le.fit_transform(df['Swollen Glands'])
      df['Congestion'] = le.fit_transform(df['Congestion'])
      df['Headache'] = le.fit_transform(df['Headache'])
      df['Diagnosis'] = le.fit_transform(df['Diagnosis'])
[7]: df.info()
      <class 'pandas.core.frame.DataFrame'>
      RangeIndex: 10 entries, 0 to 9
      Data columns (total 6 columns):
       # Column Non-Null Count Dtype
      ---
                           -----
      0 Sore Throat 10 non-null
1 Fever 10 non-null
                                             int32
                                            int32
       2 Swollen Glands 10 non-null int32
3 Congestion 10 non-null int32
       4 Headache 10 non-null int32
5 Diagnosis 10 non-null int32
      dtypes: int32(6)
      memory usage: 368.0 bytes
     df.head(11)
[8]:
[8]:
         Sore Throat Fever Swollen Glands Congestion Headache Diagnosis
      0
                   1
                          1
                                          1
                                                      1
                                                                 1
                                                                            2
                   0
                         0
                                          0
                                                                            0
                   1
                                                                 0
      2
                          1
                                          0
                                                      1
                                                                            1
      3
                         0
                                                                 0
                                                                            2
                   0
                                          0
                                                                 0
                          1
                                                      1
                                                                            1
      4
      5
                   0
                         0
                                                                 0
                                                                            0
                   0
                                                      0
                                                                 0
                                                                            2
      6
                         0
                                          1
      7
                         0
                                                                            0
      8
                   0
                          1
                                          0
                                                      1
                                                                 1
                                                                            1
```

9

```
[9]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Sore Throat'],data=df)
plt.title("Category wise count of Sore Throat")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```

## 5 -4 -3 -2 -

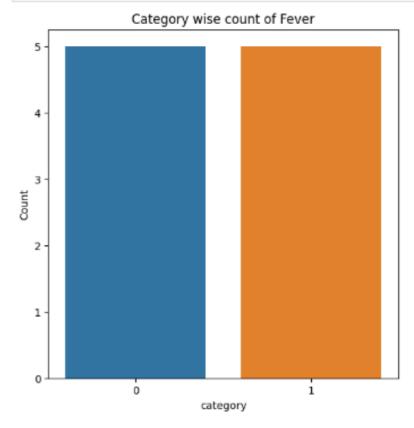
ò

Category wise count of Sore Throat

```
[10]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Fever'],data=df)
plt.title("Category wise count of Fever")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```

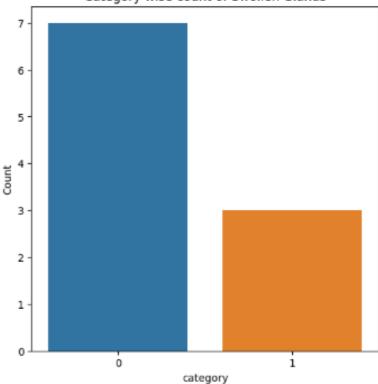
category

i



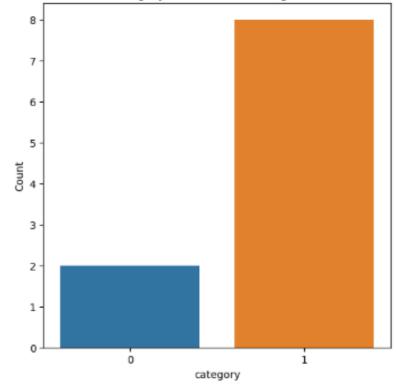
```
[11]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Swollen Glands'],data=df)
plt.title("Category wise count of Swollen Glands")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```

### Category wise count of Swollen Glands



```
[12]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Congestion'],data=df)
plt.title("Category wise count of Congestion")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```

### Category wise count of Congestion

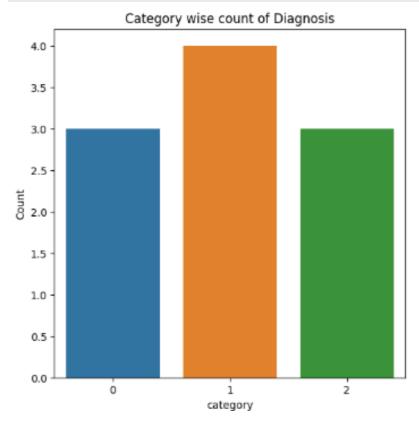


```
[13]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Headache'],data=df)
plt.title("Category wise count of Headache")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```

# Category wise count of Headache

category

```
[14]: fig , ax = plt.subplots(figsize=(6,6))
sns.countplot(x=df['Diagnosis'],data=df)
plt.title("Category wise count of Diagnosis")
plt.xlabel("category")
plt.ylabel("Count")
plt.show()
```



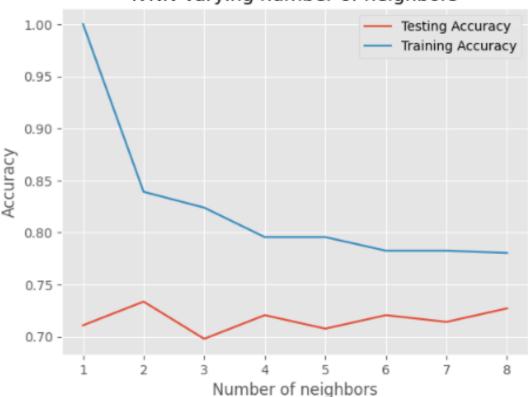
```
[15]: X = df.drop('Diagnosis',axis=1)
      y=df['Diagnosis']
[16]: classifier = MultinomialNB()
      classifier.fit(X,y)
[16]: - MultinomialNB
     MultinomialNB()
[17]: classifier = CategoricalNB()
      classifier.fit(X,y)
[17]: - CategoricalNB
     categoricalNB()
[18]: classifier = GaussianNB()
      classifier.fit(X,y)
[18]: - GaussianNB
     GaussianNB()
[19]: from sklearn.model_selection import train_test_split
      from sklearn.naive_bayes import MultinomialNB
      from sklearn.metrics import classification_report, accuracy_score, confusion_matrix, precision_score, recall_score, f1_score
[20]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
[21]: classifier = MultinomialNB()
     classifier.fit(X_train,y_train)
      y_pred = classifier.predict(X_test)
      print("confusion matrix\n",confusion_matrix(y_test,y_pred))
      print("Accuracy : ", accuracy_score(y_test, y_pred))
      print("Presicion : ",precision_score(y_test, y_pred, zero_division='warn'))
      print("Recall : ", recall_score(y_test,y_pred))
      print("F1 score : ",f1_score(y_test,y_pred))
      print("Classification report :\n", classification_report(y_test,y_pred))
      confusion matrix
       [[1 0]
       [0 1]]
      Accuracy: 1.0
      Presicion: 1.0
      Recall : 1.0
      F1 score : 1.0
      Classification report :
                   precision recall f1-score support
                      1.00
                               1.00
                                         1.00
                1
                                                        1
                      1.00 1.00
                                         1.00
                                                        1
                                           1.00
         accuracy
                                                        2
                               1.00
        macro avg 1.00
ighted avg 1.00
                                          1.00
                                                        2
      weighted avg
                                 1.00
                                           1.00
                                                        2
```

### **Practical 8: K-Nearest Neighbors**

```
[1]: import numpy as np
      import pandas as pd
      import matplotlib.pyplot as plt
      plt.style.use('ggplot')
[2]: df = pd.read_csv('D:\AI_Datasets\diabetes.csv')
[3]: df.head()
                   Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome
[3]:
        Pregnancies
                 6
                        148
                                      72
                                                    35
                                                            0 33.6
                                                                                      0.627
                                                                                             50
                                                                                                       1
     1
                 1
                         85
                                      66
                                                    29
                                                            0 26.6
                                                                                      0.351
                                                                                             31
                                                                                                       0
     2
                 8
                        183
                                       64
                                                     0
                                                            0 23.3
                                                                                      0.672
                                                                                             32
                                                                                                        1
     3
                                                           94
                                                               28.1
                                                                                      0.167
                         89
                                       66
                                                    23
                                                                                             21
     4
                 0
                        137
                                      40
                                                    35
                                                          168 43.1
                                                                                      2.288
                                                                                             33
                                                                                                       1
[4]: df.shape
[4]: (768, 9)
[5]: df.dtypes
                                     int64
[5]: Pregnancies
                                     int64
     Glucose
     BloodPressure
                                     int64
     SkinThickness
                                     int64
      Insulin
                                     int64
     BMI
                                   float64
     DiabetesPedigreeFunction
                                   float64
      Age
                                     int64
     Outcome
                                     int64
     dtype: object
[6]: x = df.drop('Outcome',axis=1).values
     y = df['Outcome'].values
[7]: from sklearn.model_selection import train_test_split
[8]: x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.4,random_state=42)
[9]: from sklearn.neighbors import KNeighborsClassifier
     neighbors = np.arange(1,9)
     train_accuracy = np.empty(len(neighbors))
     test_accuracy = np.empty(len(neighbors))
     for i,k in enumerate(neighbors):
         knn = KNeighborsClassifier(n_neighbors=k)
         knn.fit(x_train, y_train)
         train_accuracy[i] = knn.score(x_train, y_train)
         test_accuracy[i] = knn.score(x_test, y_test)
```

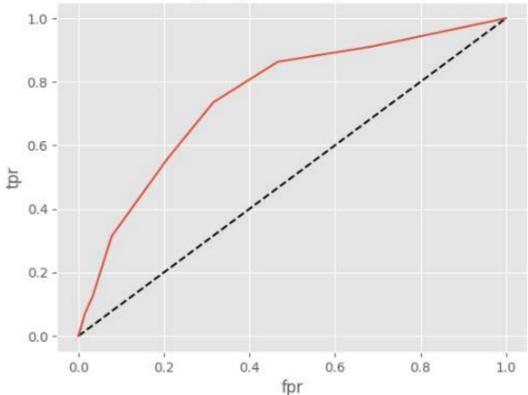
```
plt.title("K-NN Varying number of neighbors")
plt.plot(neighbors, test_accuracy, label="Testing Accuracy")
plt.plot(neighbors, train_accuracy, label="Training Accuracy")
plt.legend()
plt.xlabel("Number of neighbors")
plt.ylabel("Accuracy")
plt.show()
```

### K-NN Varying number of neighbors



```
[17]: from sklearn.metrics import classification_report
[18]: print(classification_report(y_test, y_pred))
                    precision
                                 recall f1-score
                                                     support
                 0
                         0.78
                                    0.79
                                              0.79
                                                         206
                 1
                                    0.56
                         0.57
                                              0.56
                                                         102
          accuracy
                                              0.71
                                                         308
                                                         308
                         0.68
                                    0.68
                                              0.68
         macro avg
      weighted avg
                         0.71
                                    0.71
                                              0.71
                                                         308
[19]: y_pred_proba = knn.predict_proba(x_test)[:,1]
[20]: from sklearn.metrics import roc curve
[21]: fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
[22]: plt.plot([0,1],[0,1],"k--")
      plt.plot(fpr,tpr,label="knn")
      plt.xlabel("fpr")
      plt.ylabel("tpr")
      plt.title("knn(n_neighbors=7) ROC curve")
      plt.show()
```

### knn(n\_neighbors=7) ROC curve



```
from sklearn.metrics import roc_auc_score
[23]:
      roc_auc_score(y_test,y_pred_proba)
[23]: 0.7536645726251665
[24]:
     from sklearn.model_selection import GridSearchCV
      param_grid = {'n_neighbors' : np.arange(1,50)}
[25]:
[26]:
      knn = KNeighborsClassifier()
      knn_cv = GridSearchCV(knn,param_grid,cv=5)
      knn_cv.fit(x,y)
[26]:
                  GridSearchCV
       ▶ estimator: KNeighborsClassifier
            ▶ KNeighborsClassifier
[27]:
      knn_cv.best_score_
[27]: 0.7578558696205755
[28]: knn_cv.best_params_
[28]: {'n_neighbors': 14}
```