Tab 1

Soft computing Practical

Name:

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Div:

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- 1) Implement the following:
- A) Design a simple linear neural network model.

code:

```
import numpy as np

x = np.array([0.8, 0.6,0.4])
weights = np.array([0.1, 0.3,-0.2])
bias = 0.35

y = np.dot(x, weights) + bias
print("y = ",y)
```

Output

B) Calculate the output of a neural net using both binary and bipolar sigmoidal function.

code:

```
class ActivationF:
 def bnsf(self,x): # binary sigmoid function
   return 1/(1+np.exp(-x))
 def bpsf(self,x): # bipolar sigmoidal function
   return -1+(2/(1+np.exp(-x)))
 def tanh(self,x):
   return (np.exp(x)-np.exp(-x))/(np.exp(x)+np.exp(-x))
def main():
 binary= ActivationF().bnsf(y)
 print("\n The output, after applying the binary sigmoidal function is:")
 print(round(binary,3)) # rounds off the answer by 3 decimal places
 bipolar=ActivationF().bpsf(y)
 print("\n the output, after applying the binary sigmoidal is: ")
 print(round(bipolar,3))
 tanh output=ActivationF().tanh(y)
 print("\n the output, after applying the tanh function is: ")
 print(round(tanh output,3))
if name ==" main ":
 main()
```

Output

```
y = 0.53

The output, after applying the binary sigmoidal function is: 0.629

the oupput, after applying the binary sigmoidal is: 0.259

the output, after applying the tanh function is: 0.485
```

C) Write a python code to calculate net input and apply the activation function.
code:

2) Implement the following:

A) Generate AND/NOT function using 1 neural net.

```
# Getting the weights and the threshold value
print("enter weights:")
w11=int(input("weight w11 = "))
w12=int(input("weight w12 = "))
w21=int(input("weight w21 = "))
w22=int(input("weight w22 = "))
v1=int(input("weight v1 = "))
v2=int(input("weight v2 = "))
print("enter threshold value : ")
theta = int(input("theta = "))
x1 = [0, 0, 1, 1];
x2 = [0, 1, 0, 1];
z = [0,1,1,0] #expected output for eXclusive-OR Function
con = 1;
zin1 = [0,0,0,0]
zin2 = [0,0,0,0]
y1 = [0, 0, 0, 0]
y2 = [0, 0, 0, 0]
yin = [0,0,0,0]
y = [0, 0, 0, 0]
while con:
  for i in range (0,3):
    zin1[i] = x1[i]*w11 + x2[i]*w21
    zin2[i] = x1[i]*w21 + x2[i]*w22
  for i in range (0,3):2
    if zin1[i] >= theta:
      y1[i] = 1;
    else:
      y1[i] = 0;
    if zin2[i] >= theta:
      y2[i] = 1;
    else:
      y2[i] = 0;
```

```
for i in range (0,3):
    yin[i] = y1[i]*v1 + y2[i]*v2
  print(yin)
  for i in range(0,3):
    if yin[i] >= theta:
      y[i]=1;
    else:
      y[i] = 0;
  print("output of net")
  print(y)
  if y==z:
    con = 0
  else:
    print("Net is not learning another set of weights and threshold
value")
    w11 = int(input("weight w11 = "))
    w12 = int(input("weight w12 = "))
   w21 = int(input("weight w21 = "))
    w22 = int(input("weight w22 = "))
    wv1 = int(input("weight v1 = "))
    wv2 = int(input("weight v2 = "))
    theta = int(input("theta = "))
  #endwhile
  print("McCulloh - Pitts Net for XOR Function")
  print("weight of neuron z1")
  print(w11)
  print(w12)
  print("weight of neuron z2")
  print(w21)
  print(w22)
  print(theta)
print("y:",y)
```

```
→ enter weights:
    weight w11 = 1
    weight w12 = -1
    weight w21 = -1
    weight w22 = 1
    weight v1 = 1
    weight v2 = 1
    enter threshold value :
    theta = 1
    [0, 1, 1, 0]
    output of net
    [0, 1, 1, 0]
    McCulloh - Pitts Net for XOR Function
    weight of neuron z1
    1
    -1
    weight of neuron z2
    -1
    1
    y: [0, 1, 1, 0]
```

3) Implement the Following

A) Write a program to implement Hebb's rule.

```
import numpy as np
class HebbRuleNN:
 def init (self, input size, Learning rate=0.01):
    #initialize weight randomly or to zero
    self.weights = np.zeros(input size) # Use input size here
    self.bias=0
    self.learning rate = Learning rate # Corrected parameter name
 def train(self, inputs, targets): # Corrected parameter name
    for i in range(len(inputs)):
      input vector=inputs[i]
      target output=targets[i] # Corrected parameter name
      delta_weights=self.learning_rate*input_vector*target_output
      self.weights+=delta weights
      delta bias=self.learning rate*target output # Corrected typo
      self.bias+=delta bias
 def predict(self,input vector):
    net input=np.dot(input vector, self.weights) + self.bias
    return 1 if net input>=0 else 0
inputs=np.array([[1,1],[1,-1],[-1,1],[-1,-1]])
targets=np.array([1,-1,-1,1]) # using and gate
targets1=np.array([1,1,1,-1]) # using or gate
network=HebbRuleNN(input size=2)
network.train(inputs, targets1)
print("Final Weights:", network.weights)
print("Final Bias:", network.bias)
```

→ Final Weights: [0.02 0.02]

Final Bias: 0.01999999999999997

- ✓ Overall Flow Summary
 - 1. Import library.
 - 2. Define network class → holds weights, bias, train & predict methods.
 - 3. Initialize weights/bias.
 - 4. Define Hebbian learning method to update weights/bias.
 - 5. Provide input patterns and target outputs.
 - 6. Create network object with 2 input neurons.
 - 7. Train network using Hebb rule \rightarrow adjusts weights and bias.
 - 8. Inspect learned weights/bias → network can now predict OR gate outputs.

B) Write a program to implement the delta rule.

Code:

4) Implement the Following

A) Write a program for Back Propagation Algorithm

```
import numpy as np
class NeuralNetwork:
   def init (self, input size, hidden size, output size):
        self.input size = input size
        self.hidden size = hidden size
        self.output size = output size
        self.weights input hidden = np.random.randn(self.input size,
self.hidden size)
        self.weights hidden output = np.random.randn(self.hidden size,
self.output size)
        self.bias hidden = np.zeros((1, self.hidden size))
        self.bias_output = np.zeros((1, self.output size))
   def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))
   def sigmoid derivative(self, x):
       return x * (1 - x)
    #Defining Feed Forward Network
   def feedforward(self, x):
        self.hidden activation = np.dot(x, self.weights input hidden) +
self.bias hidden
        self.hidden output = self.sigmoid(self.hidden activation)
        self.output activation = np.dot(self.hidden output,
self.weights hidden output) + self.bias output
        self.predict output = self.sigmoid(self.output activation)
        return self.predict output
    #Defining Backward Network
   def backward(self, X, y, learning rate):
        output error = y - self.predict output
```

```
output delta = output error *
self.sigmoid derivative(self.predict output)
        hidden error = np.dot(output delta, self.weights hidden output.T)
        hidden delta = hidden error *
self.sigmoid derivative(self.hidden output)
        self.weights hidden output += np.dot(self.hidden output.T,
output delta) * learning rate
        self.bias output += np.sum(output delta, axis=0, keepdims=True) *
learning rate
        self.weights input hidden += np.dot(X.T, hidden delta) *
learning rate
        self.bias hidden += np.sum(hidden delta, axis=0, keepdims=True) *
learning rate
    #Training Network
    def train(self, X, y, epochs, learning rate):
        for epoch in range (epochs):
            output = self.feedforward(X)
            self.backward(X, y, learning rate)
            if epoch % 4000 == 0:
                loss = np.mean(np.square(y - output))
                print(f"Epoch {epoch}, Loss {loss}")
# Testing Neural Network
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([[0], [1], [1], [0]])
nn = NeuralNetwork(input size=2, hidden size=4, output size=1)
nn.train(X, y, epochs=10000, learning rate=0.1)
output = nn.feedforward(X)
print("predictions after training:")
print(output)
```

```
Epoch 0, Loss 0.28296172436902217
Epoch 4000, Loss 0.019070304295013777
Epoch 8000, Loss 0.003114981528696914
predictions after training:
[[0.02971497]
        [0.95493644]
        [0.95388609]
        [0.05708703]]
```

B) Write a program for error Backpropagation algorithm				

5) Implement the Following

A) Write a program for Hopfield Network.

```
import numpy as np
nb patterns = 4
           # Number of patterns to learn
pattern width = 5
pattern height = 5
max iterations = 10
# Define Patterns
patterns = np.array([
  #
Letter J
  Letter C
  Letter M
  dtype=float)
# Train the network
W = np.zeros((pattern_width * pattern_height, pattern_width *
pattern height))
for i in range(pattern width * pattern height):
  for j in range(pattern width * pattern height):
     if i == j or W[i, j] != 0.0:
        continue
     w = 0.0
     for n in range(nb patterns):
        w += patterns[n, i] * patterns[n, j]
     W[i, j] = w / patterns.shape[0]
     W[j, i] = W[i, j]
```

```
# Test the Network
# Create a corrupted pattern S
S = np.array(
dtype=float)
h = np.zeros((pattern_width * pattern_height))
#Defining Hamming Distance matrix for seeing convergence
hamming distance = np.zeros((max iterations,nb patterns))
for iteration in range(max iterations):
   for i in range(pattern width * pattern height):
       i = np.random.randint(pattern width * pattern height)
       h[i] = 0
       for j in range(pattern_width * pattern_height):
           h[i] += W[i, j]*S[j]
       S = np.where(h<0, -1, 1)
   for i in range(nb patterns):
       hamming_distance[iteration, i] = ((patterns - S)[i]!=0).sum()
print(hamming distance)
```

```
[ 8. 10. 11. 19.]
[ 6. 8. 9. 21.]
[ 7. 7. 10. 22.]
[ 7. 7. 10. 22.]
[ 7. 7. 10. 22.]
[ 6. 8. 9. 23.]
[ 6. 8. 9. 23.]
[ 6. 8. 9. 23.]
[ 6. 8. 9. 23.]
[ 6. 8. 9. 23.]
```

- 6) Implement the Following: A) Find ratios using fuzzy logic

B) Solve Tipping problem using fuzzy logic

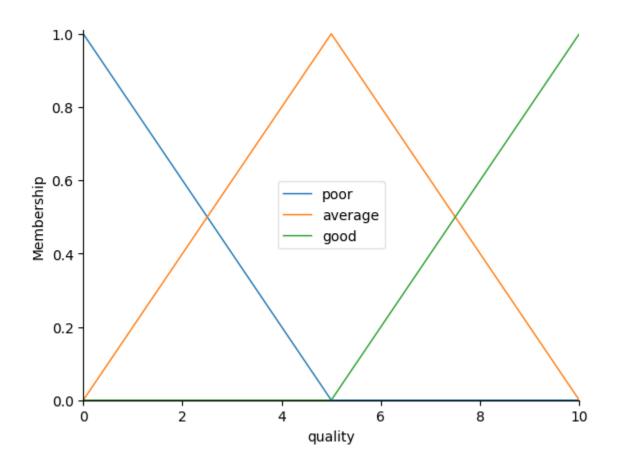
```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
# 1. Define Linguistic Variables (Inputs and Output)
# Example: Tipping problem - Quality of food, Service, and Tip
quality = ctrl.Antecedent (np.arange(0, 11, 1), 'quality')
service = ctrl.Antecedent (np.arange(0, 11, 1), 'service')
tip = ctrl.Consequent (np.arange (0, 26, 1), 'tip')
# 2. Define Membership Functions
quality ['poor'] = fuzz. trimf (quality. universe, [0, 0, 5])
quality ['average'] = fuzz. trimf (quality. universe, [0, 5, 10])
quality ['good'] = fuzz. trimf (quality.universe, [5, 10, 10])
service['poor'] = fuzz. trimf (service.universe, [0, 0, 5])
service ['average'] = fuzz. trimf (service.universe, [0, 5, 10])
service ['good'] = fuzz. trimf (service. universe, [5, 10, 10])
tip['low'] = fuzz. trimf(tip. universe, [0, 0, 13])
tip['medium'] = fuzz.trimf (tip.universe, [0, 13, 25])
tip['high'] = fuzz.trimf(tip.universe,[13,25,25])
# 3. Define Fuzzy Rules
rule1 = ctrl.Rule(quality['poor'] | service['poor'], tip['low'])
rule2 = ctrl.Rule(service['average'], tip['medium'])
rule3 = ctrl.Rule(quality['good'] | service['good'], tip['high'])
# 4. Build the Control System
tipping ctrl = ctrl.ControlSystem([rule1, rule2, rule3])
tipping simulation = ctrl.ControlSystemSimulation (tipping ctrl)
```

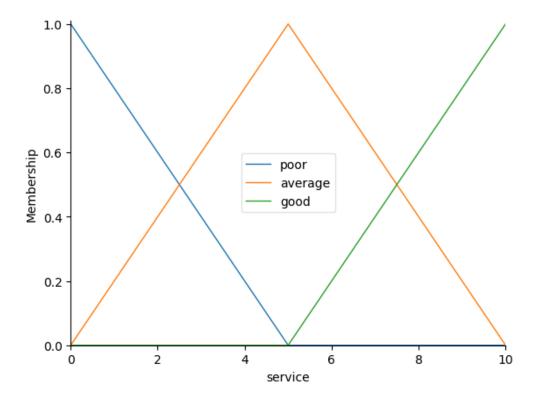
```
# 5. Provide Inputs and Compute Output
tipping_simulation. input ['quality' ] = 0
tipping_simulation. input ['service'] = 0
tipping_simulation. compute ()

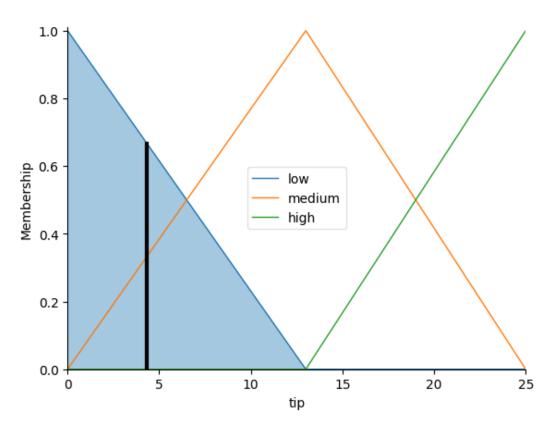
# 6. Display Result
print (f"Predicted Tip: {tipping_simulation. output['tip'] :.2f}%")

# Optional: View the membership functions and the result
quality.view()
service.view()
tip.view(sim=tipping simulation)
```

→ Predicted Tip: 4.33%







7) Implementation of Simple genetic algorithm using its following operators:

- I. Selection
- II. Mutation
- II. Crossover

```
from collections import defaultdict
import numpy as np
from sklearn.datasets import load iris
from sklearn.model selection import cross val score
from sklearn.linear model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import random
import pandas as pd
import matplotlib.pyplot as plt
# Load dataset
df = pd.read excel("/content/heart.xlsx")
print(df.describe())
# Separate features and target
data array = df.drop(columns=['target']).values
target array = df['target'].values
X = data array
y = target array
n features = X.shape[1]
# Standardize features
scaler = StandardScaler()
X = scaler.fit transform(X)
# GA parameters
population size = 10
n \text{ generations} = 10
mutation rate = 0.1
# Create initial population
def initial population(size, n features):
```

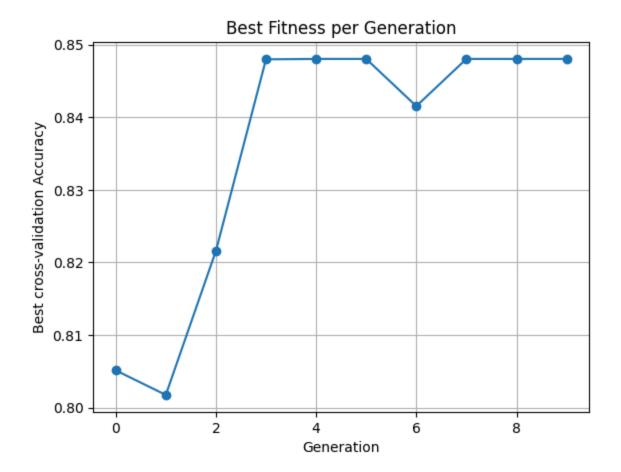
```
return [np.random.choice([0, 1], size=n features) for in
range(size)]
# Fitness function
def compute fitness(individual):
    if np.count nonzero(individual) == 0:
        return 0
    selected features = X[:, individual == 1]
    model = LogisticRegression(max iter=500)
    score = cross val score(model, selected features, y, cv=5)
    return score.mean()
# Tournament selection
def select(population, fitnesses, k=3):
    selected = []
    for in range(len(population)):
        aspirants = random.sample(list(zip(population, fitnesses)), k)
        selected.append(max(aspirants, key=lambda x: x[1])[0])
    return selected
# Crossover
def crossover(parent1, parent2):
    point = random.randint(1, n features - 1)
    child1 = np.concatenate((parent1[:point], parent2[point:]))
    child2 = np.concatenate((parent2[:point], parent1[point:]))
    return child1, child2
# Mutation
def mutate(individual, mutation rate):
    for i in range(len(individual)):
        if random.random() < mutation rate:</pre>
            individual[i] = 1 - individual[i]
    return individual
# Run Genetic Algorithm
population = initial population(population size, n features)
print("Initial population:", population)
best fitness per gen = []
```

```
for generation in range (n generations):
    fitnesses = [compute fitness(ind) for ind in population]
    best fitness = max(fitnesses)
    best fitness per gen.append(best fitness)
    print(f"Generation {generation}, Best Fitness: {best fitness:.4f}")
    selected = select(population, fitnesses)
    next population = []
    for i in range(0, population size, 2):
        p1 = selected[i]
        p2 = selected[min(i + 1, population size - 1)]
        c1, c2 = crossover(p1, p2)
        next population.extend([mutate(c1, mutation rate), mutate(c2,
mutation rate)])
    population = next population
# Final evaluation
final fitnesses = [compute fitness(ind) for ind in population]
best index = np.argmax(final fitnesses)
best individual = population[best index]
# Feature selection
feature names = df.drop(columns=['target']).columns.tolist()
selected features = np.array(feature names)[best individual == 1]
# Plot results
plt.plot(best fitness per gen, marker='o')
plt.xlabel("Generation")
plt.ylabel("Best cross-validation Accuracy")
plt.title("Best Fitness per Generation")
plt.grid(True)
plt.show()
# Best individual info
print(f"Selected feature mask: {best individual}")
print("Best individual:", best individual)
print("Selected features:", selected features.tolist())
print("Total features selected:", np.sum(best individual))
```

Generation 7, Best Fitness: 0.8480 Generation 8, Best Fitness: 0.8480 Generation 9, Best Fitness: 0.8480

```
<del>_____</del>
                                                    trestbps
                                                                      chol
                                                                                    fbs
                   age
                                sex
                                              ср
            303.000000
                                                  303.000000
                                                                            303.000000
     count
                         303.000000
                                      303.000000
                                                               303.000000
             54.366337
                           0.683168
                                        0.966997
                                                  131.623762
                                                               246.264026
                                                                              0.148515
    mean
              9.082101
                           0.466011
                                                   17.538143
                                                                              0.356198
    std
                                        1.032052
                                                                51.830751
             29.000000
                           0.000000
                                                   94.000000
                                                               126.000000
                                                                              0.000000
    min
                                        0.000000
    25%
             47.500000
                           0.000000
                                        0.000000
                                                  120.000000
                                                               211.000000
                                                                              0.000000
    50%
             55.000000
                           1.000000
                                        1.000000
                                                  130.000000
                                                               240.000000
                                                                              0.000000
    75%
             61.000000
                           1.000000
                                        2.000000
                                                  140.000000
                                                               274.500000
                                                                              0.000000
             77.000000
                           1.000000
                                        3.000000
                                                   200.000000
                                                               564.000000
                                                                              1.000000
    max
                            thalach
                                                      oldpeak
               restecg
                                                                     slope
                                                                                     ca
                                           exang
                         303.000000
                                                   303.000000
            303.000000
                                      303.000000
                                                               303.000000
                                                                            303.000000
    count
              0.528053
                         149.646865
                                                     1.039604
                                                                  1.399340
                                                                              0.729373
    mean
                                        0.326733
    std
              0.525860
                          22.905161
                                        0.469794
                                                     1.161075
                                                                  0.616226
                                                                              1.022606
    min
              0.000000
                          71.000000
                                        0.000000
                                                     0.000000
                                                                  0.000000
                                                                              0.000000
    25%
              0.000000
                         133.500000
                                        0.000000
                                                     0.000000
                                                                  1.000000
                                                                              0.000000
     50%
              1.000000
                         153.000000
                                        0.000000
                                                     0.800000
                                                                  1.000000
                                                                              0.000000
     75%
              1.000000
                         166.000000
                                        1.000000
                                                     1.600000
                                                                  2.000000
                                                                              1.000000
    max
              2.000000
                         202.000000
                                        1.000000
                                                     6.200000
                                                                  2.000000
                                                                              4.000000
                  thal
                             target
           303.000000
                         303.000000
    count
    mean
              2.313531
                           0.544554
    std
              0.612277
                           0.498835
    min
              0.000000
                           0.000000
    25%
              2.000000
                           0.000000
    50%
              2,000000
                           1,000000
              3.000000
    75%
                           1,000000
    max
              3.000000
                           1.000000
```

```
Initial population: [array([0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0]), array([1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1]), array([1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1]), array([1, 6eneration 0, Best Fitness: 0.8051
Generation 1, Best Fitness: 0.8017
Generation 2, Best Fitness: 0.8216
Generation 3, Best Fitness: 0.8480
Generation 4, Best Fitness: 0.8480
Generation 5, Best Fitness: 0.8480
Generation 6, Best Fitness: 0.8415
```



Generation

Selected feature mask: [0 1 1 0 1 0 1 1 0 1 0 1 1]

Rest individual: [0 1 1 0 1 0 1 1 0 1 1 1]

Best individual: [0 1 1 0 1 0 1 1 0 1 0 1 1]
Selected features: ['sex', 'cp', 'chol', 'restecg', 'thalach', 'oldpeak', 'ca', 'thal']

Total features selected: 8

8) Implement Ant Colony Optimization Technique