

Code implementation –

This code compares the accuracies of two code algorithms, namely traditional algorithm only KNN and KNN with Genetic algorithm (WKNNGA).

Code –

```
#Now this code clearly mentions the output of two algorithms

import csv
import random
import math
import operator
import numpy
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

#read the dataset
def loadDataset(filename, split, trainingSet=[], testSet=[]):

    with open(filename, 'rt') as csvfile:
        lines = csv.reader(csvfile)
        dataset = list(lines)[1:]
        dataset2 = dataset
        dataset = [[float(x) for x in row] for row in dataset]
        scaler = MinMaxScaler()
        scaler.fit(dataset)
        MinMaxScaler(copy=True, feature_range=(0, 1))
        dataset = scaler.transform(dataset)
        for x in range(0, len(dataset)):
            for y in range(9):
                dataset[x][y] = float(dataset[x][y])
            if random.random() < split:
                trainingSet.append(dataset[x])
            else:
                testSet.append(dataset[x])

def euclideanDistance(instance1, instance2, length, chrom2):
    distance = 0
    for x in range(1, length):
        if chrom2[x]==1:
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        distance += pow((float(instance1[x]) -
float(instance2[x])), 2)
    return math.sqrt(distance)

def getNeighbors(trainingSet, testInstance, k, chrom2):
    distances = []
    length = len(testInstance)-1
    for x in range(len(trainingSet)):
        dist = euclideanDistance(testInstance, trainingSet[x], length,
chrom2)
        distances.append((trainingSet[x], dist))
    distances.sort(key=operator.itemgetter(1))
    neighbors = []
    for x in range(k):
        neighbors.append(distances[x][0])
    return neighbors

def getResponse(neighbors):
    classVotes = {}
    for x in range(len(neighbors)):
        response = neighbors[x][-1]
        if response in classVotes:
            classVotes[response] += 1
        else:
            classVotes[response] = 1
    sortedVotes = sorted(classVotes.items(), key=operator.itemgetter(1),
reverse=True)
    return sortedVotes[0][0]

def getAccuracy(testSet, predictions):
    correct = 0
    for x in range(len(testSet)):
        if testSet[x][-1] == predictions[x]:
            correct += 1
    return (correct/float(len(testSet))) * 100.0

def fitnessValue(chrom):
    random.seed(2)
    trainingSet=[]
    testSet=[]
    split = 0.8
    loadDataset('Prostate_Cancer_dataset.csv', split, trainingSet, test
Set)
    predictions=[]
    k = 3
    selected_features = [idx for idx, val in enumerate(chrom) if val==1
]
    trainingSetReduced = []

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testSetReduced = []
for instance in trainingSet:
    reduced_instance = [instance[i] for i in selected_features]
    reduced_instance.append(instance[-1])
    trainingSetReduced.append(reduced_instance)
for instance in testSet:
    reduced_instance = [instance[i] for i in selected_features]
    reduced_instance.append(instance[-1])
    testSetReduced.append(reduced_instance)
for x in range(len(testSetReduced)):
    neighbors = getNeighbors(trainingSetReduced, testSetReduced[x],
k, chrom)
    result = getResponse(neighbors)
    predictions.append(result)
accuracy = getAccuracy(testSetReduced, predictions)
return accuracy

# from knn import fitnessValue

def generatePop(n):
    chromAsli=[]
    for x in range(n):
        temp=[]
        temp2=[]
        for x in range(10):
            temp.append(numpy.random.randint(1))
        temp2.append(temp)
        fitness=fitnessValue(temp)
        temp2.append(fitness)
        chromAsli.append(temp2)
    return chromAsli

def eliteChild(chrom2,n):
    a=sorted(chrom2,key=lambda l:l[1], reverse=True)
    bestVal=a[0][1]
    bestFt2=a[0][0]
    next2=[]
    chrom3=[]
    for x in range(2):
        next2.append(a[x][0])
    for x in range(2,n):
        chrom3.append(a[x])
    return chrom3,next2,bestVal,bestFt2

def tournament(chrom2):
    best=[]
    for x in range(2):
        a=numpy.random.randint(0,11)

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        best.append(chrom2[a])
    bestOne=best[0]
    if(best[0][1]<best[1][1]):
        bestOne=best[1]
    return bestOne[0]

def getMutation(chrom2,pm,next2,n): #pm = mutation probability
    rng=n-len(next2)
    for i in range(rng):
        a=tournament(chrom2)
        rd=[]
        for x in range(10):
            ru=numpy.random.uniform(0.0, 1.0)
            if ru<=pm:
                rd.append(1)
            else:
                rd.append(0)
        if a==rd:
            a=tournament(chrom2)
        result=toXor(a,rd)
        next2.append(result)
    return next2

def toXor(x1,x2):
    xorRes=[]
    for x in range(len(x1)):
        if x1[x]==x2[x]:
            xorRes.append(0)
        else:
            xorRes.append(1)
    return xorRes

def getCrossOver(chrom2,pr,next2): #pr = cross-over probability
    rng=int(pr*len(chrom2))
    for x in range(rng):
        a=tournament(chrom2)
        b=tournament(chrom2)
        if a==b:
            result=a
        else:
            result=toXor(a,b)
        next2.append(result)
    return next2

def getGeneration(chrom2,idx):
    chrom2,nextGen,bestFitness,bestFt2=eliteChild(chrom2,genNum)
    nextGen=getCrossOver(chrom2,0.8,nextGen)
    nextGen=getMutation(chrom2,0.3,nextGen,genNum)

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    print('Generation {} {:.3f}'.format(idx+1,float(bestFitness)),end='%\n')
    return nextGen,bestFitness,bestFt2

genNum=15
knn_chrom=[0, 1, 1, 1, 1, 1, 1, 1, 1, 1]
knn_acc=fitnessValue(knn_chrom)
limit=100
stall=100
chrom=generatePop(genNum)
counter=0
newFit=0.0
oldFit=0.0
for x in range(limit):
    oldFit=newFit
    newChrom,newFit,bestFt=getGeneration(chrom,x)
    newFit=float(newFit)
    temp2=[]
    for y in range(genNum):
        temp=[]
        temp.append(newChrom[y])
        f=fitnessValue(newChrom[y])
        temp.append(f)
        temp2.append(temp)
    chrom=temp2
    diff=newFit - oldFit
    if diff<=0.0000001:
        counter+=1
    else:
        counter=0
    if counter==stall:
        break

#This will give us the output for KNN only
print("\nAccuracy with using K-NN without GA: ",end='')
print(' {:.3f}'.format(float(knn_acc)),end='')

#This will give us the output for KNN and GA
print("\nAccuracy using K-NN with GA:",end='')
print(' {:.3f}'.format(float(newFit)),end='')

#Used features from our dataset -
print("\nUsed features:", bestFt)

```

Output snip –

Generation 1	16.000%	Generation 39	84.000%
Generation 2	16.000%	Generation 40	84.000%
Generation 3	84.000%	Generation 41	84.000%
Generation 4	84.000%	Generation 42	84.000%
Generation 5	84.000%	Generation 43	84.000%
Generation 6	84.000%	Generation 44	84.000%
Generation 7	84.000%	Generation 45	84.000%
Generation 8	84.000%	Generation 46	84.000%
Generation 9	84.000%	Generation 47	84.000%
Generation 10	84.000%	Generation 48	84.000%
Generation 11	84.000%	Generation 49	84.000%
Generation 12	84.000%	Generation 50	84.000%
Generation 13	84.000%	Generation 51	84.000%
Generation 14	84.000%	Generation 52	84.000%
Generation 15	84.000%	Generation 53	84.000%
Generation 16	84.000%	Generation 54	84.000%
Generation 17	84.000%	Generation 55	84.000%
Generation 18	84.000%	Generation 56	84.000%
Generation 19	84.000%	Generation 57	84.000%
Generation 20	84.000%	Generation 58	84.000%
Generation 21	84.000%	Generation 59	84.000%
Generation 22	84.000%	Generation 60	84.000%
Generation 23	84.000%	Generation 61	84.000%
Generation 24	84.000%	Generation 62	84.000%
Generation 25	84.000%	Generation 63	84.000%
Generation 26	84.000%	Generation 64	84.000%
Generation 27	84.000%	Generation 65	84.000%
Generation 28	84.000%	Generation 66	84.000%
Generation 29	84.000%	Generation 67	84.000%
Generation 30	84.000%	Generation 68	84.000%
Generation 31	84.000%	Generation 69	84.000%
Generation 32	84.000%	Generation 70	84.000%
Generation 33	84.000%	Generation 71	84.000%
Generation 34	84.000%	Generation 72	84.000%
Generation 35	84.000%	Generation 73	84.000%
Generation 36	84.000%	Generation 74	84.000%
Generation 37	84.000%	Generation 75	84.000%
Generation 38	84.000%	Generation 76	84.000%

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Generation 77 84.000%
Generation 78 84.000%
Generation 79 84.000%
Generation 80 84.000%
Generation 81 84.000%
Generation 82 84.000%
Generation 83 84.000%
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Generation 85 84.000%
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Generation 87 84.000%
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Generation 90 84.000%
Generation 91 84.000%
Generation 92 84.000%
Generation 93 84.000%
Generation 94 84.000%
Generation 95 84.000%
Generation 96 84.000%
Generation 97 84.000%
Generation 98 84.000%
Generation 99 84.000%
Generation 100 84.000%
```

```
Accuracy with using K-NN without GA: 8.000
```

```
Accuracy using K-NN with GA:84.000%
```

```
Used features: [0, 0, 1, 0, 1, 0, 0, 0, 0, 1]
```

It is clearly shown in the output that in the case of on KNN algorithm with no GA, the accuracy is extremely

low, 8.00%, which is not a good value for any algorithm.

Reason for this low accuracy is the poor fitness function which leads to poor selection of the features.

Fitness function used for KNN only –

```
def fitnessValue(chrom):
    random.seed(2)
    trainingSet=[]
    testSet=[]
    split = 0.8
    loadDataset('Prostate_Cancer_dataset.csv', split, trainingSet, test
Set)
    predictions=[]
    k = 3
    for x in range(len(testSet)):
        neighbors = getNeighbors(trainingSet, testSet[x], k, chrom)
        result = getResponse(neighbors)
        predictions.append(result)
    accuracy = getAccuracy(testSet, predictions)
    return repr(accuracy)
```

That's why to overcome this problem we applied our KNN algorithm with GA, which improved the fitness function.

Fitness function modified –

```
def fitnessValue(chrom):
    random.seed(2)
    trainingSet=[]
    testSet=[]
    split = 0.8
    loadDataset('Prostate_Cancer_dataset.csv', split, trainingSet, test
Set)
    predictions=[]
    k = 3
```



```

selected_features = [idx for idx, val in enumerate(chrom) if val==1
]
trainingSetReduced = []
testSetReduced = []
for instance in trainingSet:
    reduced_instance = [instance[i] for i in selected_features]
    reduced_instance.append(instance[-1])
    trainingSetReduced.append(reduced_instance)
for instance in testSet:
    reduced_instance = [instance[i] for i in selected_features]
    reduced_instance.append(instance[-1])
    testSetReduced.append(reduced_instance)
for x in range(len(testSetReduced)):
    neighbors = getNeighbors(trainingSetReduced, testSetReduced[x],
k, chrom)
    result = getResponse(neighbors)
    predictions.append(result)
accuracy = getAccuracy(testSetReduced, predictions)
return accuracy

```

This significantly improved the accuracy, up to 84.00%. Thus we have comparison base for our problem statement and implementation.

Submitted by –

Group 10