EE559_Project_DheerajPanneerSelvam

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2 Import Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import random
from scipy import spatial
from sklearn import metrics
import seaborn as sns
import math
from datetime import datetime, timedelta
import warnings
warnings.filterwarnings("ignore")
```

3 Load Datasets

[2]:
```
df = pd.read_csv('algerian_fires_train.csv')
df.head()
```

[2]:
```
         Date  Temperature          RH         Ws       Rain       FFMC  \
0  01/06/2012    18.952399   43.855865  12.292536  -0.340306  73.063752
1  01/06/2012    34.498610   46.230441  14.838211   0.939652  56.027977
2  02/06/2012    15.258665   57.084279  10.968696   1.397913  33.114404
3  02/06/2012    24.847936   99.910000  17.924025   3.958666  26.148986
4  03/06/2012    19.381227  104.398680  23.740540  13.394723  28.658020

        DMC         DC       ISI       BUI  Classes
0 -2.371083  28.543573  0.487246  6.225461        0
1  0.441002 -10.007636 -1.472158  2.268104        0
2  3.389994 -13.774588  1.338737 -3.327908        0
3  5.179630  -1.392789 -0.755090  0.131303        0
4 -2.247164  -3.432689  0.558249 -1.928471        0
```

```
[3]: dfs = df.values
X = df.iloc[:,1:-1].values
y = df.iloc[:,-1].values
```

```
[4]: df_t = pd.read_csv('algerian_fires_test.csv')
df_t.head()
```

```
[4]:         Date  Temperature          RH         Ws       Rain        FFMC  \
0  01/09/2012    15.861392  103.083493  23.929982   6.862311   18.206803
1  01/09/2012    25.127811   85.095686  16.066414  -0.332408   36.300922
2  02/09/2012    25.804539  112.848312   8.603607  10.148430   32.909853
3  02/09/2012    39.157179   40.359214  13.347197  -0.050950  101.833950
4  03/09/2012    14.943534   51.887200  14.976143   3.910505   66.608357

        DMC         DC       ISI       BUI  Classes
0  6.705575  16.934059  1.272175  1.567136        0
1  4.307622  -8.813586 -1.707135 -2.167708        0
2 -3.989974  12.276834  0.886849  5.108220        0
3  4.923229  17.509484  1.000106  1.990220        0
4  0.628217  17.332474 -1.773158  9.083053        0
```

```
[5]: dfst = df_t.values
Xt = df_t.iloc[:,1:-1].values
yt = df_t.iloc[:,-1].values
```

4 Defining Global Functions

4.1 To find the accuracy of model

```
[6]: def accuracy(y,yh):
    count = 0
    for i in range(len(y)):
        if y[i]==yh[i]:
            count += 1
    return count/len(y)
```

4.2 Provides the Accuracy, F1 Score and Confusion matrix of model

```
[7]: def scores(yt,yh,sets):
    print(f'{sets} Accuracy = {accuracy(yt,yh)}')
    print(f' F1 Score = {metrics.f1_score(yt,yh)}')
    plt.figure()
    cm = metrics.confusion_matrix(yt,yh)
    print('\nConfusion Matrix')
    sns.set(rc = {'figure.figsize':(2,2)})
    sns.heatmap(cm,annot=True)
```

4.3 Gives the indices of datapoints belonging the various classes

[8]:
```
def class_ind(X,y):
    c1=[]
    c2=[]
    for i in range(len(X)):
        if y[i] == 0:
            c1.append(i)
        else:
            c2.append(i)
    return c1,c2
```

5 Trivial Regressor

This Model doesn't use the datapoints, randomly gives output based on the overall probability of occurence of a class

5.1 Model

[9]:
```
def trivial(l,df):
    v = df['Classes'].value_counts()
    n = len(df)
    a = v[0]/n
    b = v[1]/n
    yh=random.choices([0,1],[a,b],k=l)
    return yh
```

6 N means - Baseline Classifier

The nmeans classifier was used as a baseline or refrence classifier, to compare other models. No optimization was done on this classifier. Output labels was based on eucledian distance to the closest datapoint

6.1 Model Function

[10]:
```
def nmeans(X,y,data):
    c1=[]
    c2=[]
    for i in range(len(X)):
        if y[i] == 0:
            c1.append(i)
        else:
            c2.append(i)

    s1 = X[c1,:]
    s2 = X[c2,:]
```

```
    m1 = s1.mean(axis=0)
    m2 = s2.mean(axis=0)

    val1 = []
    val2 = []

    for i in data:
        val1.append(spatial.distance.euclidean(i, m1))
        val2.append(spatial.distance.euclidean(i, m2))

    yh = []
    for j in range(len(data)):
        if val1[j]<val2[j]:
            yh.append(0)
        else:
            yh.append(1)
    return yh
```

7 Bayes Minimum-Error Classifier (Gaussian Distribution Model)

The 1st Classifier I will be using is the Bayes Minimum error classifier, where the decision boundry is given by g = -(1/2)ln(|Ei|)-(1/2)(X-mi)TE/^-1(X-mi)+ln(P(Si)) This function uses the Covariance Matrix and means to predict the labels of the datapoints

7.1 Model Function

[11]:
```
def Bayes(df,X,y,Xt):

    c = class_ind(X,y)
    s1 = X[c[0],:]
    s2 = X[c[1],:]

    m1 = s1.mean(axis=0)
    m2 = s2.mean(axis=0)

    v = df['Classes'].value_counts()
    n = len(df)
    Ps1 = v[0]/n
    Ps2 = v[1]/n

    E1 = df.iloc[c[0],:-1].cov().values
    E2 = df.iloc[c[1],:-1].cov().values

    g11 =-0.5*math.log(np.linalg.det(E1),math.exp(1))
    g13 = math.log(Ps1,math.exp(1))
    g12 = []
```

```
    for i in range(len(Xt)):
        g12.append(((Xt-m1)[i]@np.linalg.inv(E1))@(Xt-m1)[i].T)
    g12 = -0.5*np.array(g12)
    g1 = g11+g12+g13

    g21 =-0.5*math.log(np.linalg.det(E2),math.exp(1))
    g23 = math.log(Ps2,math.exp(1))
    g22 = []
    for i in range(len(Xt)):
        g22.append(((Xt-m2)[i]@np.linalg.inv(E2))@(Xt-m2)[i].T)
    g22 = -0.5*np.array(g22)
    g2 = g21+g22+g23

    yh = []
    for j in range(len(g1)):
        if g1[j]>g2[j]:
            yh.append(0)
        else:
            yh.append(1)

    return yh
```

8 Perceptron Learning Algorithm (Sequential GD and Scheduler for Eta)

8.1 Function to claculate cost J(w)

[12]:
```
def critierion_perc(w,z,x):
    val = w@x.T*z
    tot = 0
    for i in val:
        if i <= 0:
            tot = tot + i
    return -1*tot
```

8.2 Function to find optimal weights and coressponing error, for each eta overall 20 combinations

[13]:
```
def gradient_seq(df):
    w = np.random.uniform(-0.05,0.05,len(df[0]))

    A = [0.01, 0.1, 1, 10, 100]
    B = [1, 10, 100, 1000]
    Et = {}
    wt = {}
```

```
dfl = df.tolist()
dfs = random.sample(dfl,len(dfl))
dfs = np.array(dfs)
x = dfs[:,:-1]
o = np.ones((len(x),1))
x = np.hstack([o,x])
y = dfs[:,-1]


z = []
for i in dfs[:,-1]:
    if i == 0:
        z.append(1)
    elif i == 1:
        z.append(-1)
z = np.array(z)

for a in A:
    for b in B:
        m = 0
        E = []
        while True:
            m += 1
            E.append(critierion_perc(w,z,x)**0.5)
            J = {}
            k = random.sample(range(0,len(x)),len(x))
            for n in k:
                i = (m)*len(x)+(n+1)
                eta = a/(b+i)
                if w@x[n].T*z[n] <= 0:
                    w = w+(eta*z[n]*x[n])

                if m >= 100:
                    wt[a,b] = w
                    Et[a,b] = E
                    break
            if m >= 100:
                break

return wt,Et
```

8.3 Predict Class Labels based on optimal weights

[14]:
```
def classification_perc(w,x):
    o = np.ones((len(x),1))
    x = np.hstack([o,x])
    label = []
    val = w@x.T
    for i in val:
        if  i >= 0:
            label.append(0)
        else:
            label.append(1)
    return np.array(label)
```

8.4 Model Function

[116]:
```
def Perceptron(dfs,xt):
    x1 = dfs[:,:-1]
    y1 = (dfs[:,-1]).astype(int).tolist()
    w1,E1 = gradient_seq(dfs)
    minE = {}
    for i in E1.keys():
        minE[i] = (E1[i][-1])
        #print(f"\tThe Final Error of Pair: {i} is {minE[i]}")
    minpair = min(minE, key=minE.get)
    #print(f"The lowest error pair is {minpair} with Erms {minE[minpair]}")
    wl = w1[minpair]
    yh = classification_perc(wl,xt)
    return yh
```

9 Mean Square Error Classifier (Widrow-Hoff) based on Sequential GD and Scheduler

This classfier uses the MSE algorithm with weight update rule, w(i+1) = w(i) - eta(i)(w(i)TXn - bn)Xn

9.1 Function to calculate cost J(w)

[16]:
```
def criterion_mse(w,x,y):
    N = len(y)
    Jn = (1/N)*(((w@x.T)-y)**2)
    J = sum(Jn)
    return J
```

9.2 Function to find optimal weights and coressponing error, for each eta overall 6 combinations

[17]:
```
def gradient_mse(df):
    w = np.random.uniform(-0.2,0.2,len(df[0]))
    a = 0.01
    B = [0.01 , 0.1, 1, 10, 100, 1000]
    Et = {}
    wt = {}

    dfl = df.tolist()
    dfs = random.sample(dfl,len(dfl))
    dfs = np.array(dfs)
    x = dfs[:,:-1]
    o = np.ones((len(x),1))
    x = np.hstack([o,x])
    y = dfs[:,-1]
    bb = 10*np.ones(len(y))
    z = []
    for i in dfs[:,-1]:
        if i == 0:
            z.append(1)
        elif i == 1:
            z.append(-1)
    z = np.array(z)

    for b in B:
        m = 0
        E = []
        while True:

            E.append(criterion_mse(w,x,z)**0.5)


            m += 1

            k = random.sample(range(0,len(x)),len(x))
            for n in k:
                i = (m)*len(x)+(n+1)
                eta = a/(b+i)
                w = w - eta*((w@x[n].T-z[n])*x[n])

                if m >= 100:
                    wt[a,b] = w
                    Et[a,b] = E
                    break
            if m >= 100:
                break
```

```
    return wt,Et
```

9.3 Predicting labels based on optimal weights

[18]:
```
def classification_mse(w,x):
    o = np.ones((len(x),1))
    x = np.hstack([o,x])
    label = []
    val = w@x.T
    for i in val:
        if  i >= 0:
            label.append(0)
        else:
            label.append(1)
    return np.array(label)
```

9.4 Model Function

[19]:
```
def MSE(dfs,xt):
    x1 = dfs[:,:-1]
    y1 = (dfs[:,-1]).astype(int).tolist()
    w1,E1 = gradient_mse(dfs)
    minE = {}
    for i in E1.keys():
        minE[i] = (E1[i][-1])
        #print(f"\tThe Final Error of Pair: {i} is {minE[i]}")
    minpair = min(minE, key=minE.get)
    #print(f"The lowest error pair is {minpair} with Erms {minE[minpair]}")
    wl = w1[minpair]
    yh = classification_mse(wl,xt)
    return yh
```

10 SVM Linear Classifier

I have used he matrix implementation the code the svm i.e Al = p. First I found out A but differentiating with li (l=lamada) and writing it in matrix form, then found all lamada, then used it to calculate the weights and finally predicted the labels.

10.1 Function to get z from labels y

[20]:
```
 def get_z(y):
    z = []
    for i in y:
        if i == 0:
            z.append(1)
```

```
        elif i == 1:
            z.append(-1)
    z = np.array(z)
    return z
```

10.2 Model Function

[21]:
```
def SVM_linear(X,z,gamma,Xt):
    A = np.empty([len(X),len(X)])
    for i in range(len(X)):
        for j in range(len(X)):
            A[i][j] = (z[i]*z[j]*X[i].T@X[j])
    A = np.vstack([A, z])
    z2 = np.hstack([z,0])
    z2 = (-1*z2).reshape(len(X)+1,1)
    A = np.hstack([A, z2])
    p = np.ones([len(X)+1,1])
    l = np.linalg.inv(A)@p
    w = 0
    for i in range(l.shape[0]-1):
        w += l[i]*z[i]*X[i]
    w0 = 1/z[0]-(w.T@X[0])
    g = (Xt@w)+w0
    yh = []
    for i in g:
        if i>0:
            yh.append(0)
        else:
            yh.append(1)

    return yh
```

11 SVM Nonlinear RBF Classifier

Used the same technique as Linear, but used RBF kernal to make it nonlinear, tried over 100 gamma values to find best one

[22]:
```
def SVM_RBF(X,z,gamma,Xt):
    A = np.empty([len(X),len(X)])
    for i in range(len(X)):
        for j in range(len(X)):
            A[i][j] = (z[i]*z[j]*np.exp(-1*gamma*np.linalg.norm(X[i,:]-X[j,:])))
    A = np.vstack([A, z])
    z2 = np.hstack([z,0])
    z2 = (-1*z2).reshape(len(X)+1,1)
    A = np.hstack([A, z2])
```

```
    p = np.ones([len(X)+1,1])
    l = np.linalg.inv(A)@p
    w = 0
    for i in range(l.shape[0]-1):
        w += l[i]*z[i]*X[i]
    w0 = 1/z[0]-(w.T@X[0])
    g = (Xt@w)+w0
    yh = []
    for i in g:
        if i>0:
            yh.append(0)
        else:
            yh.append(1)
    return yh
```

12 Cross Validation

12.1 Function to perform Cross Validation on Base Dataset

I have made the usual 75% train and 25% validation split. So there are 4 epochs. The function contains which model to use and gives the epoch with lowest validation error

[23]:
```
def Cross_Validation(model,name,df):
    error = {}
    for i in range(4):

        if i == 3:
            q = -1
        else:
            q = 46*(i+1)

        Xval = df.iloc[46*i:q,1:-1].values
        yval = df.iloc[46*i:q,-1].values
        dfs = df.drop(df.index[46*i:q]).iloc[:,1:].values
        Xtr = df.drop(df.index[46*i:q]).iloc[:,1:-1].values
        ytr = df.drop(df.index[46*i:q]).iloc[:,-1].values
        ztr = get_z(ytr)
        if name == 'SVM_linear' or name == 'SVM_RBF':
            yh = model(Xtr,ztr,0.01,Xval)

        elif name == 'nmeans':
            yh = model(Xtr,ytr,Xval)

        elif name == 'Perceptron' or name == 'MSE':
            yh = model(dfs,Xval)

        elif name == 'Bayes':
```

```
            yh = model(df,Xtr,ytr,Xval)


        else:
            print('Enter Valid Model')

        error[i] = 1-accuracy(yval,yh)

        print(f'Epoch {i} error is = {1-accuracy(yval,yh)}')
    m = min(error, key=error.get)
    print(f'\nLowest error is at Epoch {m} with {error[m]}')
    #print(f'Accuracy at Epoch {m} = {1-error[m]}\n')
    scores(yval,yh,'Best Validation Set')


    return m
```

12.2 Function to provide the test set accuracy for the train set with lowest validation error

[24]:
```
def low_epoch(i,model,name,df,Xt,yt):

    p = 46*i

    if i == 3:
        q = -1
    else:
        q = 46*(i+1)

    dfs = df.drop(df.index[p:q]).iloc[:,1:].values
    Xtr = df.drop(df.index[p:q]).iloc[:,1:-1].values
    ytr = df.drop(df.index[p:q]).iloc[:,-1].values
    ztr = get_z(ytr)

    if name == 'SVM_linear' or name == 'SVM_RBF':
        yh = model(Xtr,ztr,0.01,Xt)

    elif name == 'nmeans':
        yh = model(Xtr,ytr,Xt)

    elif name == 'Perceptron' or name == 'MSE':
        yh = model(dfs,Xt)

    elif name == 'Bayes':
            yh = model(df,Xtr,ytr,Xt)
```

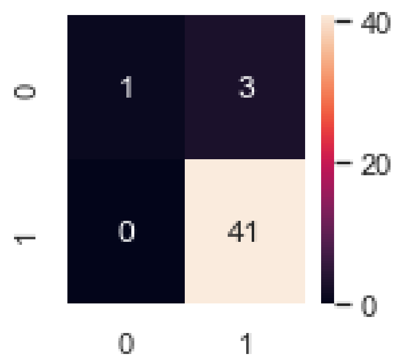
```
    else:
        print('Enter Valid Model')

    scores(yh,yt,'Test Set')
```

13 Performing Cross Validation on all models

13.1 N means

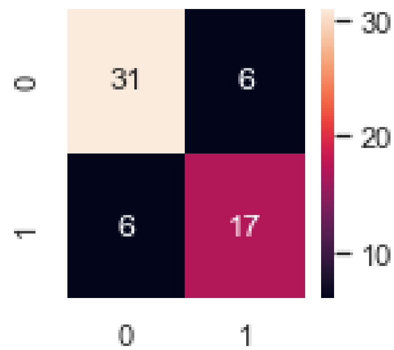
[26]:
```
nmi = Cross_Validation(nmeans,'nmeans',df)
```

```
Epoch 0 error is = 0.21739130434782605
Epoch 1 error is = 0.3695652173913043
Epoch 2 error is = 0.3913043478260869
Epoch 3 error is = 0.06666666666666665

Lowest error is at Epoch 3 with 0.06666666666666665
Best Validation Set Accuracy = 0.9333333333333333
 F1 Score = 0.9647058823529412

Confusion Matrix
```



[27]:
```
low_epoch(nmi,nmeans,'nmeans',df,Xt,yt)
```

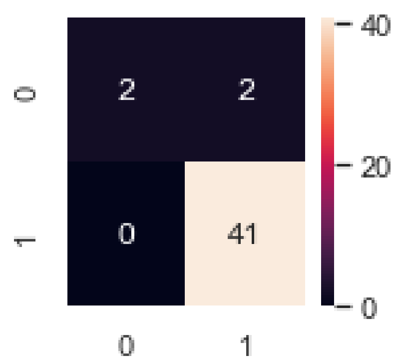
```
Test Set Accuracy = 0.8
 F1 Score = 0.7391304347826085

Confusion Matrix
```



13.2 Bayes

[28]:
```
bi = Cross_Validation(Bayes,'Bayes',df)
```

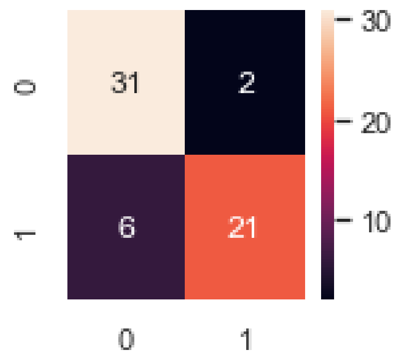
```
Epoch 0 error is = 0.34782608695652173
Epoch 1 error is = 0.15217391304347827
Epoch 2 error is = 0.17391304347826086
Epoch 3 error is = 0.044444444444444

Lowest error is at Epoch 3 with 0.0444444444444444
Best Validation Set Accuracy = 0.9555555555555556
 F1 Score = 0.9761904761904763

Confusion Matrix
```



[29]:
```
low_epoch(bi,Bayes,'Bayes',df,Xt,yt)
```

```
Test Set Accuracy = 0.8666666666666667
 F1 Score = 0.84
```

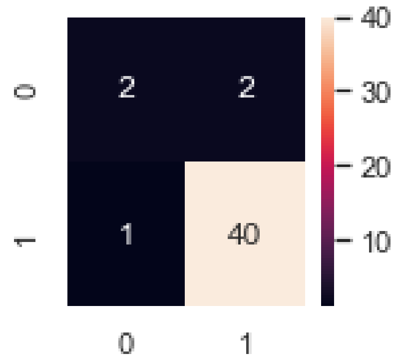
Confusion Matrix



13.3 Perceptron

[30]:
```
pi = Cross_Validation(Perceptron,'Perceptron',df)
```

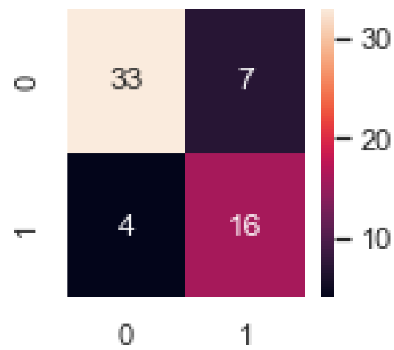
```
The lowest error pair is (0.01, 1000) with Erms 0.6946477651148641
Epoch 0 error is = 0.26086956521739135
The lowest error pair is (0.01, 1000) with Erms 0.9058096501891952
Epoch 1 error is = 0.21739130434782605
The lowest error pair is (0.01, 1000) with Erms 0.4067422804974323
Epoch 2 error is = 0.06521739130434778
The lowest error pair is (0.01, 100) with Erms 0.4515519969087185
Epoch 3 error is = 0.06666666666666665

Lowest error is at Epoch 2 with 0.06521739130434778
Best Validation Set Accuracy = 0.9333333333333333
 F1 Score = 0.963855421686747

Confusion Matrix
```



Accuracy keeps varying best I got 83.33%

[31]:
```
low_epoch(pi,Perceptron,'Perceptron',df,Xt,yt)
```

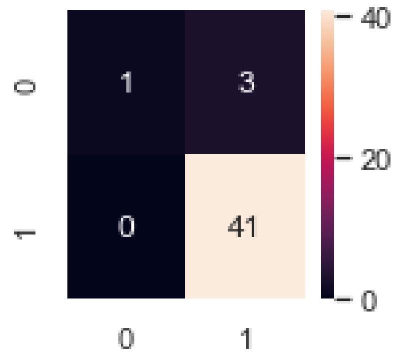
```
The lowest error pair is (0.01, 100) with Erms 0.5564158614744201
Test Set Accuracy = 0.8166666666666667
 F1 Score = 0.7441860465116279

Confusion Matrix
```



13.4 MSE

[32]:
```
msei = Cross_Validation(MSE,'MSE',df)
```

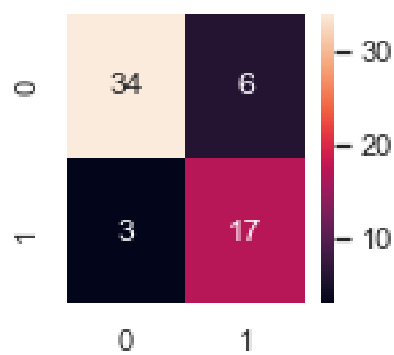
```
Epoch 0 error is = 0.23913043478260865
Epoch 1 error is = 0.19565217391304346
Epoch 2 error is = 0.13043478260869568
Epoch 3 error is = 0.06666666666666665

Lowest error is at Epoch 3 with 0.06666666666666665
Best Validation Set Accuracy = 0.9333333333333333
 F1 Score = 0.9647058823529412

Confusion Matrix
```



Accuracy keeps varying best I got 83.33%

[33]:
```
low_epoch(msei,MSE,'MSE',df,Xt,yt)
```

```
Test Set Accuracy = 0.85
 F1 Score = 0.7906976744186046

Confusion Matrix
```



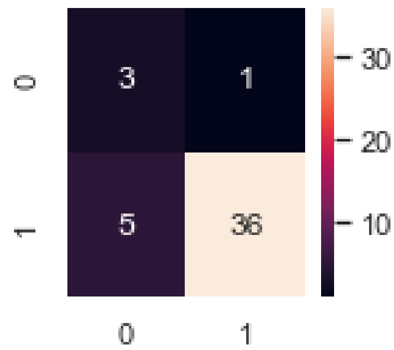
13.5 SVM Linear

[34]:
```
sli = Cross_Validation(SVM_linear,'SVM_linear',df)
```

```
Epoch 0 error is = 0.4565217391304348
Epoch 1 error is = 0.32608695652173914
Epoch 2 error is = 0.6739130434782609
Epoch 3 error is = 0.1333333333333333

Lowest error is at Epoch 3 with 0.1333333333333333
Best Validation Set Accuracy = 0.8666666666666667
```

```
F1 Score = 0.923076923076923
```

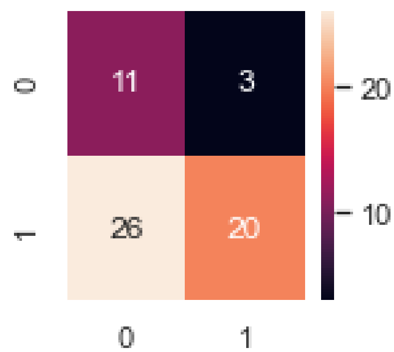
```
Confusion Matrix
```



[35]:
```
low_epoch(sli,SVM_linear,'SVM_linear',df,Xt,yt)
```

```
Test Set Accuracy = 0.5166666666666667
 F1 Score = 0.5797101449275363
```

```
Confusion Matrix
```

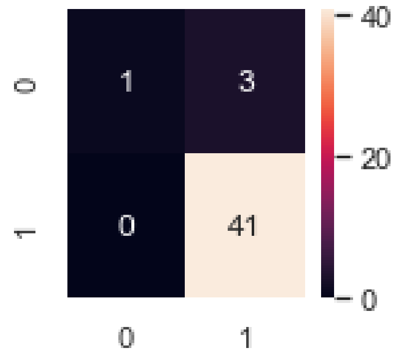


13.6 SVM RBF

[36]:
```
sbi = Cross_Validation(SVM_RBF,'SVM_RBF',df)
```

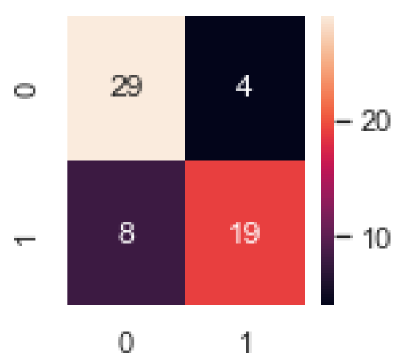
```
Epoch 0 error is = 0.10869565217391308
Epoch 1 error is = 0.23913043478260865
Epoch 2 error is = 0.19565217391304346
Epoch 3 error is = 0.06666666666666665

Lowest error is at Epoch 3 with 0.06666666666666665
```

```
Best Validation Set Accuracy = 0.9333333333333333
 F1 Score = 0.9647058823529412

Confusion Matrix
```



[37]:
```
low_epoch(sbi,SVM_RBF,'SVM_RBF',df,Xt,yt)
```

```
Test Set Accuracy = 0.8
 F1 Score = 0.76

Confusion Matrix
```



14 Testing the metrics on Test set with entire Train (no split)

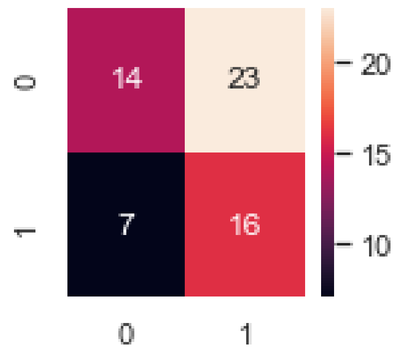
14.1 Trivial

[38]:
```
yhtri = trivial(len(Xt),df)
scores(yt,yhtri,'Test Set')
```

```
Test Set Accuracy = 0.5
```

```
F1 Score = 0.5161290322580646
```

```
Confusion Matrix
```

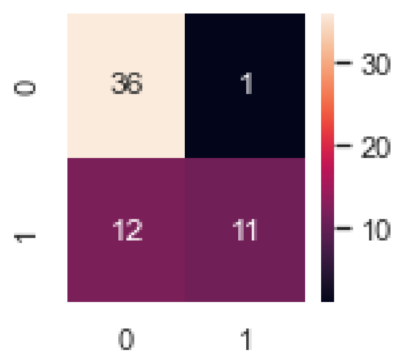


14.2 N Means

[39]:
```
yhnmean = nmeans(X,y,Xt)
scores(yt,yhnmean,'Test Set')
```

```
Test Set Accuracy = 0.7833333333333333
 F1 Score = 0.6285714285714286
```

```
Confusion Matrix
```



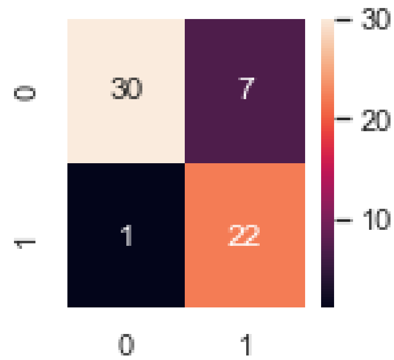
14.3 Bayes

[40]:
```
yhb = Bayes(df,X,y,Xt)
scores(yt,yhb,'Test Set')
```

```
Test Set Accuracy = 0.8666666666666667
```

```
F1 Score = 0.8461538461538461
```

```
Confusion Matrix
```



14.4 Perceptron

As we are randomly suffelling for Sequential GD the accuracy will vary, the best was 85% on base dataset

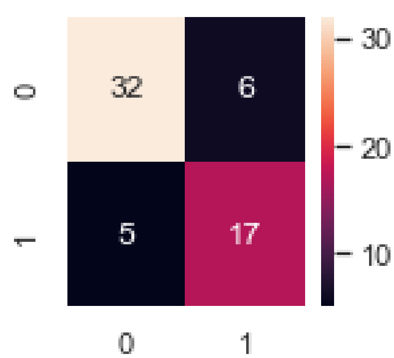
[41]:
```
yhperc = Perceptron(dfs[:,1:],Xt)
```

```
The lowest error pair is (0.01, 1000) with Erms 0.7417432701726769
```

[42]:
```
scores(yhperc,yt,'Test Set')
```

```
Test Set Accuracy = 0.8166666666666667
 F1 Score = 0.7555555555555555
```

```
Confusion Matrix
```



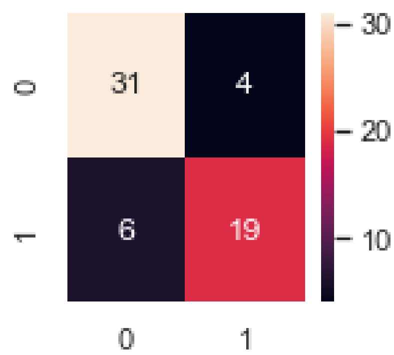
14.5 MSE

As I am using sequentaial GD the randomnes varies the accuracy, highest i achieved was 86.66%

[43]:
```
yhmse = MSE(dfs[:,1:],Xt)
```

[44]:
```
scores(yhmse,yt,'Test Set')
```

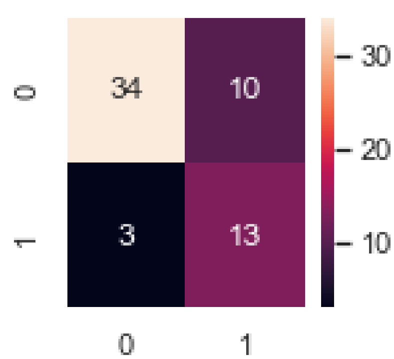
```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.7916666666666667

Confusion Matrix
```



14.6 SVM Linear

[45]:
```
z = get_z(y)
yh2 = SVM_linear(X,z,None,Xt)
scores(yh2,yt,'Test Set')
```

```
Test Set Accuracy = 0.7833333333333333
 F1 Score = 0.6666666666666667

Confusion Matrix
```



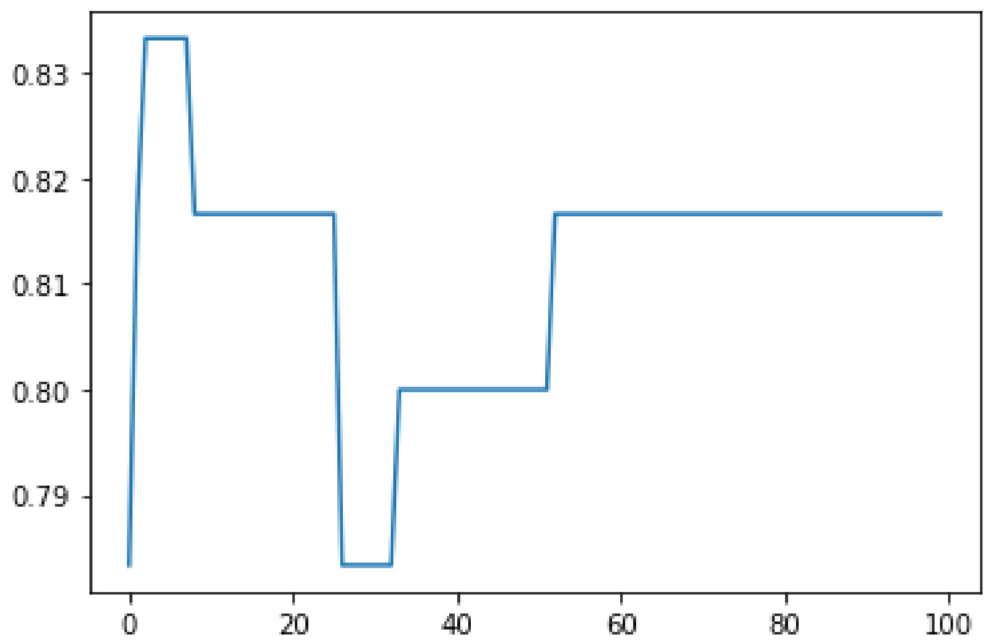
14.7 SVM RBF

14.7.1 Iterating through gamma values from 0.001 to 0.2, to find gamma with highest accuracy

[ ]:
```
acc = []
for i in np.arange(0.001,0.2,0.002):
    yh = SVM_RBF(X,get_z(y),i,Xt)
    acc.append(accuracy(yt,yh))
```

[364]:
```
plt.plot(acc)
```

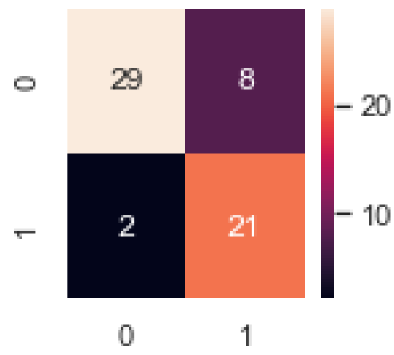
[364]:
```
[<matplotlib.lines.Line2D at 0x17c48a85d30>]
```



Optimal weight was around 0.01 giving 83.333% accuracy

[47]:
```
yh = SVM_RBF(X,z,0.01,Xt)
scores(yt,yh,'Test Set')
```

```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.8076923076923076

Confusion Matrix
```



15 Feature Expansion

Let's augment the feature space by modifying some existing features and later do feature selection

[48]:
```
dfex = pd.read_csv('algerian_fires_train.csv')
dfex.head()
```

[48]:
```
         Date  Temperature          RH         Ws       Rain       FFMC  \
0  01/06/2012    18.952399   43.855865  12.292536  -0.340306  73.063752
1  01/06/2012    34.498610   46.230441  14.838211   0.939652  56.027977
2  02/06/2012    15.258665   57.084279  10.968696   1.397913  33.114404
3  02/06/2012    24.847936   99.910000  17.924025   3.958666  26.148986
4  03/06/2012    19.381227  104.398680  23.740540  13.394723  28.658020

        DMC         DC       ISI       BUI  Classes
0 -2.371083  28.543573  0.487246  6.225461        0
1  0.441002 -10.007636 -1.472158  2.268104        0
2  3.389994 -13.774588  1.338737 -3.327908        0
3  5.179630  -1.392789 -0.755090  0.131303        0
4 -2.247164  -3.432689  0.558249 -1.928471        0
```

15.1 Change date from str to date time format

[49]:
```
dfex['Date']=pd.to_datetime(dfex['Date'],dayfirst=True)
```

15.2 Augmenting Features

I am going to take the Average, Max, Min, Median and Standard deviation of Temperature,Humidity,Wind Speed and Rain over the past 7 days, 5 days and 2 days and add them to dataset. So in total including date column, **D' = 10+(3.4.4) = 58 features**.

The basic thumb rule is **N > (3 - 10) * D+1**. So according to this as N = 184, the range for D is from **17 - 61** features. D' = 58 features falls in this range so we can train the entire expanded feature set. But we will later do feature selection.

[50]:
```
def fea_exp(dfex):
    for j in [7,5,2]:

        dfex[f'Avg Temperature - {j}'] = np.zeros(len(dfex))
        dfex[f'Avg RH - {j}'] = np.zeros(len(dfex))
        dfex[f'Avg Ws - {j}'] = np.zeros(len(dfex))
        dfex[f'Avg Rain - {j}'] = np.zeros(len(dfex))

        dfex[f'Max Temperature - {j}'] = np.zeros(len(dfex))
        dfex[f'Max RH - {j}'] = np.zeros(len(dfex))
        dfex[f'Max Ws - {j}'] = np.zeros(len(dfex))
        dfex[f'Max Rain - {j}'] = np.zeros(len(dfex))

        dfex[f'Min Temperature - {j}'] = np.zeros(len(dfex))
        dfex[f'Min RH - {j}'] = np.zeros(len(dfex))
        dfex[f'Min Ws - {j}'] = np.zeros(len(dfex))
        dfex[f'Min Rain - {j}'] = np.zeros(len(dfex))

        dfex[f'Median Temperature - {j}'] = np.zeros(len(dfex))
        dfex[f'Median RH - {j}'] = np.zeros(len(dfex))
        dfex[f'Median Ws - {j}'] = np.zeros(len(dfex))
        dfex[f'Median Rain - {j}'] = np.zeros(len(dfex))

        for i in range(len(dfex)):

            data = dfex[(dfex['Date']>=dfex['Date'][i]-pd.Timedelta(days=j)) &␣
↪(dfex['Date']<dfex['Date'][i])]
            dfex[f'Avg Temperature - {j}'][i] = data['Temperature'].mean()
            dfex[f'Avg RH - {j}'][i] = data['RH'].mean()
            dfex[f'Avg Ws - {j}'][i] = data['Ws'].mean()
            dfex[f'Avg Rain - {j}'][i] = data['Rain'].mean()

            dfex[f'Max Temperature - {j}'][i] = data['Temperature'].max()
            dfex[f'Max RH - {j}'][i] = data['RH'].max()
            dfex[f'Max Ws - {j}'][i] = data['Ws'].max()
            dfex[f'Max Rain - {j}'][i] = data['Rain'].max()

            dfex[f'Min Temperature - {j}'][i] = data['Temperature'].min()
            dfex[f'Min RH - {j}'][i] = data['RH'].min()
            dfex[f'Min Ws - {j}'][i] = data['Ws'].min()
            dfex[f'Min Rain - {j}'][i] = data['Rain'].min()

            dfex[f'Median Temperature - {j}'][i] = data['Temperature'].median()
            dfex[f'Median RH - {j}'][i] = data['RH'].median()
            dfex[f'Median Ws - {j}'][i] = data['Ws'].median()
```

```python
            dfex[f'Median Rain - {j}'][i] = data['Rain'].median()
    return dfex
```

[51]:
```python
dfex = fea_exp(dfex)
```

15.3 Replacing Nan values for the starting values with the mean of that column

[52]:
```python
dfex.iloc[:,8:13].head()
```

[52]:

	ISI	BUI	Classes	Avg Temperature - 7	Avg RH - 7
0	0.487246	6.225461	0	NaN	NaN
1	-1.472158	2.268104	0	NaN	NaN
2	1.338737	-3.327908	0	26.725504	45.043153
3	-0.755090	0.131303	0	26.725504	45.043153
4	0.558249	-1.928471	0	23.389402	61.770146

[53]:
```python
for i in dfex.columns[11:]:
    for j in range(2):
        dfex[i][j] = dfex[i].mean()
```

[54]:
```python
dfex.iloc[:,8:13].head()
```

[54]:

	ISI	BUI	Classes	Avg Temperature - 7	Avg RH - 7
0	0.487246	6.225461	0	32.773747	60.305950
1	-1.472158	2.268104	0	32.773747	60.305950
2	1.338737	-3.327908	0	26.725504	45.043153
3	-0.755090	0.131303	0	26.725504	45.043153
4	0.558249	-1.928471	0	23.389402	61.770146

15.4 ** Removing the last 7 days from train set as it will contain data in the test set **

As 7 days is the maximum we are considering

[55]:
```python
dfex.tail()
```

[55]:

	Date	Temperature	RH	Ws	Rain	FFMC	\
179	2012-08-29	28.449213	57.127011	15.195444	-0.161958	71.450733	
180	2012-08-30	26.680911	73.619431	17.054505	0.127765	61.231373	
181	2012-08-30	44.750966	58.428753	21.687939	0.995222	62.921683	
182	2012-08-31	33.298270	79.558329	20.464269	17.019373	47.242905	
183	2012-08-31	32.762295	84.322685	21.653932	-0.213253	67.294270	

	DMC	DC	ISI	BUI	…	Max Ws - 2	\
179	57.128627	239.290670	11.267031	68.680725	…	25.236657	
180	18.986399	170.968390	9.496533	39.281865	…	18.919395	
181	27.594857	176.118476	-0.271474	30.340267	…	18.919395	

```
182   6.039570  -11.298033   0.035798   4.744741  …   21.687939
183  33.599199  165.945211  10.440299  35.986552  …   21.687939

     Max Rain - 2  Min Temperature - 2  Min RH - 2  Min Ws - 2  Min Rain - 2  \
179      0.441210            25.427053   33.537444    7.323591     -0.052653
180      0.704918            25.427053   33.537444    9.172789     -0.161958
181      0.704918            25.427053   33.537444    9.172789     -0.161958
182      0.995222            26.680911   42.920337   12.860767     -0.161958
183      0.995222            26.680911   42.920337   12.860767     -0.161958

     Median Temperature - 2  Median RH - 2  Median Ws - 2  Median Rain - 2
179               32.267581      50.071274      14.046092         0.302474
180               32.908271      49.187007      14.028106         0.194279
181               32.908271      49.187007      14.028106         0.194279
182               32.908271      57.777882      16.124974         0.416342
183               32.908271      57.777882      16.124974         0.416342

[5 rows x 59 columns]
```

[56]:
```
dfex = dfex[dfex['Date']<(dfex['Date'][len(dfex)-1]-pd.Timedelta(days=7))]
```

Checking if the last 7 days are removed

[57]:
```
dfex.tail()
```

[57]:
```
           Date  Temperature         RH         Ws      Rain        FFMC  \
163 2012-08-21    38.974406  38.708515  21.078248 -0.196080  114.270824
164 2012-08-22    30.896242  48.836994  20.114324  0.278984   91.425389
165 2012-08-22    39.904877  62.449343  11.446256  0.033836   91.196227
166 2012-08-23    48.038777  63.133020  16.675465 -0.333441  104.399432
167 2012-08-23    39.287463  54.760134  18.612077  0.320175   86.555473

           DMC          DC       ISI        BUI  …  Max Ws - 2  \
163  28.324008  156.279593  9.850906  36.338345  …   25.719072
164  37.232181  114.531143  6.745771  41.499593  …   25.719072
165  34.722303  142.729175  9.831573  39.743423  …   25.719072
166  48.922137  144.539130  9.747095  53.349689  …   21.078248
167  33.090678  144.795556  8.520974  43.813670  …   21.078248

     Max Rain - 2  Min Temperature - 2  Min RH - 2  Min Ws - 2  Min Rain - 2  \
163      0.216639            29.276266   37.988082   16.775674     -0.278088
164      0.164612            22.306773   38.708515   16.775674     -0.278088
165      0.164612            22.306773   38.708515   16.775674     -0.278088
166      0.278984            22.306773   38.708515   11.446256     -0.196080
167      0.278984            22.306773   38.708515   11.446256     -0.196080

     Median Temperature - 2  Median RH - 2  Median Ws - 2  Median Rain - 2
```

```
163                  36.558474     46.510156     20.237203           0.184716
164                  34.794234     53.520168     18.980650          -0.044174
165                  34.794234     53.520168     18.980650          -0.044174
166                  34.935324     55.643169     18.498688           0.070785
167                  34.935324     55.643169     18.498688           0.070785

[5 rows x 59 columns]
```

15.5 Entire process is repeated for the test set

[58]:
```python
dfext = pd.read_csv('algerian_fires_test.csv')
dfext['Date']=pd.to_datetime(dfext['Date'],dayfirst=True)
dfext.head()
```

[58]:
```
        Date  Temperature          RH         Ws       Rain        FFMC  \
0 2012-09-01    15.861392  103.083493  23.929982   6.862311   18.206803
1 2012-09-01    25.127811   85.095686  16.066414  -0.332408   36.300922
2 2012-09-02    25.804539  112.848312   8.603607  10.148430   32.909853
3 2012-09-02    39.157179   40.359214  13.347197  -0.050950  101.833950
4 2012-09-03    14.943534   51.887200  14.976143   3.910505   66.608357

        DMC         DC       ISI       BUI  Classes
0  6.705575  16.934059  1.272175  1.567136        0
1  4.307622  -8.813586 -1.707135 -2.167708        0
2 -3.989974  12.276834  0.886849  5.108220        0
3  4.923229  17.509484  1.000106  1.990220        0
4  0.628217  17.332474 -1.773158  9.083053        0
```

[59]:
```python
dfext = fea_exp(dfext)
```

[60]:
```python
dfext.iloc[:,8:13].head()
```

[60]:
```
        ISI       BUI  Classes  Avg Temperature - 7  Avg RH - 7
0  1.272175  1.567136        0                  NaN         NaN
1 -1.707135 -2.167708        0                  NaN         NaN
2  0.886849  5.108220        0            20.494601   94.089590
3  1.000106  1.990220        0            20.494601   94.089590
4 -1.773158  9.083053        0            26.487730   85.346677
```

[61]:
```python
for i in dfext.columns[11:]:
    for j in range(2):
        dfext[i][j] = dfext[i].mean()
```

[62]:
```python
dfext.head()
```

[62]:
```
         Date  Temperature          RH         Ws       Rain        FFMC  \
0 2012-09-01    15.861392  103.083493  23.929982   6.862311   18.206803
1 2012-09-01    25.127811   85.095686  16.066414  -0.332408   36.300922
2 2012-09-02    25.804539  112.848312   8.603607  10.148430   32.909853
3 2012-09-02    39.157179   40.359214  13.347197  -0.050950  101.833950
4 2012-09-03    14.943534   51.887200  14.976143   3.910505   66.608357

        DMC         DC        ISI        BUI  …  Max Ws - 2  Max Rain - 2  \
0  6.705575  16.934059  1.272175  1.567136  …   21.621763      3.600236
1  4.307622  -8.813586 -1.707135 -2.167708  …   21.621763      3.600236
2 -3.989974  12.276834  0.886849  5.108220  …   23.929982      6.862311
3  4.923229  17.509484  1.000106  1.990220  …   23.929982      6.862311
4  0.628217  17.332474 -1.773158  9.083053  …   23.929982     10.148430

   Min Temperature - 2  Min RH - 2  Min Ws - 2  Min Rain - 2  \
0            20.095227   46.306863   10.720009     -0.131692
1            20.095227   46.306863   10.720009     -0.131692
2            15.861392   85.095686   16.066414     -0.332408
3            15.861392   85.095686   16.066414     -0.332408
4            15.861392   40.359214    8.603607     -0.332408

   Median Temperature - 2  Median RH - 2  Median Ws - 2  Median Rain - 2
0               31.296135      64.904185      15.745523         0.751244
1               31.296135      64.904185      15.745523         0.751244
2               20.494601      94.089590      19.998198         3.264951
3               20.494601      94.089590      19.998198         3.264951
4               25.466175      94.089590      14.706806         3.405680

[5 rows x 59 columns]
```

15.6 Manual Shifting the Classes feature to last column to ease operations later

[63]:
```python
print(dfex.columns)
```

```
Index(['Date', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI',
       'BUI', 'Classes', 'Avg Temperature - 7', 'Avg RH - 7', 'Avg Ws - 7',
       'Avg Rain - 7', 'Max Temperature - 7', 'Max RH - 7', 'Max Ws - 7',
       'Max Rain - 7', 'Min Temperature - 7', 'Min RH - 7', 'Min Ws - 7',
       'Min Rain - 7', 'Median Temperature - 7', 'Median RH - 7',
       'Median Ws - 7', 'Median Rain - 7', 'Avg Temperature - 5', 'Avg RH - 5',
       'Avg Ws - 5', 'Avg Rain - 5', 'Max Temperature - 5', 'Max RH - 5',
       'Max Ws - 5', 'Max Rain - 5', 'Min Temperature - 5', 'Min RH - 5',
       'Min Ws - 5', 'Min Rain - 5', 'Median Temperature - 5', 'Median RH - 5',
       'Median Ws - 5', 'Median Rain - 5', 'Avg Temperature - 2', 'Avg RH - 2',
       'Avg Ws - 2', 'Avg Rain - 2', 'Max Temperature - 2', 'Max RH - 2',
       'Max Ws - 2', 'Max Rain - 2', 'Min Temperature - 2', 'Min RH - 2',
       'Min Ws - 2', 'Min Rain - 2', 'Median Temperature - 2', 'Median RH - 2',
```

```
       'Median Ws - 2', 'Median Rain - 2'],
      dtype='object')
```

[64]:
```
cm = ['Date', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI',
       'BUI', 'Avg Temperature - 7', 'Avg RH - 7', 'Avg Ws - 7',
       'Avg Rain - 7', 'Max Temperature - 7', 'Max RH - 7', 'Max Ws - 7',
       'Max Rain - 7', 'Min Temperature - 7', 'Min RH - 7', 'Min Ws - 7',
       'Min Rain - 7', 'Median Temperature - 7', 'Median RH - 7',
       'Median Ws - 7', 'Median Rain - 7', 'Avg Temperature - 5', 'Avg RH - 5',
       'Avg Ws - 5', 'Avg Rain - 5', 'Max Temperature - 5', 'Max RH - 5',
       'Max Ws - 5', 'Max Rain - 5', 'Min Temperature - 5', 'Min RH - 5',
       'Min Ws - 5', 'Min Rain - 5', 'Median Temperature - 5', 'Median RH - 5',
       'Median Ws - 5', 'Median Rain - 5', 'Avg Temperature - 2', 'Avg RH - 2',
       'Avg Ws - 2', 'Avg Rain - 2', 'Max Temperature - 2', 'Max RH - 2',
       'Max Ws - 2', 'Max Rain - 2', 'Min Temperature - 2', 'Min RH - 2',
       'Min Ws - 2', 'Min Rain - 2', 'Median Temperature - 2', 'Median RH - 2',
       'Median Ws - 2', 'Median Rain - 2', 'Classes']
dfex = dfex[cm]
dfext = dfext[cm]
```

16 Cross Validation on Expanded Dataset

After expanding the dataset, we have to make sure the last x days of the validation set is removed if followed by train set and vice versa. So the function is modified to accomodate this.

[65]:
```
def Cross_Validation_expand(model,name,df):
    error = {}
    for i in range(4):


        if i == 0:
            p = 0
        else:
            p = df[df['Date']==(df['Date'].iloc[46*(i)]-pd.Timedelta(days=7))].
 ↪index.values[0]

        if i == 3:
            q = -1
        else:
            q = 46*(i+1)

        dftran = df[(df['Date']>=df['Date'].iloc[46*(i)]) &␣
 ↪(df['Date']<(df['Date'].iloc[q]-pd.Timedelta(days=7)))]
        Xval = dftran.iloc[:,1:-1].values
        yval = dftran.iloc[:,-1].values
        dfs = df.drop(df.index[p:q]).iloc[:,1:].values
        Xtr = df.drop(df.index[p:q]).iloc[:,1:-1].values
```

```
        ytr = df.drop(df.index[p:q]).iloc[:,-1].values
        ztr = get_z(ytr)

        if name == 'SVM_linear' or name == 'SVM_RBF':
            yh = model(Xtr,ztr,0.01,Xval)

        elif name == 'nmeans':
            yh = model(Xtr,ytr,Xval)

        elif name == 'Perceptron' or name == 'MSE':
            yh = model(dfs,Xval)

        elif name == 'Bayes':
                yh = model(df,Xtr,ytr,Xval)


        else:
            print('Enter Valid Model')

        error[i] = 1-accuracy(yval,yh)

        print(f'Epoch {i} error is = {1-accuracy(yval,yh)}')
    m = min(error, key=error.get)
    print(f'\nLowest error is at Epoch {m} with {error[m]}')

    scores(yh,yval,'Best Validation Set')


    return m
```

[66]:
```
def low_epoch_expand(i,model,name,df,Xt,yt):
    if i == 0:
        p = 0
    else:
        p = df[df['Date']==(df['Date'].iloc[46*(i)]-pd.Timedelta(days=7))].
 ↪index.values[0]

    if i == 3:
        q = -1
    else:
        q = 46*(i+1)

    dfs = df.drop(df.index[p:q]).iloc[:,1:].values
    Xtr = df.drop(df.index[p:q]).iloc[:,1:-1].values
    ytr = df.drop(df.index[p:q]).iloc[:,-1].values
    ztr = get_z(ytr)
```

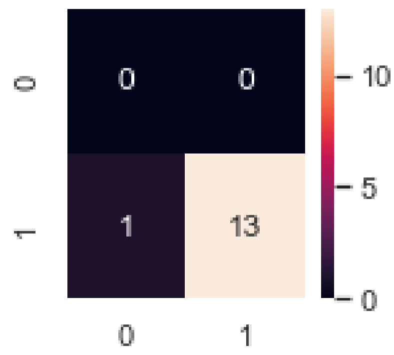
```
    if name == 'SVM_linear' or name == 'SVM_RBF':
        yh = model(Xtr,ztr,0.007,Xt)

    elif name == 'nmeans':
        yh = model(Xtr,ytr,Xt)

    elif name == 'Perceptron' or name == 'MSE':
        yh = model(dfs,Xt)

    elif name == 'Bayes':
            yh = model(df,Xtr,ytr,Xt)


    else:
        print('Enter Valid Model')

    scores(yh,yt,'Test Set')
```

[67]:
```
dfsn = dfex.iloc[:,1:].values
Xn = dfex.iloc[:,1:-1].values
yn = dfex.iloc[:,-1].values
zn = get_z(yn)
Xtn = dfext.iloc[:,1:-1].values
ytn = dfext.iloc[:,-1].values
```

16.0.1 N means

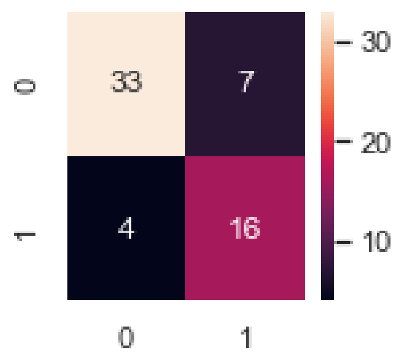
[68]:
```
nmi = Cross_Validation_expand(nmeans,'nmeans',dfex)
```

```
Epoch 0 error is = 0.1875
Epoch 1 error is = 0.3125
Epoch 2 error is = 0.25
Epoch 3 error is = 0.07142857142857142

Lowest error is at Epoch 3 with 0.07142857142857142
Best Validation Set Accuracy = 0.9285714285714286
 F1 Score = 0.962962962962963

Confusion Matrix
```



[69]:
```
low_epoch_expand(nmi,nmeans,'nmeans',dfex,Xtn,ytn)
```

```
Test Set Accuracy = 0.8166666666666667
 F1 Score = 0.7441860465116279

Confusion Matrix
```

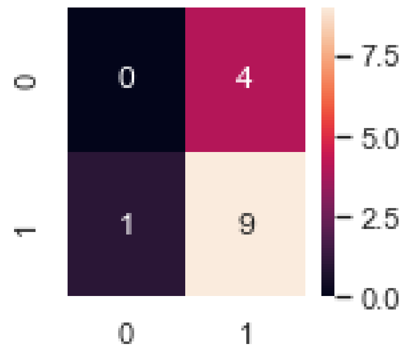


16.0.2 SVM Linear

[70]:
```
sli = Cross_Validation_expand(SVM_linear,'SVM_linear',dfex)
```

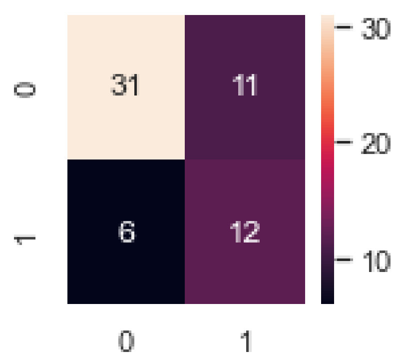
```
Epoch 0 error is = 0.40625
Epoch 1 error is = 0.46875
Epoch 2 error is = 0.59375
Epoch 3 error is = 0.3571428571428571

Lowest error is at Epoch 3 with 0.3571428571428571
Best Validation Set Accuracy = 0.6428571428571429
 F1 Score = 0.7826086956521738
```

```
Confusion Matrix
```



[71]:
```
low_epoch_expand(sli,SVM_linear,'SVM_linear',dfex,Xtn,ytn)
```

```
Test Set Accuracy = 0.7166666666666667
 F1 Score = 0.5853658536585366

Confusion Matrix
```

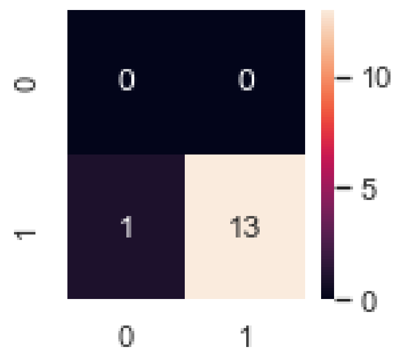


16.0.3 SVM RBF

[72]:
```
sbi = Cross_Validation_expand(SVM_RBF,'SVM_RBF',dfex)
```

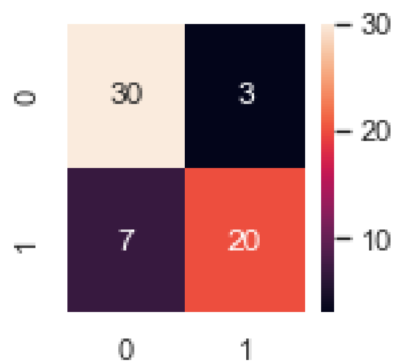
```
Epoch 0 error is = 0.125
Epoch 1 error is = 0.28125
Epoch 2 error is = 0.15625
Epoch 3 error is = 0.07142857142857142

Lowest error is at Epoch 3 with 0.07142857142857142
Best Validation Set Accuracy = 0.9285714285714286
 F1 Score = 0.962962962962963
```

```
Confusion Matrix
```



[73]:
```
low_epoch_expand(sbi,SVM_RBF,'SVM_RBF',dfex,Xtn,ytn)
```

```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.7999999999999999

Confusion Matrix
```

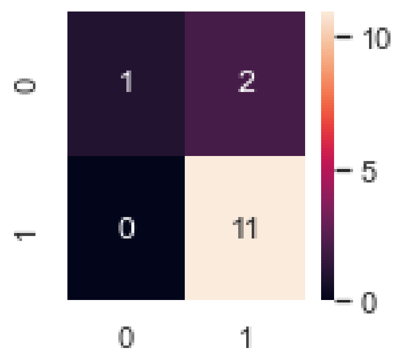


16.0.4 Perceptron

[74]:
```
pi = Cross_Validation_expand(Perceptron,'Perceptron',dfex)
```

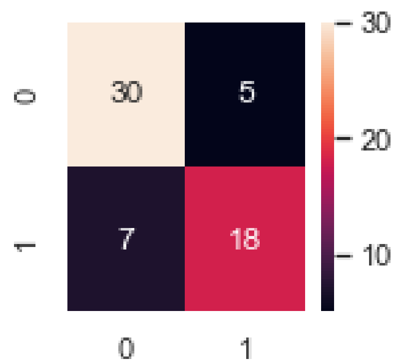
```
The lowest error pair is (0.01, 1000) with Erms 1.303973916663879
Epoch 0 error is = 0.21875
The lowest error pair is (0.01, 1000) with Erms 1.4090771633431005
Epoch 1 error is = 0.15625
The lowest error pair is (0.01, 1000) with Erms 0.9355581253658861
Epoch 2 error is = 0.25
```

```
The lowest error pair is (0.01, 1000) with Erms 1.6476756802063017
Epoch 3 error is = 0.14285714285714285

Lowest error is at Epoch 3 with 0.14285714285714285
Best Validation Set Accuracy = 0.8571428571428571
 F1 Score = 0.9166666666666666

Confusion Matrix
```



[78]:
```
low_epoch_expand(pi,Perceptron,'Perceptron',dfex,Xtn,ytn)
```

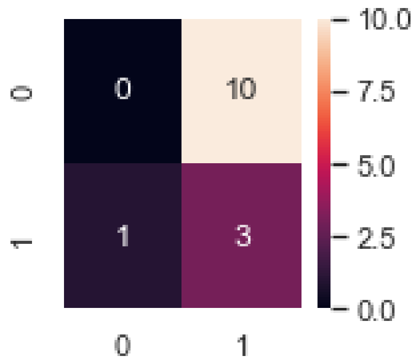
```
The lowest error pair is (0.01, 1000) with Erms 1.7171637819786887
Test Set Accuracy = 0.8
 F1 Score = 0.7499999999999999

Confusion Matrix
```



16.0.5 MSE

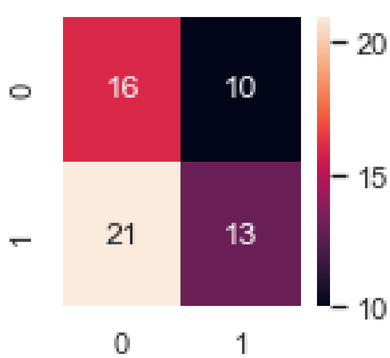
[76]:
```
msei = Cross_Validation_expand(MSE,'MSE',dfex)
```

```
Epoch 0 error is = 0.53125
Epoch 1 error is = 0.4375
Epoch 2 error is = 0.28125
Epoch 3 error is = 0.7857142857142857

Lowest error is at Epoch 2 with 0.28125
Best Validation Set Accuracy = 0.21428571428571427
 F1 Score = 0.3529411764705882

Confusion Matrix
```



[81]:
```
low_epoch_expand(msei,MSE,'MSE',dfex,Xtn,ytn)
```

```
Test Set Accuracy = 0.48333333333333334
 F1 Score = 0.45614035087719296

Confusion Matrix
```



16.0.6 Bayes

Wasn't able to perform cross validation as E was too small while taking inverse and math domain error was caused

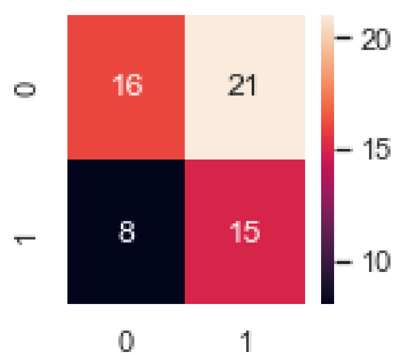
17 Checking Metrics on new complete expanded train set (no split)

[82]:
```
dfsn = dfex.iloc[:,1:].values
Xn = dfex.iloc[:,1:-1].values
yn = dfex.iloc[:,-1].values
zn = get_z(yn)
Xtn = dfext.iloc[:,1:-1].values
ytn = dfext.iloc[:,-1].values
```

17.1 Trivial

[83]:
```
yhtri = trivial(len(Xtn),dfex)
scores(ytn,yhtri,'Test Set')
```

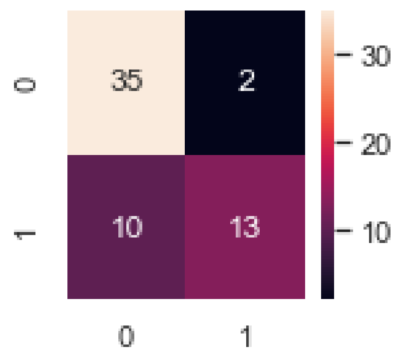
```
Test Set Accuracy = 0.5166666666666667
 F1 Score = 0.5084745762711865

Confusion Matrix
```



17.1.1 N means

[84]:
```
yhnme = nmeans(Xn,yn,Xtn)
scores(ytn,yhnme,'Test Set')
```

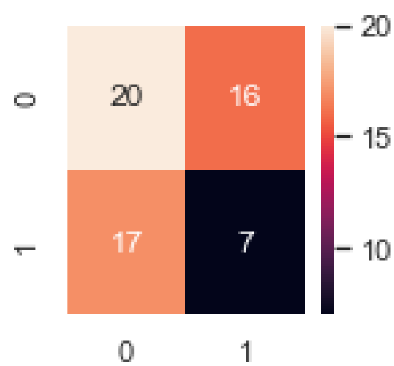
```
Test Set Accuracy = 0.8
 F1 Score = 0.6842105263157895

Confusion Matrix
```



17.1.2 SVM Linear

[85]:
```python
yhsvml = SVM_linear(Xn,zn,None,Xtn)
scores(yhsvml,ytn,'Test Set')
```

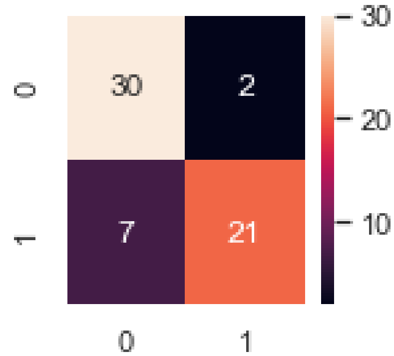
```
Test Set Accuracy = 0.45
 F1 Score = 0.2978723404255319

Confusion Matrix
```



17.1.3 SVM RBF

[86]:
```
yhsvmr = SVM_RBF(Xn,zn,0.002,Xtn)
scores(yhsvmr,ytn,'Test Set')
```

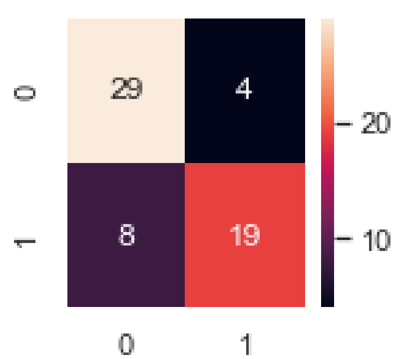
```
Test Set Accuracy = 0.85
 F1 Score = 0.8235294117647057

Confusion Matrix
```



17.1.4 Perceptron

[87]:
```
yhpc = Perceptron(dfsn,Xtn)
scores(yhpc,ytn,'Test Set')
```

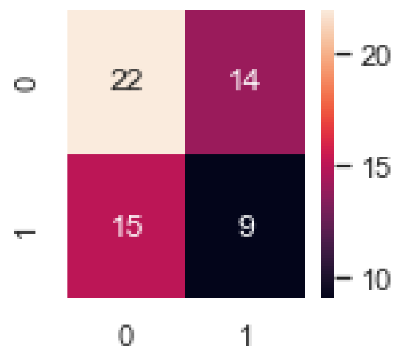
```
The lowest error pair is (0.01, 1000) with Erms 1.7280755995363988
Test Set Accuracy = 0.8
 F1 Score = 0.76

Confusion Matrix
```



17.1.5 MSE

[88]:
```
yhmse = MSE(dfsn,Xtn)
scores(yhmse,ytn,'Test Set')
```

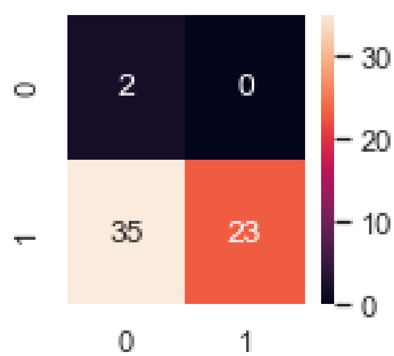
```
Test Set Accuracy = 0.5166666666666667
 F1 Score = 0.3829787234042554

Confusion Matrix
```



17.1.6 Bayes

[89]:
```
yhbay = Bayes(dfex,Xn,yn,Xtn)
scores(yhbay,ytn,'Test Set')
```

```
Test Set Accuracy = 0.4166666666666667
 F1 Score = 0.5679012345679012

Confusion Matrix
```



18 Feature Selection

18.1 Using Pearson correlation coefficient

Use pandas derive the correlation matrix and find the features with more than a desired value. I have considered 0.33 as it gave me the best accuracies for most models

[90]:
```
def pcc_fea_sel(dfex,val):
    cols = []
    for i in range(len(dfex.columns)-1):
        if (abs(dfex.corr()['Classes'])>val)[i] == True:
            cols.append((dfex.corr()['Classes']).index[i])
    return cols
```

[91]:
```
cols = pcc_fea_sel(dfex,0.33)
```

[92]:
```
len(cols)
```

[92]:
```
16
```

Cols has **16** features ewhich is almost in the **17 - 61** range which is the optimal range according to the thumb rule **N > (3-10)D+1**

[93]:
```
dfn = dfex[cols]
dfnt = dfext[cols]
```

[94]:
```
dfnt.head()
```

[94]:
```
        Rain        FFMC       DMC         DC       ISI       BUI  \
0   6.862311   18.206803  6.705575  16.934059  1.272175  1.567136
1  -0.332408   36.300922  4.307622  -8.813586 -1.707135 -2.167708
2  10.148430   32.909853 -3.989974  12.276834  0.886849  5.108220
3  -0.050950  101.833950  4.923229  17.509484  1.000106  1.990220
4   3.910505   66.608357  0.628217  17.332474 -1.773158  9.083053

   Avg Temperature - 7  Max Temperature - 7  Median Temperature - 7  \
0            30.546717            43.304756               31.114061
1            30.546717            43.304756               31.114061
2            20.494601            25.127811               20.494601
3            20.494601            25.127811               20.494601
4            26.487730            39.157179               25.466175

   Avg Temperature - 5  Max Temperature - 5  Avg Rain - 2  \
0            30.510891            42.144910      1.242758
1            30.510891            42.144910      1.242758
2            20.494601            25.127811      3.264951
3            20.494601            25.127811      3.264951
4            26.487730            39.157179      4.156846
```

```
   Max Temperature - 2  Max Rain - 2  Median Rain - 2  Classes
0            39.466890      3.600236         0.751244        0
1            39.466890      3.600236         0.751244        0
2            25.127811      6.862311         3.264951        0
3            25.127811      6.862311         3.264951        0
4            39.157179     10.148430         3.405680        0
```

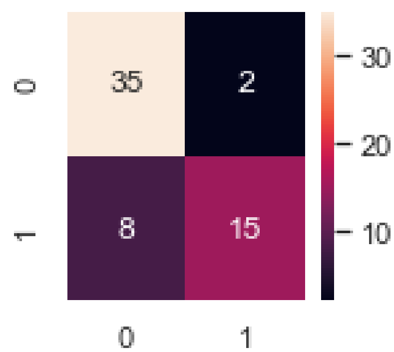
18.2 Checking Metrics on entire new selected features

[95]:
```
dfsn = dfn.values
Xn = dfn.iloc[:,:-1].values
yn = dfn.iloc[:,-1].values
zn = get_z(yn)
Xtn = dfnt.iloc[:,:-1].values
ytn = dfnt.iloc[:,-1].values
```

18.2.1 N means

[96]:
```
yhnme = nmeans(Xn,yn,Xtn)
scores(ytn,yhnme,'Test Set')
```

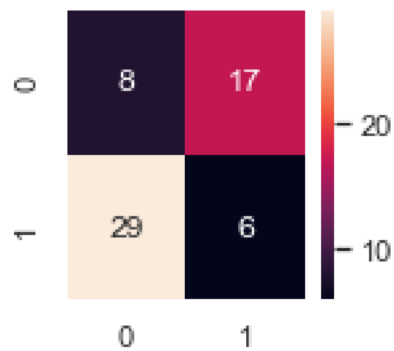
```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.75

Confusion Matrix
```



18.2.2 SVM Linear

[97]:
```
yhsvml = SVM_linear(Xn,zn,0.01,Xtn)
scores(yhsvml,ytn,'Test Set')
```

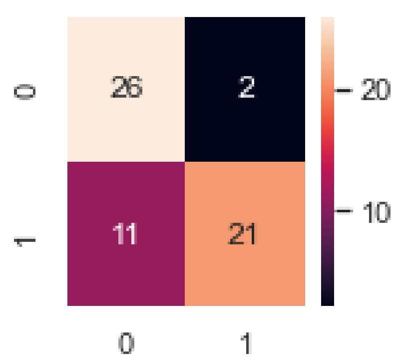
```
Test Set Accuracy = 0.23333333333333334
 F1 Score = 0.20689655172413796

Confusion Matrix
```



18.2.3 SVM RBF

[98]:
```
yhsvmr = SVM_RBF(Xn,zn,0.01,Xtn)
scores(yhsvmr,ytn,'Test Set')
```

```
Test Set Accuracy = 0.7833333333333333
 F1 Score = 0.7636363636363634

Confusion Matrix
```

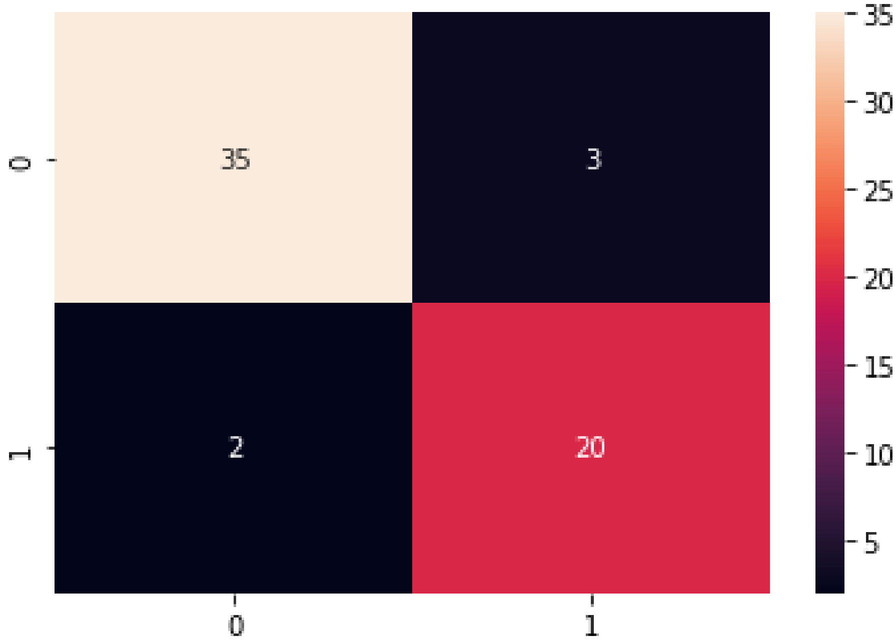


18.2.4 Perceptron

The accuracies varied due to the randomness, highest accuracy = 91%, F1 score = 0.888, while the pearson corelation is atleast 0.33 or more. It is to be noted this accuracy cannot be achieved every single time.

[504]:
```
yhpc = Perceptron(dfsn,Xtn)
scores(yhpc,ytn,'Test Set')
```

```
The lowest error pair is (0.01, 10) with Erms 0.19476245641577777
 Accuracy = 0.9166666666666666
 F1 Score = 0.888888888888889

Confusion Matrix
```

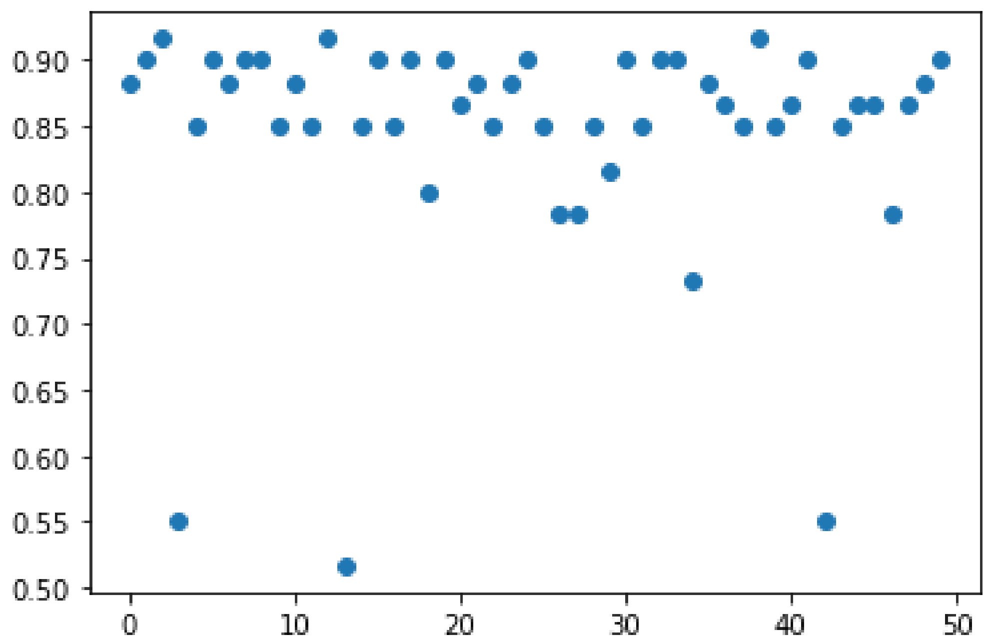


Run the model for 50 iterations, to find how well it performs

[714]:
```
accu = []
for i in range(50):
    yhpc = Perceptron(dfsn,Xtn)
    accu.append(accuracy(yhpc,ytn))
```

[715]:
```
plt.scatter(list(range(50)),accu)
```

[715]: <matplotlib.collections.PathCollection at 0x2671822e9d0>



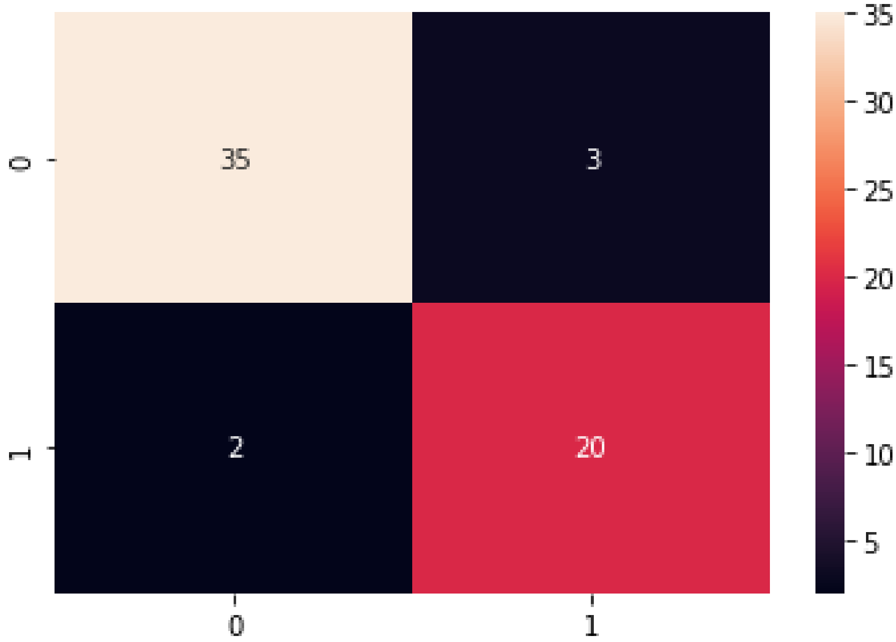
As we can see most of the times the accuracy is close to 90%, hence we can use this model to recieve an accuracy for around 88-90 %

18.2.5 MSE

The accuracies varied due to the randomness, highest accuracy = 95%, F1 score = 0.92, while the pearson corelation is atleast 0.33 or more. It is to be noted this accuracy cannot be achieved every single time.

[815]:
```
yhmse = MSE(dfsn,Xtn)
scores(yhmse,ytn,'Test Set')
```

```
Test Set Accuracy = 0.9166666666666666
 F1 Score = 0.888888888888889


Confusion Matrix
```

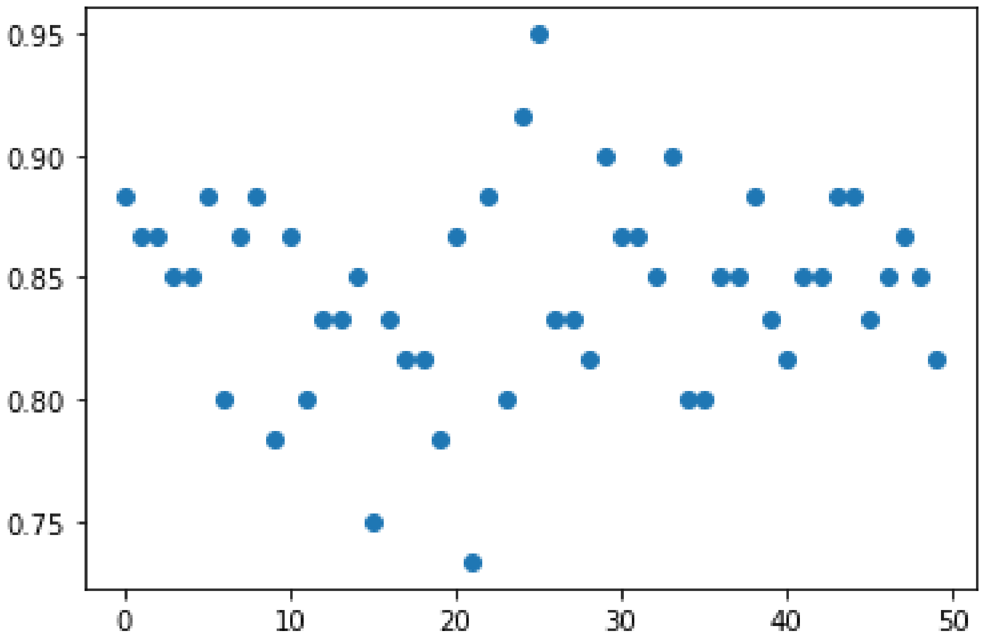


Run the model for 50 iterations, to find how well it performs

[781]:
```
accu2 = []
for i in range(50):
    yhmse = MSE(dfsn,Xtn)
    accu2.append(accuracy(yhmse,ytn))
```

[782]:
```
plt.scatter(list(range(50)),accu2)
```

[782]: <matplotlib.collections.PathCollection at 0x2671c69d970>



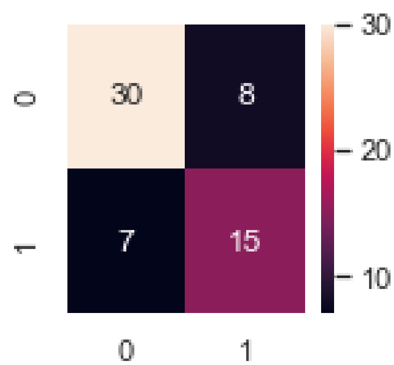
Even though this model was able to achieve the highest accuracy that is 95%, this model is not reliable as the spread or the randomness affects it very much and avg accuracy is around 85%.

18.2.6 Bayes

[99]:
```
yhbay = Bayes(dfn,Xn,yn,Xtn)
scores(yhbay,ytn,'Test Set')
```

```
Test Set Accuracy = 0.75
 F1 Score = 0.6666666666666666
```

```
Confusion Matrix
```



18.3 Based on Individual features accuracy based on model

I predicted the output using every single features on all the model and choose the features with arounf 65% accuracy or more

[105]:
```python
def fet_sel_acc(df,df_t,model,name,desired_acc):
    feat = []
    for i in df.columns:
        if i == 'Date' or i == 'Classes':
            continue
        cols = [i,'Classes']
        dfn = df[cols]
        dfnt = df_t[cols]
        dfsn = dfn.values
        Xn = dfn.iloc[:,:-1].values
        yn = dfn.iloc[:,-1].values
        zn = get_z(yn)
        Xtn = dfnt.iloc[:,:-1].values
        ytn = dfnt.iloc[:,-1].values


        try:
            if name == 'SVM_linear' or name == 'SVM_RBF':
                yh = model(Xn,zn,0.01,Xtn)

            elif name == 'nmeans':
                yh = model(Xn,yn,Xtn)

            elif name == 'Perceptron' or name == 'MSE':
                yh = model(dfsn,Xtn)

            elif name == 'Bayes':
                yh = model(dfn,Xn,yn,Xtn)

            else:
                print('Enter Valid Model')

        except:
            pass

        acc = accuracy(yh,ytn)
        #print(f'{i} = {accuracy(yh,ytn)}')
        if acc > desired_acc:
            feat.append(i)
    feat.append('Classes')
    return feat
```

[106]:
```
def acc_feat_sel(feat,df,df_t,model,name):
    dfn = df[feat]
    dfnt = df_t[feat]
    dfsn = dfn.values
    Xn = dfn.iloc[:,:-1].values
    yn = dfn.iloc[:,-1].values
    zn = get_z(yn)
    Xtn = dfnt.iloc[:,:-1].values
    ytn = dfnt.iloc[:,-1].values

    if name == 'SVM_linear' or name == 'SVM_RBF':
        yh = model(Xn,zn,0.01,Xtn)

    elif name == 'nmeans':
        yh = model(Xn,yn,Xtn)

    elif name == 'Perceptron' or name == 'MSE':
        yh = model(dfsn,Xtn)

    elif name == 'Bayes':
        yh = model(dfn,Xn,yn,Xtn)

    else:
        print('Enter Valid Model')
    scores(yh,ytn,'Test Set')
```

18.3.1 N means

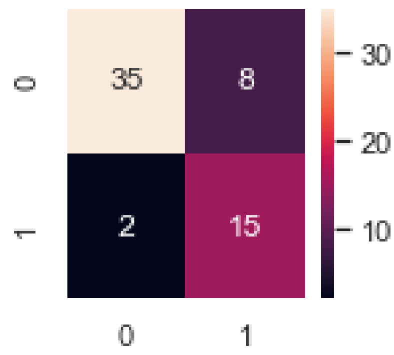
[104]:
```
feat = fet_sel_acc(dfex,dfext,nmeans,'nmeans',0.65)
```

```
Temperature = 0.65
RH = 0.6
Ws = 0.5166666666666667
Rain = 0.6833333333333333
FFMC = 0.6666666666666666
DMC = 0.7666666666666667
DC = 0.8
ISI = 0.8833333333333333
BUI = 0.7333333333333333
Avg Temperature - 7 = 0.6166666666666667
Avg RH - 7 = 0.6166666666666667
Avg Ws - 7 = 0.5166666666666667
Avg Rain - 7 = 0.55
Max Temperature - 7 = 0.55
Max RH - 7 = 0.65
Max Ws - 7 = 0.5166666666666667
Max Rain - 7 = 0.55
```

```
Min Temperature - 7 = 0.6166666666666667
Min RH - 7 = 0.5833333333333334
Min Ws - 7 = 0.6166666666666667
Min Rain - 7 = 0.55
Median Temperature - 7 = 0.65
Median RH - 7 = 0.5166666666666667
Median Ws - 7 = 0.55
Median Rain - 7 = 0.5833333333333334
Avg Temperature - 5 = 0.65
Avg RH - 5 = 0.65
Avg Ws - 5 = 0.5166666666666667
Avg Rain - 5 = 0.5833333333333334
Max Temperature - 5 = 0.6166666666666667
Max RH - 5 = 0.7166666666666667
Max Ws - 5 = 0.45
Max Rain - 5 = 0.5833333333333334
Min Temperature - 5 = 0.6166666666666667
Min RH - 5 = 0.6166666666666667
Min Ws - 5 = 0.48333333333333334
Min Rain - 5 = 0.55
Median Temperature - 5 = 0.6833333333333333
Median RH - 5 = 0.6166666666666667
Median Ws - 5 = 0.55
Median Rain - 5 = 0.55
Avg Temperature - 2 = 0.6833333333333333
Avg RH - 2 = 0.6166666666666667
Avg Ws - 2 = 0.5166666666666667
Avg Rain - 2 = 0.6833333333333333
Max Temperature - 2 = 0.6833333333333333
Max RH - 2 = 0.65
Max Ws - 2 = 0.45
Max Rain - 2 = 0.6833333333333333
Min Temperature - 2 = 0.6833333333333333
Min RH - 2 = 0.65
Min Ws - 2 = 0.5166666666666667
Min Rain - 2 = 0.48333333333333334
Median Temperature - 2 = 0.7166666666666667
Median RH - 2 = 0.5833333333333334
Median Ws - 2 = 0.48333333333333334
Median Rain - 2 = 0.5833333333333334
```

[107]:
```
acc_feat_sel(feat,dfex,dfext,nmeans,'nmeans')
```

```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.75

Confusion Matrix
```

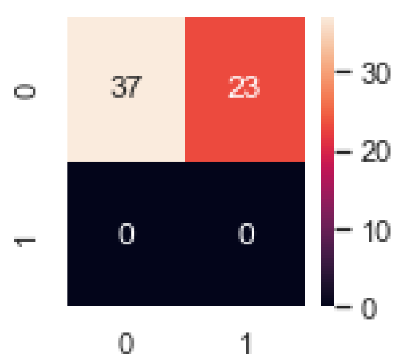


18.3.2 MSE

[108]:
```
feat = fet_sel_acc(dfex,dfext,MSE,'MSE',0.7)
```

[109]:
```
acc_feat_sel(feat,dfex,dfext,MSE,'MSE')
```

```
Test Set Accuracy = 0.6166666666666667
 F1 Score = 0.0

Confusion Matrix
```



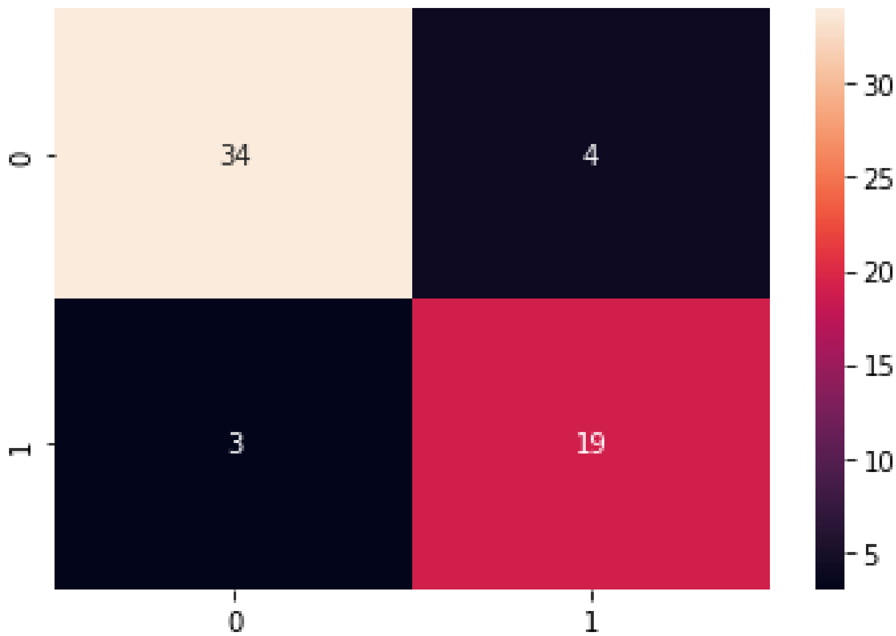
18.3.3 Bayes

This is most reliable and best model among the others, with accuracy 88.33% and F1-score of 0.844, it is a bit lower than the perceptron model with pearsons feature selection but is more reliable.

[835]:
```
feat = fet_sel_acc(dfex,dfext,Bayes,'Bayes',0.65)
```

[836]:
```
acc_feat_sel(feat,dfex,dfext,Bayes,'Bayes')
```

```
Test Set Accuracy = 0.8833333333333333
 F1 Score = 0.8444444444444444

Confusion Matrix
```

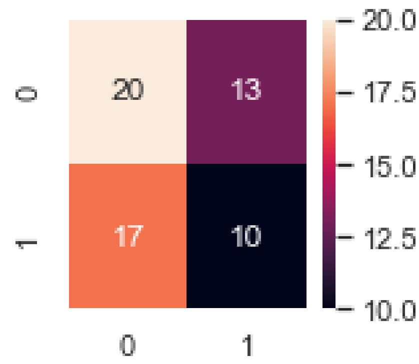


18.3.4 SVM Linear

[110]:
```python
feat = fet_sel_acc(dfex,dfext,SVM_linear,'SVM_linear',0.71)
```

[111]:
```python
acc_feat_sel(feat,dfex,dfext,SVM_linear,'SVM_linear')
```

```
Test Set Accuracy = 0.5
 F1 Score = 0.39999999999999997

Confusion Matrix
```

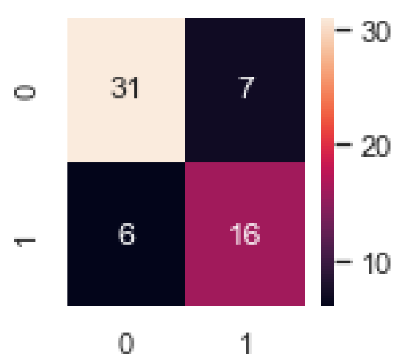


18.3.5 SVM RBF

[112]:
```
feat = fet_sel_acc(dfex,dfext,SVM_RBF,'SVM_RBF',0.71)
```

[113]:
```
acc_feat_sel(feat,dfex,dfext,SVM_RBF,'SVM_RBF')
```

```
Test Set Accuracy = 0.7833333333333333
 F1 Score = 0.711111111111111

Confusion Matrix
```



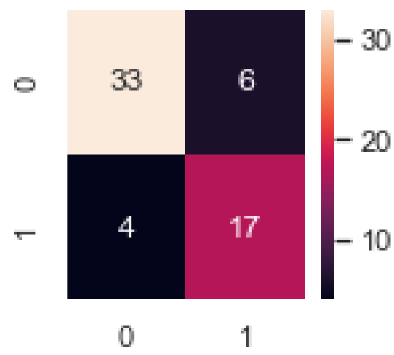
18.3.6 Perceptron

[117]:
```
feat = fet_sel_acc(dfex,dfext,Perceptron,'Perceptron',0.65)
```

[118]:
```
acc_feat_sel(feat,dfex,dfext,Perceptron,'Perceptron')
```

```
Test Set Accuracy = 0.8333333333333334
 F1 Score = 0.7727272727272727
```

```
Confusion Matrix
```



19 Performing Normalization and Standardization on best models after feature selection to see if there is improvement or deterioration

19.1 Normalization

[119]:
```python
ndf = dfex[:]
for i in dfex.columns:
    if i == 'Date' or i == 'Classes':
        continue
    ndf[i] = (ndf[i]-ndf[i].min())/(ndf[i].max()-ndf[i].min())
```

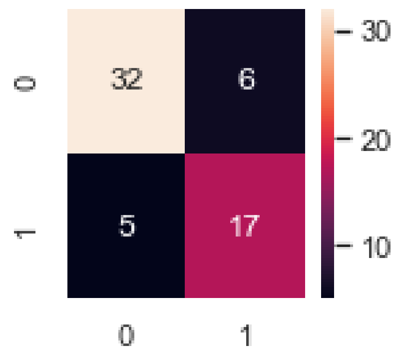
[120]:
```python
ndft = dfext[:]
for i in dfext.columns:
    if i == 'Date' or i == 'Classes':
        continue
    ndft[i] = (ndft[i]-ndft[i].min())/(ndft[i].max()-ndft[i].min())
```

19.1.1 N means Accuracy feature selection

[121]:
```python
feat = fet_sel_acc(ndf,ndft,nmeans,'nmeans',0.65)
```

[122]:
```python
acc_feat_sel(feat,ndf,ndft,nmeans,'nmeans')
```

```
Test Set Accuracy = 0.8166666666666667
 F1 Score = 0.7555555555555555

Confusion Matrix
```

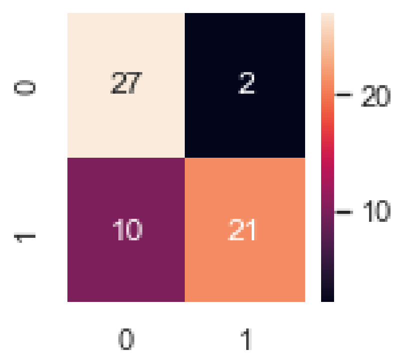


19.1.2 Bayes Accuracy feature selection

[123]:
```
feat = fet_sel_acc(ndf,ndft,Bayes,'Bayes',0.65)
```

[124]:
```
acc_feat_sel(feat,ndf,ndft,Bayes,'Bayes')
```

```
Test Set Accuracy = 0.8
 F1 Score = 0.7777777777777777

Confusion Matrix
```



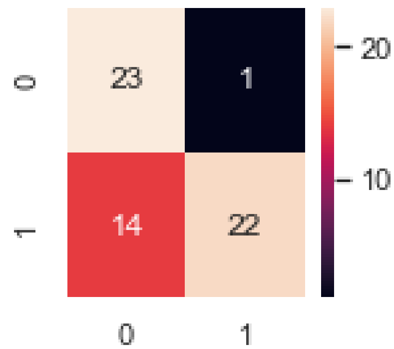
19.1.3 Perceptron Accuracy feature selection

[125]:
```
feat = fet_sel_acc(ndf,ndft,Perceptron,'Perceptron',0.65)
```

[126]:
```
acc_feat_sel(feat,ndf,ndft,Perceptron,'Perceptron')
```

```
Test Set Accuracy = 0.75
 F1 Score = 0.7457627118644068
```

```
Confusion Matrix
```

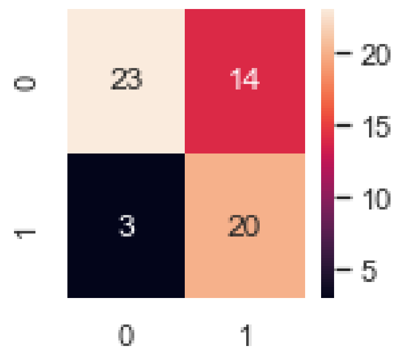



```
[127]: cols = pcc_fea_sel(ndf,0.33)

dfn = ndf[cols]
dfnt = ndft[cols]

dfsn = dfn.values
Xn = dfn.iloc[:,:-1].values
yn = dfn.iloc[:,-1].values
zn = get_z(yn)
Xtn = dfnt.iloc[:,:-1].values
ytn = dfnt.iloc[:,-1].values
```

19.1.4 N means Pearson feature selection

```
[128]: yhnme = nmeans(Xn,yn,Xtn)
scores(ytn,yhnme,'Test Set')
```

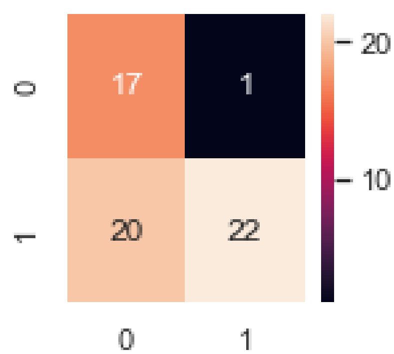
```
Test Set Accuracy = 0.7166666666666667
 F1 Score = 0.7017543859649124

Confusion Matrix
```



19.1.5 Perceptron Pearson feature selection

[129]:
```
yhpc = Perceptron(dfsn,Xtn)
scores(yhpc,ytn,'Test Set')
```

```
Test Set Accuracy = 0.65
 F1 Score = 0.6769230769230768

Confusion Matrix
```



19.2 Standardiation

[130]:
```
sdf = dfex.iloc[:]
for i in dfex.columns:
    if i == 'Date' or i == 'Classes':
        continue
    sdf[i] = (dfex[i]-dfex[i].mean())/(dfex[i].std())
```

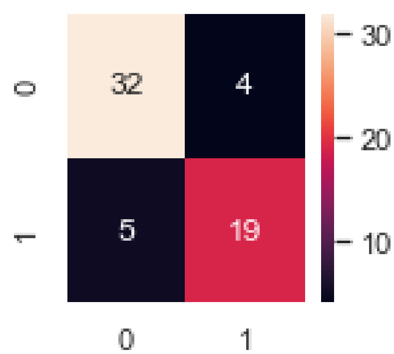
[131]:
```
sdft = dfext[:]
for i in dfext.columns:
    if i == 'Date' or i == 'Classes':
        continue
    sdft[i] = (dfext[i]-dfext[i].mean())/(dfext[i].std())
```

19.2.1 N means Accuracy feature selection

[132]:
```
feat = fet_sel_acc(sdf,sdft,nmeans,'nmeans',0.65)
```

[133]:
```
acc_feat_sel(feat,sdf,sdft,nmeans,'nmeans')
```

```
Test Set Accuracy = 0.85
 F1 Score = 0.8085106382978724

Confusion Matrix
```

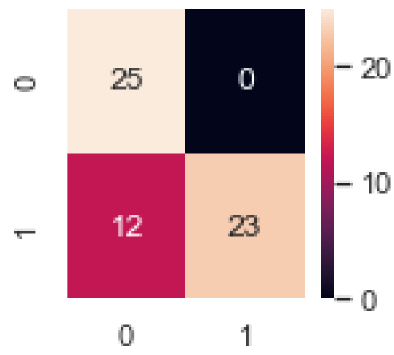


19.2.2 Bayes Accuracy feature selection

[134]:
```
feat = fet_sel_acc(sdf,sdft,Bayes,'Bayes',0.65)
```

[135]:
```
acc_feat_sel(feat,sdf,sdft,Bayes,'Bayes')
```

```
Test Set Accuracy = 0.8
 F1 Score = 0.7931034482758621

Confusion Matrix
```

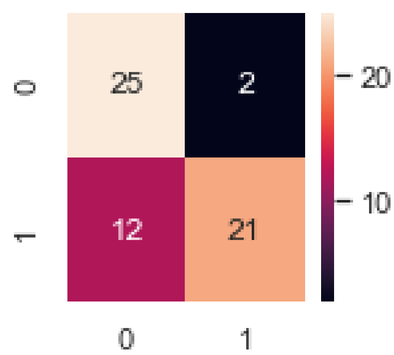


19.2.3 Perceptron Accuracy selection

[136]:
```
feat = fet_sel_acc(sdf,sdft,Perceptron,'Perceptron',0.65)
```

[137]:
```
acc_feat_sel(feat,sdf,sdft,Perceptron,'Perceptron')
```

```
Test Set Accuracy = 0.7666666666666667
 F1 Score = 0.75

Confusion Matrix
```



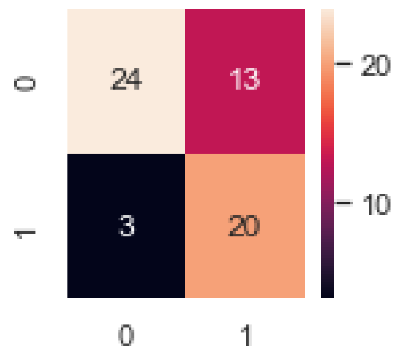
[138]:
```
cols = pcc_fea_sel(sdf,0.33)

dfn = sdf[cols]
dfnt = sdft[cols]

dfsn = dfn.values
Xn = dfn.iloc[:,:-1].values
yn = dfn.iloc[:,-1].values
zn = get_z(yn)
```

```
Xtn = dfnt.iloc[:,:-1].values
ytn = dfnt.iloc[:,-1].values
```

19.2.4 N means Pearson feature selection

[139]:
```
yhnme = nmeans(Xn,yn,Xtn)
scores(ytn,yhnme,'Test Set')
```

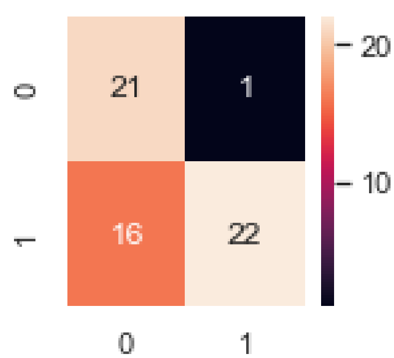
```
Test Set Accuracy = 0.7333333333333333
 F1 Score = 0.7142857142857143

Confusion Matrix
```



19.2.5 Perceptron Pearson selection

[140]:
```
yhpc = Perceptron(dfsn,Xtn)
scores(yhpc,ytn,'Test Set')
```

```
Test Set Accuracy = 0.7166666666666667
 F1 Score = 0.721311475409836

Confusion Matrix
```



As we can see normalizing or standardizing the best models reduced the accuracy so I would not be performing those tweaks.

20 Summary

[141]:
```
vcv = [[0.933,0.955,0.933,0.955,0.866,0.933],[0.964,0.976,0.962,0.976,0.923,0.
↪964]]
dvcv=pd.DataFrame(vcv, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
tcv = [[0.8,0.866,0.833,0.833,0.516,0.8],[0.739,0.84,0.744,0.756,0.597,0.76]]
dtcv = pd.DataFrame(tcv, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
t = [[0.783,0.866,0.85,0.866,0.783,0.833],[0.628,0.846,0.808,0.755,0.666,0.807]]
dt = pd.DataFrame(t, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
vcve = [[0.928,'na',0.57,0.714,0.692,0.928],[0.962,'na',0.916,0.833,0.782,0.
↪962]]
dvcve = pd.DataFrame(vcve, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
tcve = [[0.816,'na',0.816,0.483,0.716,0.833],[0.744,'na',0.784,0.311,0.585,0.
↪799]]
dtcve = pd.DataFrame(tcve, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
te = [[0.8,0.416,0.866,0.45,0.45,0.85],[0.684,0.567,0.84,0.326,0.297,0.823]]
dte = pd.DataFrame(te, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
pc = [[0.833,0.75,0.916,0.95,0.233,0.783],[.75,0.666,0.888,0.92,0.206,0.763]]
dpc = pd.DataFrame(pc, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
afs = [[0.833,0.883,0.8,0.616,0.5,0.783],[0.75,0.844,0.749,0.0,0.399,0.711]]
dafs = pd.DataFrame(afs, columns=['N means','Bayes','Perceptron','MSE','SVM␣
↪Linear','SVM RBF'],index=['Accuracy','F1 Score'])
nor = [[0.816,0.8,0.85,0.716,0.716],[0.755,0.777,0.823,0.701,0.730]]
dnor = pd.DataFrame(nor, columns=['N means Acc','Bayes Acc','Perceptron Acc','N␣
↪means Pea','Perceptron Pea'],index=['Accuracy','F1 Score'])
std = [[0.85,0.8,0.766,0.733,0.733],[0.808,0.793,0.766,0.714,0.733]]
dstd = pd.DataFrame(std, columns=['N means Acc','Bayes Acc','Perceptron Acc','N␣
↪means Pea','Perceptron Pea'],index=['Accuracy','F1 Score'])
```

20.1 Below is the accuracy and F1 score I have got for various models, for various tuning and parameters

20.1.1 Validation Set accoracy and F1 score on base dataset

[142]:
```
dvcv
```

[142]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.933	0.955	0.933	0.955	0.866	0.933
F1 Score	0.964	0.976	0.962	0.976	0.923	0.964

20.1.2 Test set accuracy and F1 score after spliting into train and validation set

[143]:
```
dtcv
```

[143]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.800	0.866	0.833	0.833	0.516	0.80
F1 Score	0.739	0.840	0.744	0.756	0.597	0.76

20.1.3 Test Set accuracy and f1 score after training on entire train set (no split)

[144]:
```
dt
```

[144]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.783	0.866	0.850	0.866	0.783	0.833
F1 Score	0.628	0.846	0.808	0.755	0.666	0.807

20.1.4 Validation set accuracy and f1 score after expanding feature set

[145]:
```
dvcve
```

[145]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.928	na	0.570	0.714	0.692	0.928
F1 Score	0.962	na	0.916	0.833	0.782	0.962

20.1.5 Test set accuracy and F1 score after spliting into train and validation set ,expanded feature set

[146]:
```
dtcve
```

[146]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.816	na	0.816	0.483	0.716	0.833
F1 Score	0.744	na	0.784	0.311	0.585	0.799

20.1.6 Test Set accuracy and f1 score after training on entire train set (no split) expanded feature set

[147]:
```
dte
```

[147]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.800	0.416	0.866	0.450	0.450	0.850
F1 Score	0.684	0.567	0.840	0.326	0.297	0.823

20.1.7 After Pearsons corelation feature selection

[148]:
```
dpc
```

[148]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.833	0.750	0.916	0.95	0.233	0.783
F1 Score	0.750	0.666	0.888	0.92	0.206	0.763

20.1.8 After Accuracy based feature selection

[149]:
```
dafs
```

[149]:

	N means	Bayes	Perceptron	MSE	SVM Linear	SVM RBF
Accuracy	0.833	0.883	0.800	0.616	0.500	0.783
F1 Score	0.750	0.844	0.749	0.000	0.399	0.711

20.1.9 After normalizing best models

[150]:
```
dnor
```

[150]:

	N means Acc	Bayes Acc	Perceptron Acc	N means Pea	Perceptron Pea
Accuracy	0.816	0.800	0.850	0.716	0.716
F1 Score	0.755	0.777	0.823	0.701	0.730

20.1.10 After standardizing best models

[151]:
```
dstd
```

[151]:

	N means Acc	Bayes Acc	Perceptron Acc	N means Pea	Perceptron Pea
Accuracy	0.850	0.800	0.766	0.733	0.733
F1 Score	0.808	0.793	0.766	0.714	0.733

The highest accuracy attained was on the MSE model after pearsons corelation based feature selection at 95%, but I achieved this only once and the model is not reliable due to the random shuffle used for sequential gradient descent. The same thing goes for the Perceptron model based on pearson feature selection, though it is more reliavle and gives accuracy of about 89-90% most of the times, it is still unpredictable. So I would choose the Bayes model using the accuracy feature selection where min accuracy required is 65%, with this model I got an accuracy of 88.33% and is the most reliable.

20.1.11 Best Accuracy ever achieved 95% MSE (LMS algorithm) model using pearsons corelation feature selection with threshold 0.33 or 0.5, using eta = a/(b+1) for constant a = 0.01 and b = [0.01,0.1,1,10,100,1000]. But in reliable and doesn't give consistent results.

20.1.12 Best and Most reliable model is the Bayes model with accracy based feature selection > 0.65, without normalizing or standardizing

20.1.13 Accuracy = 88.33% F1 score = 0.8444

[ ]:
```

```