Hybrid System for Lung Cancer Classification

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Here i will create a Hybrid System using **Particle Swarm Optimisation** and **Logistic Regression**.

We will see how to use **PSO** to extract usefull features from dataset and then train our model on these features.

Importing Useful Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="darkgrid")

def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn

from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)
```

Importing Dataset

Dataset that we are using here is taken from **UCI Machine Learning Repository**.
Link to dataset is Lung Cancer Dataset

This dataset contain 32 examples and 56 attributes.
some of its fields are missing So we need to Purify this dataset before using it in out ML model.

Note :

This dataset is not big enough to train good Machine Learning Model

In [2]:
```
data_url = "http://archive.ics.uci.edu/ml/machine-learning-databases/lung-cancer/lung-cance
r.data"
data = pd.read_csv(data_url,header=None)
data.head()
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	...	47	48	49	50	51	52	53	54	55	56
0	1	0	3	0	?	0	2	2	2	1	...	2	2	2	2	2	1	1	1	2	2
1	1	0	3	3	1	0	3	1	3	1	...	2	2	2	2	2	2	2	1	2	2
2	1	0	3	3	2	0	3	3	3	1	...	2	2	2	2	2	2	2	2	1	2
3	1	0	2	3	2	1	3	3	3	1	...	2	2	2	2	2	2	2	2	2	2
4	1	0	3	2	1	1	3	3	3	2	...	2	2	2	2	2	2	2	1	2	2

5 rows × 57 columns

In [3]:
```
data.describe()
```

Out[3]:

	0	1	2	3	5	6	7	8	9	10	...	
count	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	...	32.0
mean	2.031250	0.031250	2.375000	2.031250	0.281250	2.187500	2.125000	2.406250	1.156250	1.406250	...	2.0
std	0.782237	0.176777	0.553581	1.031265	0.456803	0.737804	0.751343	0.756024	0.514899	0.559918	...	0.2
min	1.000000	0.000000	1.000000	0.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	2.0
25%	1.000000	0.000000	2.000000	1.750000	0.000000	2.000000	2.000000	2.000000	1.000000	1.000000	...	2.0
50%	2.000000	0.000000	2.000000	2.000000	0.000000	2.000000	2.000000	3.000000	1.000000	1.000000	...	2.0
75%	3.000000	0.000000	3.000000	3.000000	1.000000	3.000000	3.000000	3.000000	1.000000	2.000000	...	2.0
max	3.000000	1.000000	3.000000	3.000000	1.000000	3.000000	3.000000	3.000000	3.000000	3.000000	...	3.0

8 rows × 55 columns

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 57 columns):
0     32 non-null int64
1     32 non-null int64
2     32 non-null int64
3     32 non-null int64
4     32 non-null object
5     32 non-null int64
6     32 non-null int64
7     32 non-null int64
8     32 non-null int64
9     32 non-null int64
10    32 non-null int64
11    32 non-null int64
12    32 non-null int64
13    32 non-null int64
14    32 non-null int64
15    32 non-null int64
16    32 non-null int64
17    32 non-null int64
18    32 non-null int64
19    32 non-null int64
20    32 non-null int64
21    32 non-null int64
22    32 non-null int64
23    32 non-null int64
24    32 non-null int64
25    32 non-null int64
26    32 non-null int64
27    32 non-null int64
28    32 non-null int64
29    32 non-null int64
30    32 non-null int64
31    32 non-null int64
32    32 non-null int64
33    32 non-null int64
34    32 non-null int64
35    32 non-null int64
36    32 non-null int64
37    32 non-null int64
38    32 non-null object
39    32 non-null int64
40    32 non-null int64
41    32 non-null int64
42    32 non-null int64
43    32 non-null int64
44    32 non-null int64
45    32 non-null int64
46    32 non-null int64
47    32 non-null int64
48    32 non-null int64
49    32 non-null int64
50    32 non-null int64
51    32 non-null int64
52    32 non-null int64
53    32 non-null int64
54    32 non-null int64
55    32 non-null int64
56    32 non-null int64
dtypes: int64(55), object(2)
memory usage: 14.4+ KB
```

Preprocessing

In [5]:
```
# Convert the column name
data.columns = [str(x) for x in range(len(data.columns))]
```

We will find the Columns with missing data and then fill the missing values

In [6]:
```
cols = [ c for c in data.columns if np.dtype(data[c]) == 'O']
print("Columns with missing values are : ",cols)

print("Missing data is given with '?' ")
data[cols].head()
```

```
Columns with missing values are :  ['4', '38']
Missing data is given with '?'
```

Out[6]:

	4	38
0	?	2
1	1	1
2	2	2
3	2	2
4	1	1

Now we will convert these values to **np.int64** and convert **?** to **-1**
Then we will fill these -1 (missing values) with **mean** of the columnn.

In [7]:
```
def convertValues(x):
    try : x = np.int64(x)
    except : x = -1
    return x

for c in cols:
    data[c] = pd.Series([convertValues(x) for x in data[c]])

print("Convert '?' to -1")
data[cols].head()
```

```
Convert '?' to -1
```

Out[7]:

	4	38
0	-1	2
1	1	1
2	2	2
3	2	2
4	1	1

Now fill missing values

In [8]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(missing_values= -1,strategy = "mean")
data[cols] = imputer.fit_transform(data[cols])
data[cols].head()
```

Out[8]:

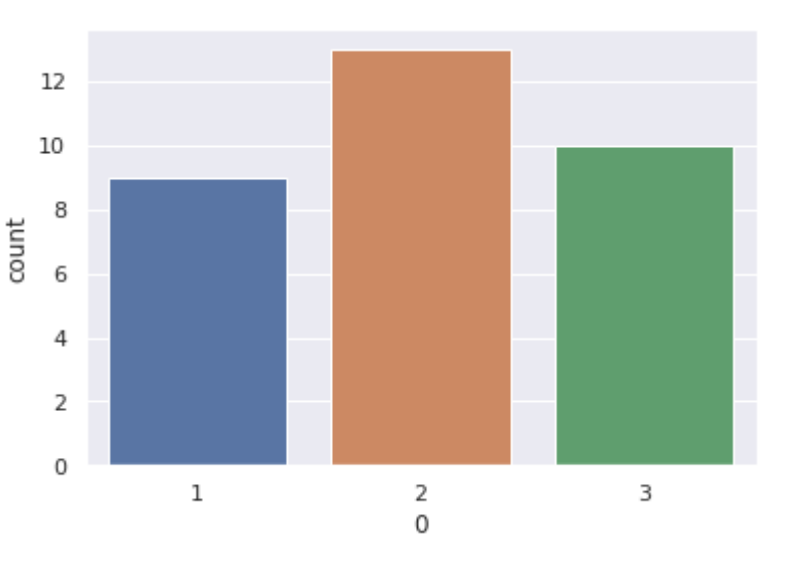
	4	38
0	1.392857	2.0
1	1.000000	1.0
2	2.000000	2.0
3	2.000000	2.0
4	1.000000	1.0

Visualising Data

First column is our target values

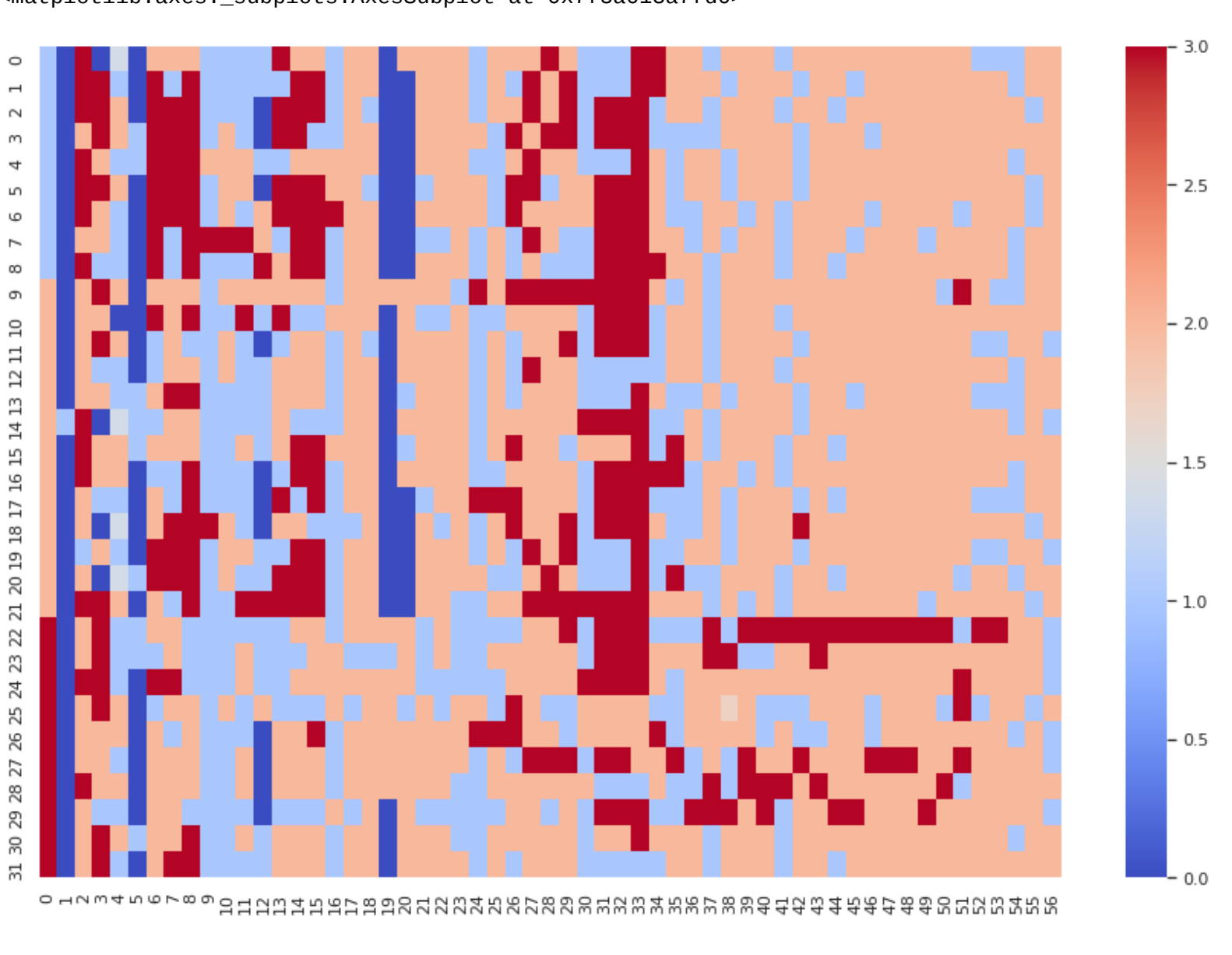
In [9]:
```
sns.countplot(x='0',data=data)
```

Out[9]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f8a057b0c88>`



In [10]:
```
plt.subplots(figsize=(15,10))
sns.heatmap(cmap="coolwarm",data=data)
```

Out[10]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f8a018a7fd0>`



In above graph we can see a number of features are **Higly -vely corelated** while some are also **highly +vely corelated**. So now we need to extract only useful features that can esure us good Machine Learning Model

Extracting useful features using PSO

Out of all these features, may be not all will participate for
good accuracy. So we may have to choose only those features whose
contribution can give us useful information.

So we will use **Particle Swarm Optimization** - *(PSO)* to
extract usefull features from our dataset

In [11]:
```
# Installing Pyswarm Library

!python -m pip install pyswarms;
```

```
Collecting pyswarms
  Downloading pyswarms-1.1.0-py2.py3-none-any.whl (96 kB)
     |████████████████████████████████| 96 kB 1.9 MB/s eta 0:00:011
Requirement already satisfied: matplotlib>=1.3.1 in /opt/conda/lib/python3.6/site-packages (f
rom pyswarms) (3.2.1)
Requirement already satisfied: attrs in /opt/conda/lib/python3.6/site-packages (from pyswarm
s) (19.3.0)
Requirement already satisfied: scipy in /opt/conda/lib/python3.6/site-packages (from pyswarm
s) (1.4.1)
Requirement already satisfied: future in /opt/conda/lib/python3.6/site-packages (from pyswarm
s) (0.18.2)
Requirement already satisfied: numpy in /opt/conda/lib/python3.6/site-packages (from pyswarm
s) (1.18.2)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.6/site-packages (from pyswarms)
(4.42.0)
Requirement already satisfied: python-dateutil>=2.1 in /opt/conda/lib/python3.6/site-packages
(from matplotlib>=1.3.1->pyswarms) (2.8.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /opt/conda/lib/pyt
hon3.6/site-packages (from matplotlib>=1.3.1->pyswarms) (2.4.6)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/python3.6/site-packages (f
rom matplotlib>=1.3.1->pyswarms) (1.1.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.6/site-packages (from m
atplotlib>=1.3.1->pyswarms) (0.10.0)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.6/site-packages (from pytho
n-dateutil>=2.1->matplotlib>=1.3.1->pyswarms) (1.14.0)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.6/site-packages (from kiw
isolver>=1.0.1->matplotlib>=1.3.1->pyswarms) (46.1.3.post20200330)
Installing collected packages: pyswarms
Successfully installed pyswarms-1.1.0
```

In [12]:
```
# importing the libraries
import pyswarms as ps
```

Spliting data in Train and Test set

In [13]:
```
from sklearn.model_selection import train_test_split
X,y = data.iloc[:,1:].values, data.iloc[:,0].values

Xtrain,Xtest,ytrain,ytest = train_test_split(X,y,test_size=0.3)
print("Xtrain shape ; {} \nytrain shape : {}".format(Xtrain.shape,ytrain.shape))
```

```
Xtrain shape ; (22, 56)
ytrain shape : (22,)
```

Use of PSO

In [14]:
```
from sklearn.linear_model import LogisticRegression

# Logistic Regression Classifier
clf = LogisticRegression(solver='saga')

def cal_per_particle(mask,alpha,no_of_features=56):
    subset=None
    if np.count_nonzero(mask) == 0:
        subset = Xtrain
    else :
        subset = Xtrain[:,mask==1]
    clf.fit(subset,ytrain)
    pred = (clf.predict(subset)==ytrain).mean()
    tmp = (alpha * (1.0 - pred) + (1.0 - alpha)* (1 - (subset.shape[1]/no_of_features)))
    return tmp

def calc(x,alpha=0.81):
    number_of_particles = x.shape[0]
    arr = [cal_per_particle(x[i],alpha) for i in range(number_of_particles)]
    return np.array(arr)
```

In [15]:
```
%%time

op1 = ['c1','c2']
ops = {'w':0.9,'k':30,'p':2}
for o in op1:
    ops[o] = np.random.random()
dims = Xtrain.shape[1]
optimizer = ps.discrete.BinaryPSO(n_particles=32, dimensions=dims, options=ops)
cost, pos = optimizer.optimize(calc, iters=800)
print("Options are : {}".format(ops))
```

```
2020-04-10 15:12:59,087 - pyswarms.discrete.binary - INFO - Optimize for 800 iters with {'w':
0.9, 'k': 30, 'p': 2, 'c1': 0.2172599464533037, 'c2': 0.5490737549116664}
pyswarms.discrete.binary: 100%|██████████|800/800, best_cost=0.0271
2020-04-10 15:14:29,168 - pyswarms.discrete.binary - INFO - Optimization finished | best cos
t: 0.027142857142857146, best pos: [0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 0 1 0 1 1 1 1 1
1 1 1 1 1 1 1 1
 1 0 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 1 1]
```

```
Options are : {'w': 0.9, 'k': 30, 'p': 2, 'c1': 0.2172599464533037, 'c2': 0.5490737549116664}
CPU times: user 1min 29s, sys: 880 ms, total: 1min 30s
Wall time: 1min 30s
```

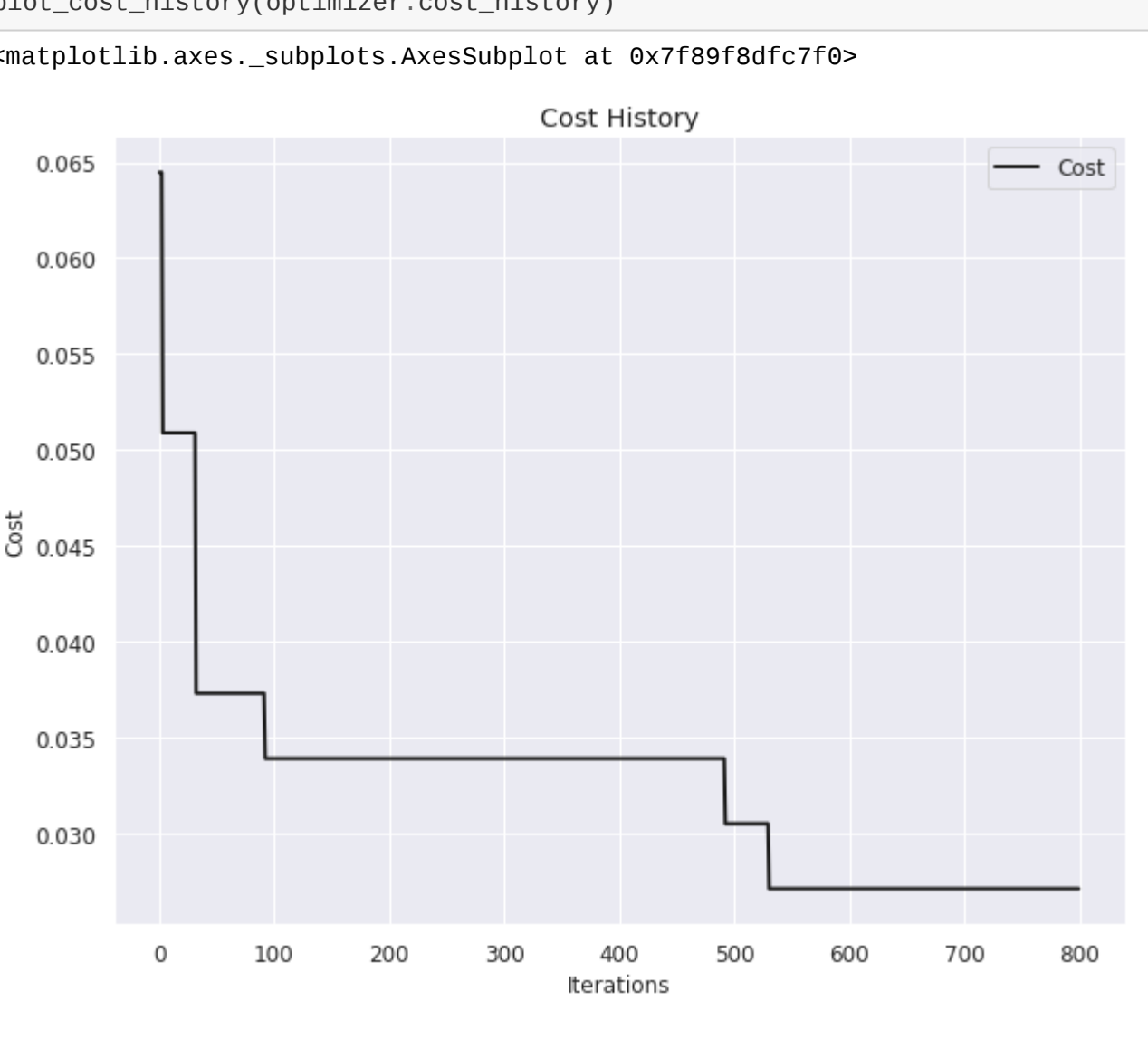
In [16]:
```
cols = data.columns[1:]
print("Selected features are : ")
print([c for c,p in zip(cols,pos) if p==1 ])
print("Excluded features are : ")
print([c for c,p in zip(cols,pos) if p==0 ])
```

```
Selected features are :
['2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12', '13', '14', '15', '17', '18', '1
9', '20', '21', '23', '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
'37', '38', '40', '41', '43', '44', '45', '46', '47', '48', '51', '52', '53', '54', '55', '5
6']
Excluded features are :
['1', '16', '22', '24', '39', '42', '49', '50']
```

Visualising PSO Optimizer Cost History

In [17]:
```
from pyswarms.utils.plotters import plot_cost_history

plot_cost_history(optimizer.cost_history)
```

Out[17]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f89f8dfc7f0>`

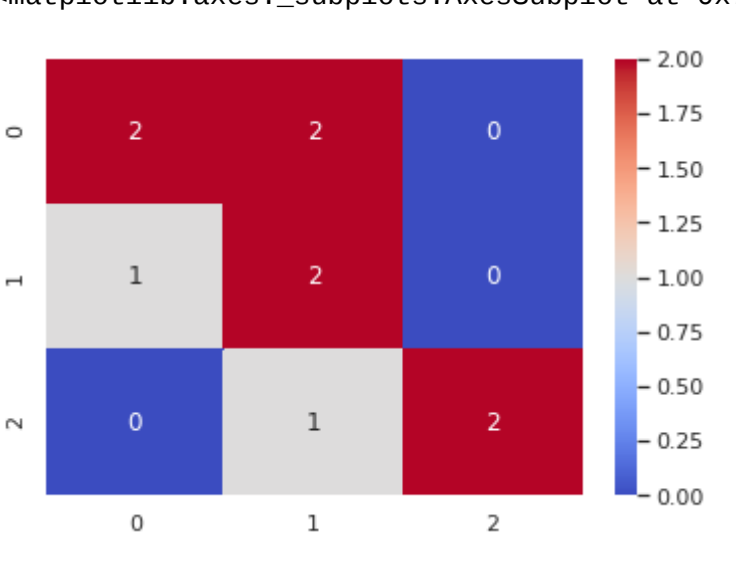


Checking Model performance over Selected Features

In [18]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix

clf = LogisticRegression(solver='saga')
# selected trainging features
s_xtrain = Xtrain[:,pos==1]
clf.fit(s_xtrain,ytrain)

# selected testing features
s_xtest = Xtest[:,pos==1]

pred = clf.predict(s_xtest)
```

In [19]:
```
mat = confusion_matrix(ytest,pred)
sns.heatmap(mat, cmap="coolwarm",fmt='d',annot=True)
```

Out[19]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f89f8cf0320>`



In [20]:
```
from sklearn.metrics import accuracy_score as ac

print("Accuracy Score : ",ac(ytest,pred))
```

```
Accuracy Score :  0.6
```

Hyper Parameter Tunning

As we see that after extracting the features with the help of **PSO**
We were able to achieve **0.6 accuracy score**.

So now we will try to Tune our model so that we can increase our accuracy with the selected features.

In [21]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
```

Some parameters for Tunning. We will create different combinations of paramerters to check for best solution.

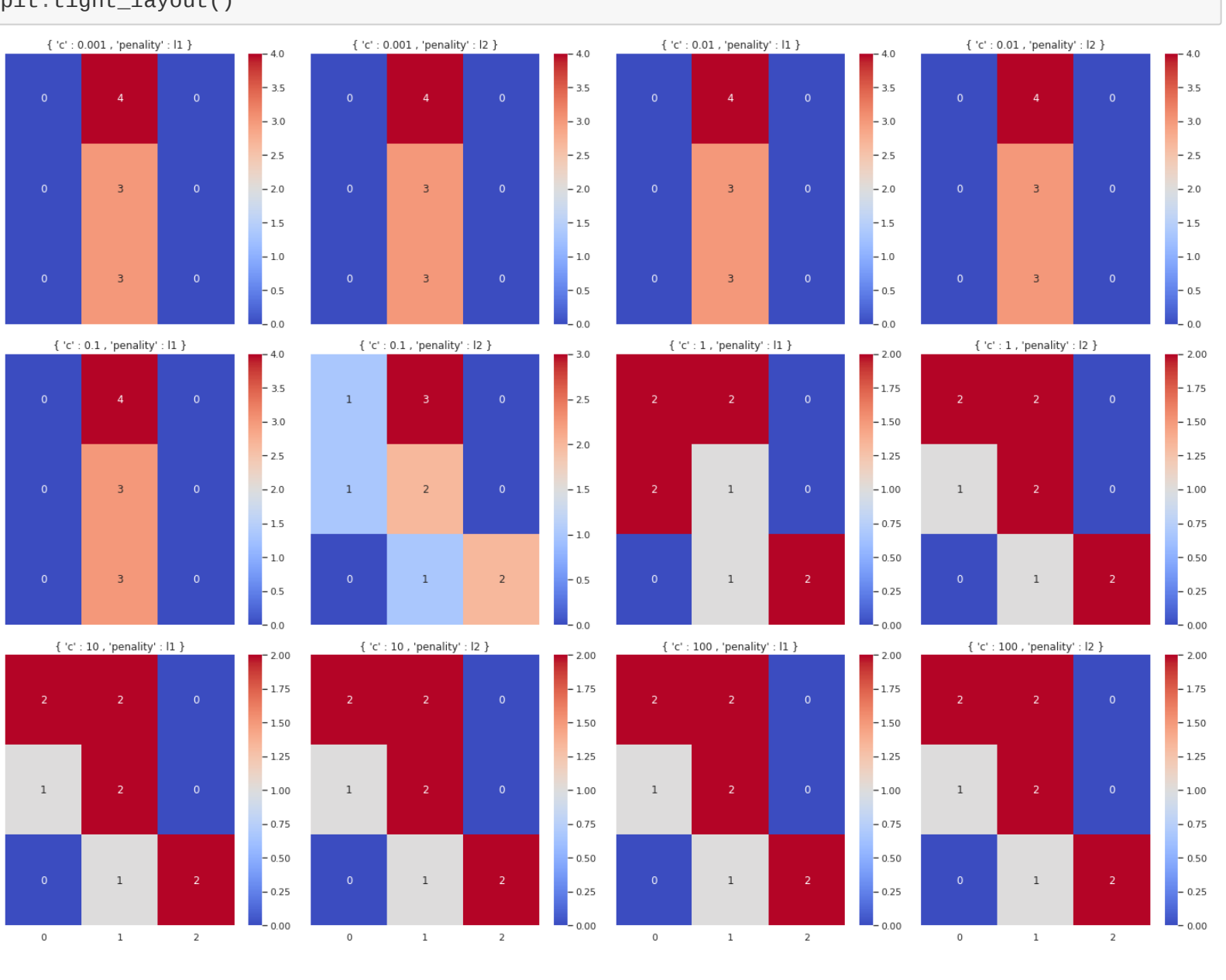
In [22]:
```
c_param = [0.001, 0.01, 0.1, 1, 10, 100]
p_param = ['l1','l2']

param_list = [(c,p) for c in c_param for p in p_param]
print("Combinations are : ",param_list)
```

```
Combinations are :  [(0.001, 'l1'), (0.001, 'l2'), (0.01, 'l1'), (0.01, 'l2'), (0.1, 'l1'),
(0.1, 'l2'), (1, 'l1'), (1, 'l2'), (10, 'l1'), (10, 'l2'), (100, 'l1'), (100, 'l2')]
```

We will keep a track of **C**, **penality** and **accuracy** so that we can use hyper parameters in our final Model.

In [23]:
```
C=None
P=None
Accu=0.0
```

In [24]:
```
i,j=0,0
f, axes = plt.subplots(3, 4, figsize=(20, 15), sharex=True)
sns.despine(left=True)
s_xtrain = Xtrain[:,pos==1]
s_xtest = Xtest[:,pos==1]

for c,p in param_list:
    clf = LogisticRegression(solver='saga',penalty=p,C=c)
    clf.fit(s_xtrain,ytrain)
    pred = clf.predict(s_xtest)
    acc_score = accuracy_score(ytest,pred)
    if acc_score > Accu:
        Accu = acc_score
        C,P=c,p
    cm = confusion_matrix(ytest,pred)
    axes[i,j].set_title("{ 'c' : "+str(c)+" , 'penality' : "+p+" }")
    sns.heatmap(cm,cmap="coolwarm",fmt='d',annot=True,ax=axes[i,j])
    if j == 3: i = (i+1)%4
    j = (j+1)%4

plt.setp(axes, yticks=[])
plt.tight_layout()
```



Result after Hyper Parameter Tunning

In [25]:
```
print("Best Accuracy : ",Accu)
print("Penalty : ",P)
print("C : ",c)
```

```
Best Accuracy :  0.6
Penalty :  l2
C :  100
```

As we can see that after Hyper Parameter Tunning the
accuracy score os **0.6** which is quite good as per dataset.

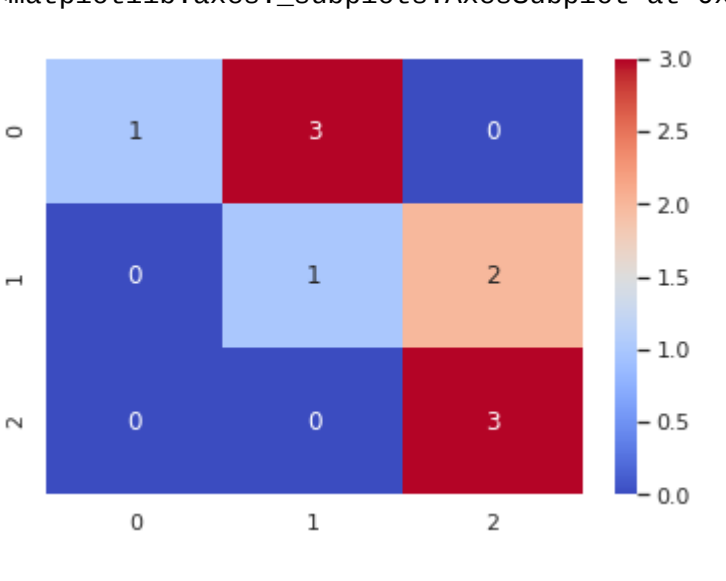
Finalizing the Hybrid Model

In [26]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix , accuracy_score, classification_report
from sklearn.model_selection import cross_val_predict, cross_val_score, KFold
```

In [27]:
```
xtrain,xtest,ytrain,ytest = train_test_split(X[:,pos==1],y,test_size=0.3)

model = LogisticRegression(penalty=P,C=C,solver='saga')
model.fit(xtrain,ytrain)

pred = model.predict(xtest)

print("Accuracy Score : ",accuracy_score(ytest,pred))
c_mat = confusion_matrix(ytest,pred)
sns.heatmap(c_mat,cmap="coolwarm",fmt='d',annot=True)
```

```
Accuracy Score :  0.5
```

Out[27]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f89f3e47320>`



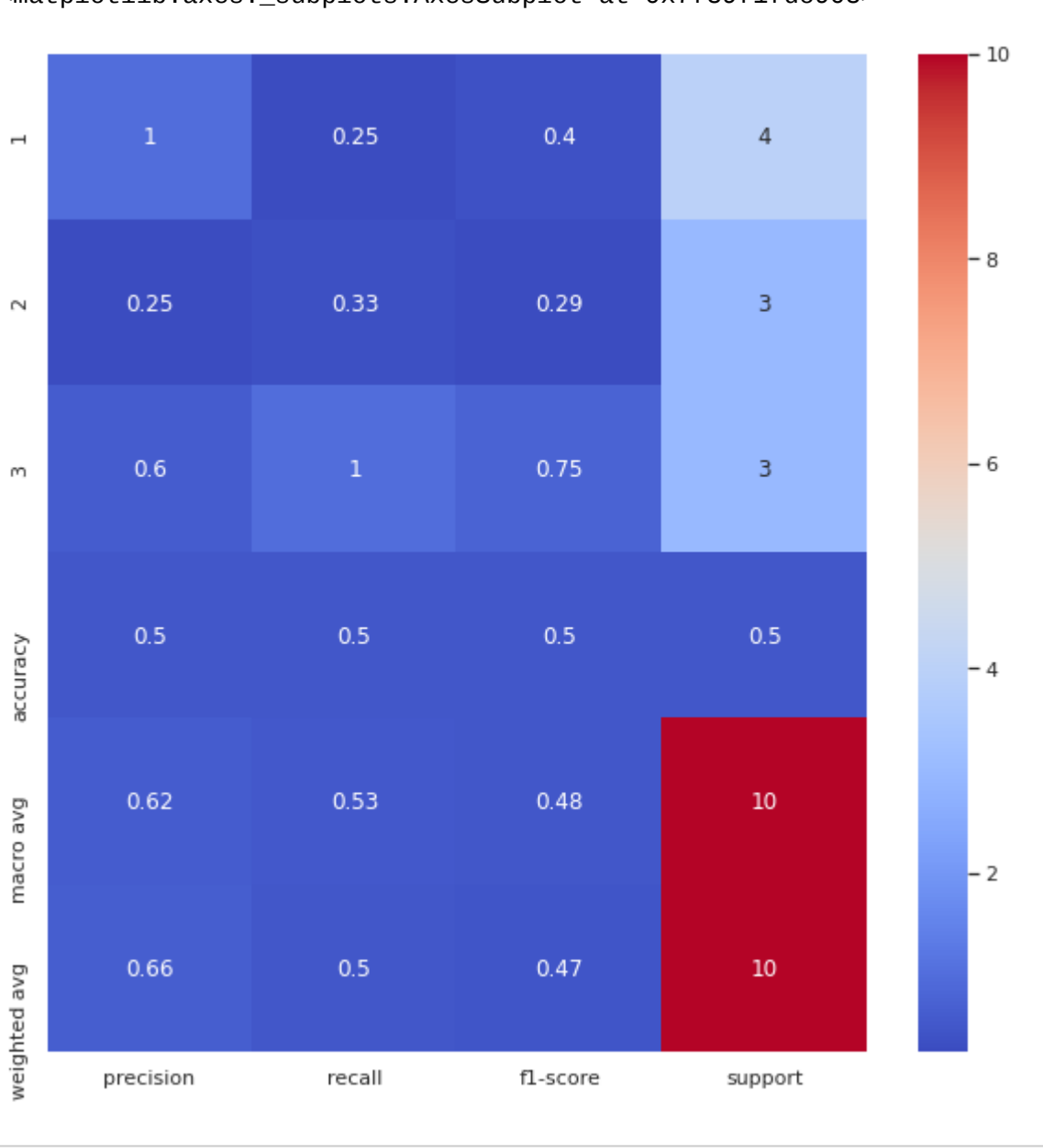
In [28]:
```
cr = classification_report(ytest,pred,output_dict=True)
print(cr)
```

```
{'1': {'precision': 1.0, 'recall': 0.25, 'f1-score': 0.4, 'support': 4}, '2': {'precision':
0.25, 'recall': 0.3333333333333333, 'f1-score': 0.28571428571428575, 'support': 3}, '3': {'pr
ecision': 0.6, 'recall': 1.0, 'f1-score': 0.7499999999999999, 'support': 3}, 'accuracy': 0.5,
'macro avg': {'precision': 0.6166666666666667, 'recall': 0.5277777777777778, 'f1-score': 0.47
85714285714285, 'support': 10}, 'weighted avg': {'precision': 0.655, 'recall': 0.5, 'f1-scor
e': 0.47071428571428575, 'support': 10}}
```

In [29]:
```
cr_df = pd.DataFrame(cr)
cr_df = cr_df.transpose()
```

In [30]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cr_df,annot=True,cmap="coolwarm",ax=ax)
```

Out[30]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f89f1fdc908>`



In [31]:
```
cr_df
```

Out[31]:

	precision	recall	f1-score	support
1	1.000000	0.250000	0.400000	4.0
2	0.250000	0.333333	0.285714	3.0
3	0.600000	1.000000	0.750000	3.0
accuracy	0.500000	0.500000	0.500000	0.5
macro avg	0.616667	0.527778	0.478571	10.0
weighted avg	0.655000	0.500000	0.470714	10.0

Summary

During this project the main motive was to use Soft Computing to make Hybrid System.
So i used **Particle Swarm Optimization - (PSO)** with **Logistic Regression** to create a
Hybrid System which extract features using PSO and then apply logistic Regression
on the data to classify different type of Lung Cancer.

The data we used in this Project is available opensource on UCI Machine Learning
Repository. At last i was able to create Hybrid model that i used on this dataset.

Main Concepts used in this are

- Preprocessing Dataset
- Visualizing Data
- Feature Extraction using PSO
- Check Model Perfomance over Selected Features
- Hyper Parameter Tunning
- Finalising Model with Logistic Regression
- Classification Report