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In [1]:

```
# Importing libraries

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report,confusion_matrix
threshold = 0.5
```

In [2]:

```
# Reading dataset

dataset = pd.read_csv('bank.csv')
dataset
```

Out[2]:

	variance	skewness	curtosis	entropy	class
0	3.62160	8.66610	-2.8073	-0.44699	0
1	4.54590	8.16740	-2.4586	-1.46210	0
2	3.86600	-2.63830	1.9242	0.10645	0
3	3.45660	9.52280	-4.0112	-3.59440	0
4	0.32924	-4.45520	4.5718	-0.98880	0
...	...	...	...	...	...
1367	0.40614	1.34920	-1.4501	-0.55949	1
1368	-1.38870	-4.87730	6.4774	0.34179	1
1369	-3.75030	-13.45860	17.5932	-2.77710	1
1370	-3.56370	-8.38270	12.3930	-1.28230	1
1371	-2.54190	-0.65804	2.6842	1.19520	1

1372 rows × 5 columns

In [3]:

```
# Checking min and max values of each column

dataset.describe()
```

Out[3]:

	variance	skewness	curtosis	entropy	class
count	1372.000000	1372.000000	1372.000000	1372.000000	1372.000000
mean	0.433735	1.922353	1.397627	-1.191657	0.444606
std	2.842763	5.869047	4.310030	2.101013	0.497103
min	-7.042100	-13.773100	-5.286100	-8.548200	0.000000
25%	-1.773000	-1.708200	-1.574975	-2.413450	0.000000

	variance	skewness	curtosis	entropy	class
50%	0.496180	2.319650	0.616630	-0.586650	0.000000
75%	2.821475	6.814625	3.179250	0.394810	1.000000
max	6.824800	12.951600	17.927400	2.449500	1.000000

In [4]:

```
X = dataset[['variance','skewness','curtosis','entropy']]
y = dataset['class']
X.insert(0, 'x0', 1)
X
```

Out[4]:

	x0	variance	skewness	curtosis	entropy
0	1	3.62160	8.66610	-2.8073	-0.44699
1	1	4.54590	8.16740	-2.4586	-1.46210
2	1	3.86600	-2.63830	1.9242	0.10645
3	1	3.45660	9.52280	-4.0112	-3.59440
4	1	0.32924	-4.45520	4.5718	-0.98880
...	...	...	...	...	...
1367	1	0.40614	1.34920	-1.4501	-0.55949
1368	1	-1.38870	-4.87730	6.4774	0.34179
1369	1	-3.75030	-13.45860	17.5932	-2.77710
1370	1	-3.56370	-8.38270	12.3930	-1.28230
1371	1	-2.54190	-0.65804	2.6842	1.19520

1372 rows × 5 columns

In [5]:

```
y
```

Out[5]:

```
0       0
1       0
2       0
3       0
4       0
       ..
1367    1
1368    1
1369    1
1370    1
1371    1
Name: class, Length: 1372, dtype: int64
```

In [6]:

```
# Splitting dataset into training and testing set : 75% for training

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.25,
                                                     random_state = 13)
X_train
```

Out[6]:

	x0	variance	skewness	curtosis	entropy
320	1	0.51950	-3.2633	3.08950	-0.98490

	x0	variance	skewness	curtosis	entropy
976	1	-2.29870	-5.2270	5.63000	0.91722
685	1	4.07150	7.6398	-2.08240	-1.16980
230	1	-1.33890	1.5520	7.08060	1.03100
691	1	0.57060	-0.0248	1.24210	-0.56210
...	...	...	...	...	...
866	1	-4.14090	3.4619	-0.47841	-3.88790
742	1	0.66191	9.6594	-0.28819	-1.66380
74	1	4.40690	10.9072	-4.57750	-4.42710
176	1	0.19081	9.1297	-3.72500	-5.82240
338	1	0.96414	5.6160	2.21380	-0.12501

1029 rows × 5 columns

In [7]:

```
# Functions required for Logistic Regression

def sigmoid(z):
    return 1/(1+np.exp(-z))

def predict(X, theta):
    return sigmoid(np.matmul(X,theta))

def calculate_cost(y_actual,y_pred):
    return (-1/len(y_actual))*(np.sum(((y_actual)*np.log10(y_pred)) +
                                       ((1-y_actual)*np.log10(1-y_pred))))

def calculate_gradient(X,y_actual,y_pred):
    return np.array(np.sum(np.multiply(y_pred-y_actual,X),axis=0)).reshape(len(X[0]),1)

def fit(X,y,learning_rate=0.0001,epochs=30):
    X = X.values
    y = y.values.reshape(len(y),1)
    theta = np.array([0.3,0.2,0.4,0.5,0.6]).reshape(len(X[0]),1)
    cost = []
    for epoch in range(1,epochs+1):
        y_pred = predict(X,theta)
        y_actual = y
        J = calculate_cost(y_actual,y_pred)
        cost.append(J)
        print('Epoch: ',epoch,', Cost Function Value (J) = ',"{:.3f}".format(J),
              ', Theta values : ',theta.T)
        grads = calculate_gradient(X,y_actual,y_pred)
        theta = theta - (learning_rate*grads)
    return theta,cost
```

In [8]:

```
# Training the Logistic Regression model to learn parameter vector theta

theta, cost = fit(X_train,y_train)
```

```
Epoch:  1 , Cost Function Value (J) =  0.755 , Theta values :  [[0.3 0.2 0.4 0.5 0.6]]
Epoch:  2 , Cost Function Value (J) =  0.558 , Theta values :  [[0.27615442 0.04823653 0.2
2119171 0.45947838 0.59223527]]
Epoch:  3 , Cost Function Value (J) =  0.446 , Theta values :  [[ 0.25894469 -0.07306558
0.14810471  0.37486473  0.56057643]]
```

```
Epoch:  4 , Cost Function Value (J) =  0.362 , Theta values :  [[ 0.2466168  -0.17546681
0.10585627  0.28848248  0.52404742]]
Epoch:  5 , Cost Function Value (J) =  0.299 , Theta values :  [[ 0.23816852 -0.26168589
0.07395583  0.20942598  0.48805732]]
Epoch:  6 , Cost Function Value (J) =  0.253 , Theta values :  [[ 0.23311351 -0.33368733
0.0452629   0.14097928  0.45435263]]
Epoch:  7 , Cost Function Value (J) =  0.219 , Theta values :  [[ 0.23096491 -0.39387812
0.01802941  0.08331069  0.42322239]]
Epoch:  8 , Cost Function Value (J) =  0.194 , Theta values :  [[ 0.23116737 -0.44470797 -
0.00767918  0.03498833  0.39445697]]
Epoch:  9 , Cost Function Value (J) =  0.174 , Theta values :  [[ 0.23318411 -0.48824869 -
0.03161661 -0.00579398  0.36777526]]
Epoch:  10 , Cost Function Value (J) =  0.159 , Theta values :  [[ 0.23656173 -0.52609528
-0.05373882 -0.04064864  0.34293793]]
Epoch:  11 , Cost Function Value (J) =  0.147 , Theta values :  [[ 0.24094541 -0.55943505
-0.07415409 -0.07086007  0.31975089]]
Epoch:  12 , Cost Function Value (J) =  0.138 , Theta values :  [[ 0.24606776 -0.58914951
-0.09303296 -0.09741006  0.2980521 ]]
Epoch:  13 , Cost Function Value (J) =  0.129 , Theta values :  [[ 0.2517304  -0.61590061
-0.11055598 -0.12103965  0.27770216]]
Epoch:  14 , Cost Function Value (J) =  0.122 , Theta values :  [[ 0.25778662 -0.64019353
-0.12689092 -0.14230846  0.25857898]]
Epoch:  15 , Cost Function Value (J) =  0.116 , Theta values :  [[ 0.26412763 -0.66242047
-0.14218536 -0.16164219  0.24057477]]
Epoch:  16 , Cost Function Value (J) =  0.111 , Theta values :  [[ 0.27067228 -0.68289086
-0.15656584 -0.17936814  0.22359393]]
Epoch:  17 , Cost Function Value (J) =  0.107 , Theta values :  [[ 0.27735958 -0.7018525
-0.17013975 -0.19574116  0.20755147]]
Epoch:  18 , Cost Function Value (J) =  0.103 , Theta values :  [[ 0.28414338 -0.71950642
-0.18299797 -0.21096227  0.19237168]]
Epoch:  19 , Cost Function Value (J) =  0.099 , Theta values :  [[ 0.29098848 -0.73601767
-0.19521744 -0.22519211  0.17798694]]
Epoch:  20 , Cost Function Value (J) =  0.096 , Theta values :  [[ 0.29786792 -0.7515232
-0.20686355 -0.23856068  0.16433671]]
Epoch:  21 , Cost Function Value (J) =  0.093 , Theta values :  [[ 0.30476091 -0.7661377
-0.21799212 -0.25117439  0.15136663]]
Epoch:  22 , Cost Function Value (J) =  0.090 , Theta values :  [[ 0.31165139 -0.77995809
-0.22865107 -0.26312135  0.13902774]]
Epoch:  23 , Cost Function Value (J) =  0.088 , Theta values :  [[ 0.31852692 -0.79306688
-0.23888176 -0.2744752   0.12727581]]
Epoch:  24 , Cost Function Value (J) =  0.086 , Theta values :  [[ 0.32537785 -0.80553485
-0.24872011 -0.28529811  0.11607079]]
Epoch:  25 , Cost Function Value (J) =  0.083 , Theta values :  [[ 0.33219675 -0.81742307
-0.25819749 -0.29564296  0.10537627]]
Epoch:  26 , Cost Function Value (J) =  0.082 , Theta values :  [[ 0.33897788 -0.8287846
-0.26734145 -0.30555514  0.09515909]]
Epoch:  27 , Cost Function Value (J) =  0.080 , Theta values :  [[ 0.34571686 -0.83966579
-0.27617634 -0.31507383  0.08538896]]
Epoch:  28 , Cost Function Value (J) =  0.078 , Theta values :  [[ 0.35241038 -0.8501073
-0.28472373 -0.3242331   0.07603815]]
Epoch:  29 , Cost Function Value (J) =  0.077 , Theta values :  [[ 0.359056   -0.86014501
-0.29300292 -0.33306274  0.0670812 ]]
Epoch:  30 , Cost Function Value (J) =  0.075 , Theta values :  [[ 0.36565195 -0.86981072
-0.30103117 -0.34158896  0.05849472]]
```

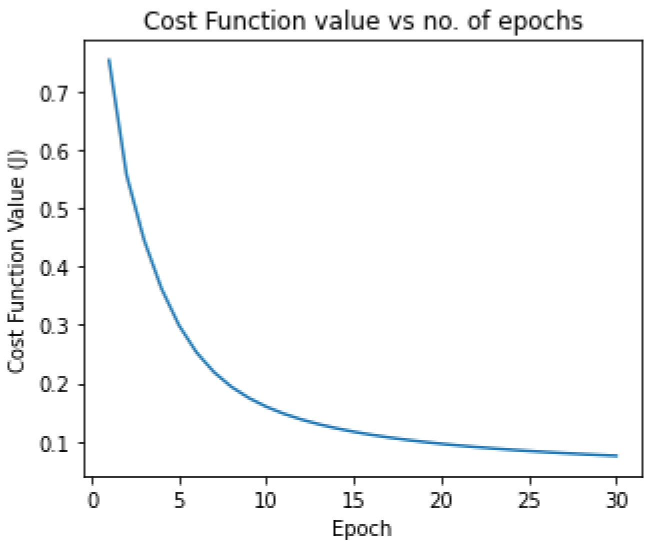
In [9]:

```python
print('Learned parameter vector Theta : ')
print(theta)
```

```
Learned parameter vector Theta :
[[ 0.37219698]
 [-0.87913272]
 [-0.30882403]
 [-0.34983492]
 [ 0.05025714]]
```

In [10]:
```
# Plotting Cost function value vs no. of epochs

plt.figure(figsize=(5, 4))
ax = plt.axes()
plt.plot(range(1,31),cost)
plt.title('Cost Function value vs no. of epochs')
ax.set_xlabel('Epoch')
ax.set_ylabel('Cost Function Value (J)')
plt.show()
```



In [11]:
```
# Evaluating model performance on Training set

y_train_pred = [0 if value < threshold else 1
                for value in predict(X_train.values,theta).flatten()]
print('Training set performance : \n')
print(classification_report(y_train,y_train_pred))
```

```
Training set performance :

              precision    recall  f1-score   support

           0       0.94      1.00      0.96       567
           1       1.00      0.92      0.95       462

    accuracy                           0.96      1029
   macro avg       0.97      0.96      0.96      1029
weighted avg       0.96      0.96      0.96      1029
```

In [12]:
```
# Evaluating model performance on Test set

y_test_pred = [0 if value < threshold else 1
               for value in predict(X_test.values,theta).flatten()]
print('Test set performance : \n')
print(classification_report(y_test,y_test_pred))
```

```
Test set performance :

              precision    recall  f1-score   support

           0       0.96      0.99      0.97       195
           1       0.99      0.95      0.97       148

    accuracy                           0.97       343
   macro avg       0.97      0.97      0.97       343
```

```
weighted avg       0.97      0.97      0.97       343
```

In [13]:

```
# Confusion Matrix for Test set

print('Confusion Matrix :\n')
print(confusion_matrix(y_test,y_test_pred))
```

```
Confusion Matrix :

[[193   2]
 [  8 140]]
```

In [14]:

```
result = pd.DataFrame({'Actual':y_test,'Predicted':y_test_pred})
result
```

Out[14]:

	Actual	Predicted
308	0	0
1330	1	1
472	0	0
304	0	0
33	0	0
...	...	...
435	0	0
181	0	0
165	0	0
80	0	0
647	0	0

343 rows × 2 columns

In [15]:

```
# Classifying note using user input

X_ip = [1] + list(map(float,input("Enter variance, skewness, curtosis,",
                                  " entropy of bank note image wavelet transform : ")
                      .split()))[:4]
X_ip = np.array(X_ip).reshape(1,len(X_ip))
prediction = [0 if value < threshold else 1 for value in predict(X_ip,theta).flatten()]
print('Predicted class label : ',prediction[0])
```

```
Enter variance, skewness, curtosis, entropy of bank note image wavelet transform : -3.2 -
7.4 3.4 2.2
Predicted class label :  1
```

Hence the Logistic Regression model has achieved a 96% accuracy on training set and a 97% accuracy on test set