

I am implementing the NUMBER RECOGNITION MODEL using the load_digits dataset From the sklearn

```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 %matplotlib inline
5 import seaborn as sns
6 from sklearn.datasets import load_digits
7
8 digits = load_digits()                                #imported the load_digits data to digits(variable)
9 print(digits.data[0])                                #gives the 1-d array of that particular digit matrix
```

[0. 0. 5. 13. 9. 1. 0. 0. 0. 0. 13. 15. 10. 15. 5. 0. 0. 3.
15. 2. 0. 11. 8. 0. 0. 4. 12. 0. 0. 8. 8. 0. 0. 5. 8. 0.
 0. 9. 8. 0. 0. 4. 11. 0. 1. 12. 7. 0. 0. 2. 14. 5. 10. 12.
 0. 0. 0. 0. 6. 13. 10. 0. 0. 0.]

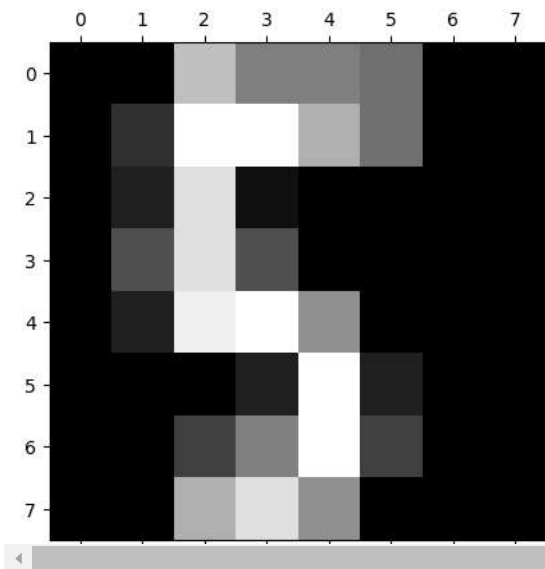
```
1 print(f"Size of the data(X) : {digits.data.shape}")
2 print(f"Size of the Target (Y) : {digits.target.shape}")
```

Size of the data(X) : (1797, 64)
Size of the Target (Y) : (1797,)

To get the image of the digits we can use the matplotlib

```
1 plt.gray()
2 plt.matshow(digits.images[25])                        # prints the image of number which is at position at 25
3 plt.show()
```

<matplotlib.image.AxesImage at 0x79f67906bc10>
<Figure size 640x480 with 0 Axes>



Splitting the dataset into train_data and test_data

```
1 from sklearn.model_selection import train_test_split
2
3 x = digits.data
4 y = digits.target
5 x_train , x_test , y_train , y_test = train_test_split(x , y , test_size = 0.2 , random_state = 42)
```

Importing the LogisticRegression and training the model

```
1 from sklearn.linear_model import LogisticRegression
2
3 model = LogisticRegression(multi_class = 'multinomial' , solver = 'lbfgs' , max_iter = 200)
4 model.fit(x_train , y_train)
```

```

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1
warnings.warn(

```

```

LogisticRegression
LogisticRegression(max_iter=200, multi_class='multinomial')

```

Testing the data using the model

```
1 predicted_result = model.predict(x_test)
```

Calculating the Score of the Model

```

1 from sklearn.metrics import accuracy_score , confusion_matrix , classification_report
2
3 print(f"Accuracy Score of Testing data : {accuracy_score(y_test , predicted_result)*100}")
4 print(f"Confusion Matrix : {confusion_matrix(y_test , predicted_result)}")
5 print(f"Classification Report : {classification_report(y_test , predicted_result)}")

```

```

Accuracy Score of Testing data : 97.5
Confusion Matrix : [[33  0  0  0  0  0  0  0  0  0]
 [ 0 28  0  0  0  0  0  0  0  0]
 [ 0  0 33  0  0  0  0  0  0  0]
 [ 0  0  0 33  0  1  0  0  0  0]
 [ 0  1  0  0 45  0  0  0  0  0]
 [ 0  0  0  0  0 45  1  0  0  1]
 [ 0  0  0  0  0  1 34  0  0  0]
 [ 0  0  0  0  0  1  0 33  0  0]
 [ 0  0  0  0  0  1  0  0 29  0]
 [ 0  0  0  1  0  0  0  0  1 38]]
Classification Report :

```

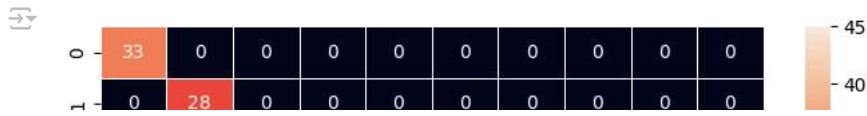
		precision	recall	f1-score	support
0	1.00	1.00	1.00	33	
1	0.97	1.00	0.98	28	
2	1.00	1.00	1.00	33	
3	0.97	0.97	0.97	34	
4	1.00	0.98	0.99	46	
5	0.92	0.96	0.94	47	
6	0.97	0.97	0.97	35	
7	1.00	0.97	0.99	34	
8	0.97	0.97	0.97	30	
9	0.97	0.95	0.96	40	
accuracy			0.97	360	
macro avg	0.98	0.98	0.98	360	
weighted avg	0.98	0.97	0.98	360	

Visualizing the confusion matrix using the seaborn

```

1 cn = confusion_matrix(y_test , predicted_result)
2 plt.figure(figsize = (8,5))
3 sns.heatmap(cn , annot = True , linewidth = 0.5)
4 plt.show()

```



printing the intercepts and coef of the of model each individual digit has its own intercept and coef(weights)



```
1 print(model.intercept_.shape)
2 print(model.coef_.shape)
```

```
(10,)
(10, 64)
```



Printing the intercept and weights of digit '0'.... In this way we can print intercepts and weights of number(0-9)



```
1 print(model.intercept_[0])
2 print(model.coef_[0])
```

```
0.005526295878635729
[ 0.00000000e+00 -5.15350463e-03 -1.40862905e-02  8.44001883e-02
 2.70552351e-02 -4.58767174e-02 -1.46596794e-01 -2.26156928e-02
-2.57412474e-05 -7.46892821e-02 -2.22591127e-04  1.82950843e-01
 4.58725220e-04  7.96568438e-02 -5.51853265e-02 -2.07434750e-02
-7.77469056e-04  5.06073047e-03  9.39548399e-02 -3.26803575e-02
-3.54010758e-01  1.56936268e-01  5.09337964e-02 -5.36142765e-03
-3.87306374e-04  1.45157802e-01  1.31507663e-01 -7.87094415e-02
-4.02076554e-01  5.62993512e-02  5.56172804e-02 -1.09226900e-04
 0.00000000e+00  1.80701961e-01  4.81080008e-02 -1.20399999e-01
-3.62043425e-01  5.11453634e-02  5.88826590e-02  0.00000000e+00
-2.40709560e-04 -5.12007528e-02  2.61564221e-01 -1.98276068e-01
-1.53055812e-01  9.08531843e-02  2.80404960e-02 -1.32430108e-04
-8.31464092e-04 -1.38501536e-01  1.25362591e-01 -9.53550909e-02
 1.79252586e-01  1.04022589e-02 -1.26172454e-02 -4.33327778e-03
-3.06386151e-06 -5.87699279e-03 -6.86919749e-02  2.12758661e-01
-3.92647187e-02 -4.40627541e-02 -1.00284457e-02 -1.01487278e-02]
```