

```
In [39]: import pandas as pd
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold, cross_val_score
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

```
In [40]: data = pd.read_csv('Zoo.csv')
data
```

Out[40]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes
0	aardvark	1	0	0	1	0	0	1	1	1	✓
1	antelope	1	0	0	1	0	0	0	1	1	✓
2	bass	0	0	1	0	0	1	1	1	1	(
3	bear	1	0	0	1	0	0	1	1	1	✓
4	boar	1	0	0	1	0	0	1	1	1	✓
...	...	...	...	...	...	...	...	...	...	...	...
96	wallaby	1	0	0	1	0	0	0	1	1	✓
97	wasp	1	0	1	0	1	0	0	0	0	✓
98	wolf	1	0	0	1	0	0	1	1	1	✓
99	worm	0	0	1	0	0	0	0	0	0	✓
100	wren	0	1	1	0	1	0	0	0	1	✓

101 rows × 18 columns



In [41]: data.describe()

Out[41]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toc
<b>count</b>	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.00
<b>mean</b>	0.425743	0.198020	0.584158	0.405941	0.237624	0.356436	0.554455	0.60
<b>std</b>	0.496921	0.400495	0.495325	0.493522	0.427750	0.481335	0.499505	0.49
<b>min</b>	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
<b>25%</b>	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
<b>50%</b>	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	1.00
<b>75%</b>	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1.000000	1.00
<b>max</b>	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

In [42]: data.shape

Out[42]: (101, 18)

In [43]: data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101 entries, 0 to 100
Data columns (total 18 columns):
#   Column          Non-Null Count  Dtype
---  -
0   animal name     101 non-null   object
1   hair            101 non-null   int64
2   feathers        101 non-null   int64
3   eggs            101 non-null   int64
4   milk            101 non-null   int64
5   airborne        101 non-null   int64
6   aquatic         101 non-null   int64
7   predator        101 non-null   int64
8   toothed         101 non-null   int64
9   backbone        101 non-null   int64
10  breathes        101 non-null   int64
11  venomous        101 non-null   int64
12  fins            101 non-null   int64
13  legs            101 non-null   int64
14  tail            101 non-null   int64
15  domestic        101 non-null   int64
16  catsize         101 non-null   int64
17  type            101 non-null   int64
dtypes: int64(17), object(1)
memory usage: 14.3+ KB
```

In [44]: data.dtypes

```
Out[44]: animal name    object
         hair          int64
         feathers      int64
         eggs         int64
         milk         int64
         airborne      int64
         aquatic       int64
         predator      int64
         toothed       int64
         backbone      int64
         breathes      int64
         venomous      int64
         fins          int64
         legs          int64
         tail          int64
         domestic      int64
         catsize       int64
         type          int64
         dtype: object
```

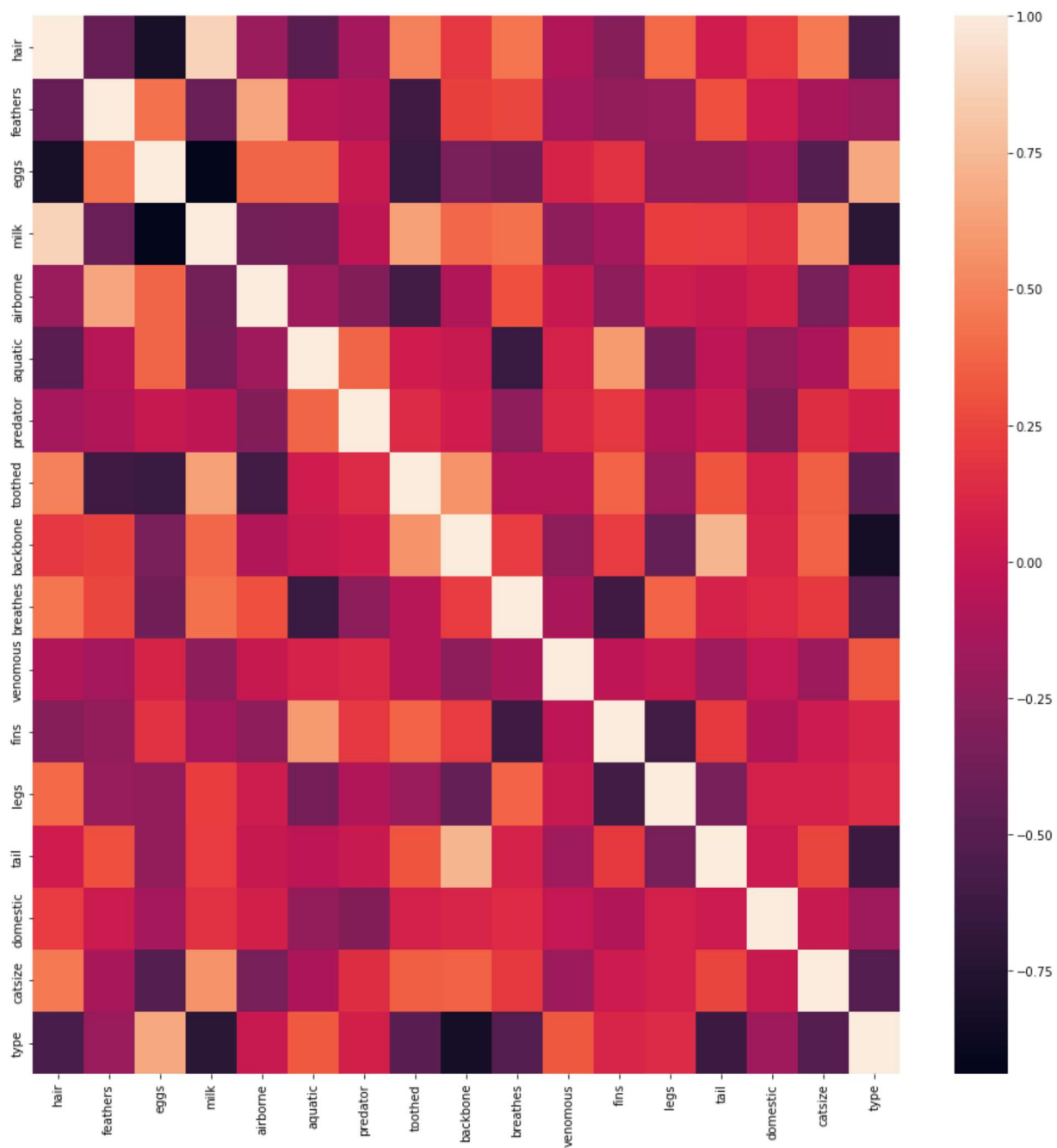
In [45]: correlation = data.corr()  
correlation

Out[45]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize	type
hair	1.000000	-0.427851	-0.817382	0.878503	-0.198431	-0.473554	-0.154769	0.492531	0.191681	0.441149	-0.104245	-0.280313	0.394009	0.048973	0.207208	0.455020	-0.562384
feathers	-0.427851	1.000000	0.419248	-0.410761	0.656553	-0.058552	-0.104430	-0.613631	0.231403	0.254588	-0.145739	-0.223541	-0.206686	0.292569	0.031586	-0.135934	-0.197520
eggs	-0.817382	0.419248	1.000000	-0.938848	0.376646	0.376244	0.011605	-0.642150	-0.340420	-0.382777	0.098689	0.164796	-0.224918	-0.221090	-0.155610	-0.514650	0.661825
milk	0.878503	-0.410761	-0.938848	1.000000	-0.366765	-0.362613	-0.029721	0.628168	0.384958	0.423527	-0.242449	-0.156328	0.214196	0.210026	0.163928	0.574906	-0.723683
airborne	-0.198431	0.656553	0.376646	-0.366765	1.000000	-0.172638	-0.295181	-0.594311	-0.104718	0.286039	0.008528	-0.251157	0.043712	0.009482	0.063274	-0.349768	0.022677
aquatic	-0.473554	-0.058552	0.376244	-0.362613	-0.172638	1.000000	0.375978	0.053150	0.022463	-0.637506	0.087915	0.604492	-0.360638	-0.034642	-0.224308	-0.111866	0.326639
predator	-0.154769	-0.104430	0.011605	-0.029721	-0.295181	0.375978	1.000000	0.129452	0.051022	-0.262931	0.115391	0.190302	-0.099723	0.018947	-0.309794	0.144790	0.061179
toothed	0.492531	-0.613631	-0.642150	0.628168	-0.594311	0.053150	0.129452	1.000000	0.575085	-0.065690	-0.062344	0.364292	-0.193476	0.310368	0.069430	0.344010	-0.471527
backbone	0.191681	0.231403	-0.340420	0.384958	-0.104718	0.022463	0.051022	0.575085	1.000000	0.262931	0.062344	0.364292	-0.193476	0.310368	0.069430	0.344010	-0.471527
breathes	0.441149	0.254588	-0.382777	0.423527	0.286039	-0.637506	-0.262931	-0.065690	0.262931	1.000000	0.062344	0.364292	-0.193476	0.310368	0.069430	0.344010	-0.471527
venomous	-0.104245	-0.145739	0.098689	-0.242449	0.008528	0.087915	0.115391	-0.062344	0.062344	0.062344	1.000000	0.364292	-0.193476	0.310368	0.069430	0.344010	-0.471527
fins	-0.280313	-0.223541	0.164796	-0.156328	-0.251157	0.604492	0.190302	0.364292	0.364292	0.364292	0.364292	1.000000	-0.193476	0.310368	0.069430	0.344010	-0.471527
legs	0.394009	-0.206686	-0.224918	0.214196	0.043712	-0.360638	-0.099723	-0.193476	-0.193476	-0.193476	-0.193476	-0.193476	1.000000	0.310368	0.069430	0.344010	-0.471527
tail	0.048973	0.292569	-0.221090	0.210026	0.009482	-0.034642	0.018947	0.310368	0.310368	0.310368	0.310368	0.310368	0.310368	1.000000	0.069430	0.344010	-0.471527
domestic	0.207208	0.031586	-0.155610	0.163928	0.063274	-0.224308	-0.309794	0.069430	0.069430	0.069430	0.069430	0.069430	0.069430	0.069430	1.000000	0.344010	-0.471527
catsize	0.455020	-0.135934	-0.514650	0.574906	-0.349768	-0.111866	0.144790	0.344010	0.344010	0.344010	0.344010	0.344010	0.344010	0.344010	0.344010	1.000000	-0.471527
type	-0.562384	-0.197520	0.661825	-0.723683	0.022677	0.326639	0.061179	-0.471527	-0.471527	-0.471527	-0.471527	-0.471527	-0.471527	-0.471527	-0.471527	-0.471527	1.000000

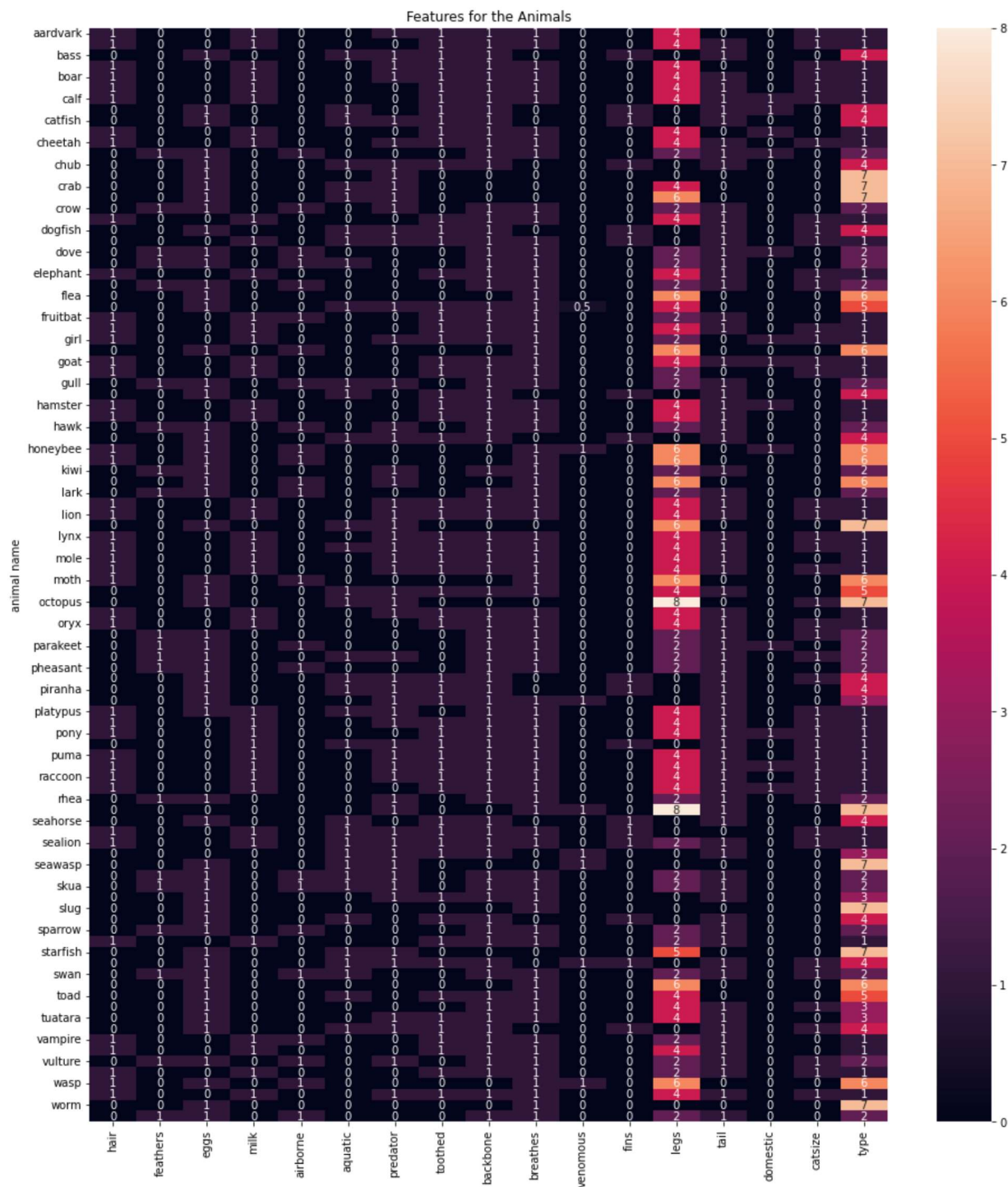
```
In [46]: plt.figure(figsize=(16,16))  
sns.heatmap(correlation)
```

Out[46]: <AxesSubplot:>



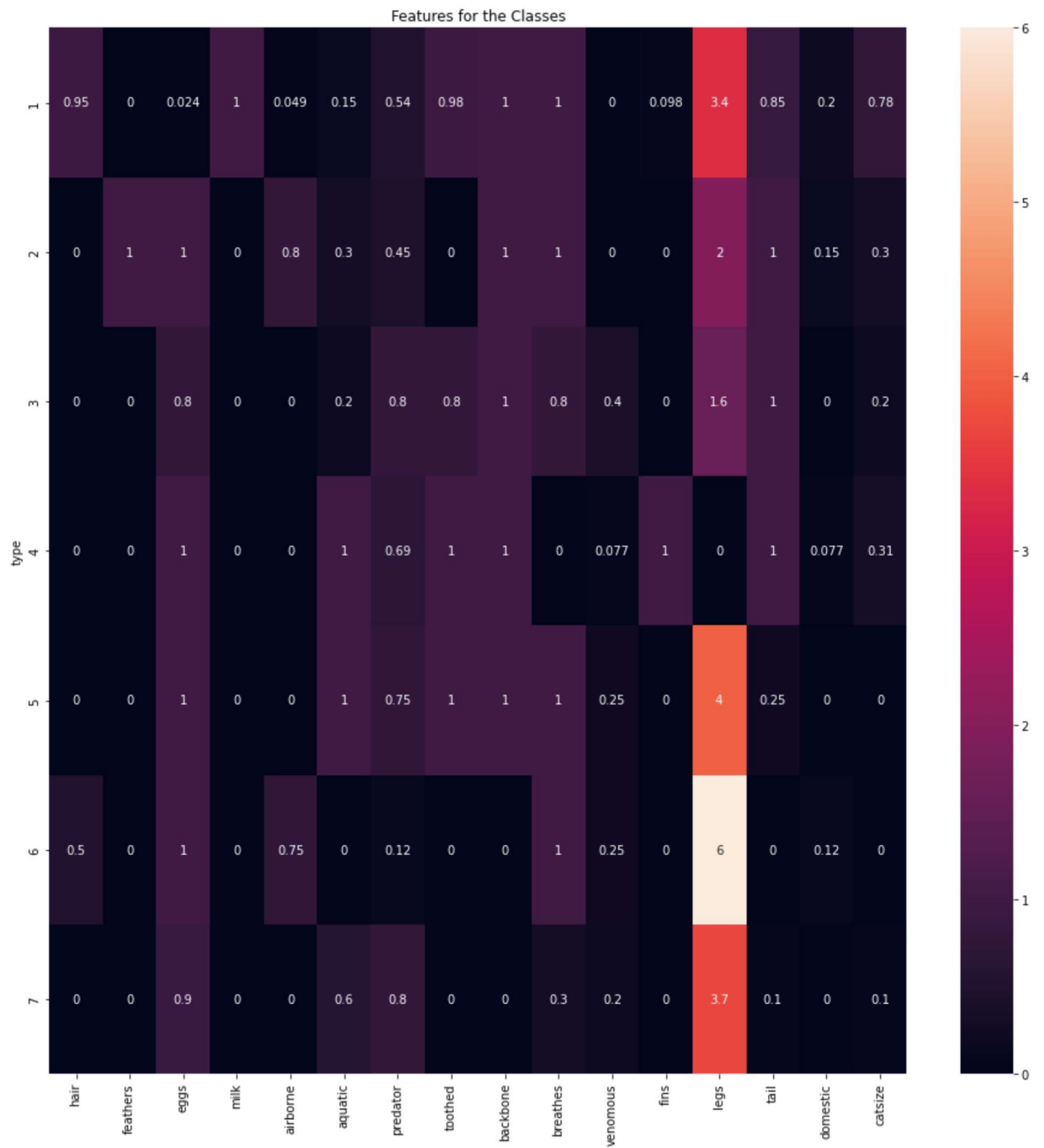
```
In [47]: data_temp = data.groupby(by = 'animal name').mean()
plt.figure(figsize=(16,18))
sns.heatmap(data_temp,annot=True)
plt.title('Features for the Animals')
```

```
Out[47]: Text(0.5, 1.0, 'Features for the Animals')
```



```
In [48]: data_temp = data.groupby(by='type').mean()
plt.figure(figsize=(16,16))
sns.heatmap(data_temp,annot = True)
plt.title('Features for the Classes')
```

```
Out[48]: Text(0.5, 1.0, 'Features for the Classes')
```



```
In [49]: data_1 = data.drop('animal name',axis=1)
data_1
```

Out[49]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous
0	1	0	0	1	0	0	1	1	1	1	
1	1	0	0	1	0	0	0	1	1	1	
2	0	0	1	0	0	1	1	1	1		0
3	1	0	0	1	0	0	1	1	1	1	
4	1	0	0	1	0	0	1	1	1	1	
...	...	...	...	...	...	...	...	...	...	...	...
96	1	0	0	1	0	0	0	1	1	1	
97	1	0	1	0	1	0	0	0	0		1
98	1	0	0	1	0	0	1	1	1	1	
99	0	0	1	0	0	0	0	0	0		1
100	0	1	1	0	1	0	0	0	1	1	

101 rows × 17 columns

```
In [50]: x = data_1.drop('type',axis=1)
y = data_1[['type']]
```

```
In [51]: x_train,x_test,y_train,y_test = train_test_split(x,y,random_state=0)
```

```
In [52]: x_train.shape,y_train.shape
```

Out[52]: ((75, 16), (75, 1))

```
In [53]: x_test.shape,y_test.shape
```

Out[53]: ((26, 16), (26, 1))

```
In [54]: knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.9466666666666667

```
In [55]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.9466666666666667

```
In [56]: knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.8533333333333334

```
In [57]: knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.8133333333333334

```
In [58]: std_scalar = StandardScaler()
std_scalar = std_scalar.fit_transform(x)
x_scaled = pd.DataFrame(data = std_scalar,columns=x.columns)
x_scaled
```

Out[58]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backboi
0	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	0.896421	0.809776	0.4650
1	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	-1.115547	0.809776	0.4650
2	-0.861034	-0.496904	0.843721	-0.826640	-0.558291	1.343710	0.896421	0.809776	0.4650
3	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	0.896421	0.809776	0.4650
4	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	0.896421	0.809776	0.4650
...	...	...	...	...	...	...	...	...	...
96	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	-1.115547	0.809776	0.4650
97	1.161395	-0.496904	0.843721	-0.826640	1.791182	-0.744208	-1.115547	-1.234909	-2.1470
98	1.161395	-0.496904	-1.185227	1.209717	-0.558291	-0.744208	0.896421	0.809776	0.4650
99	-0.861034	-0.496904	0.843721	-0.826640	-0.558291	-0.744208	-1.115547	-1.234909	-2.1470
100	-0.861034	2.012461	0.843721	-0.826640	1.791182	-0.744208	-1.115547	-1.234909	0.4650

101 rows × 16 columns



```
In [59]: x_train,x_test,y_train,y_test = train_test_split(x_scaled,y,random_state=0)
```

```
In [60]: x_train.shape,y_train.shape
```

Out[60]: ((75, 16), (75, 1))

```
In [61]: x_test.shape,y_test.shape
```

Out[61]: ((26, 16), (26, 1))



```
In [62]: knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.9733333333333334

```
In [63]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.96

```
In [64]: knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.8933333333333333

```
In [65]: knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(x_train,y_train)
y_pred = knn.predict(x_train)
print('Accuracy score :',accuracy_score(y_train,y_pred))
```

Accuracy score : 0.84

```
In [80]: kfold = KFold(n_splits=5,shuffle=True,random_state=14)
cv_scores = []

for i in range(1,50,2):
    knn_model = KNeighborsClassifier(n_neighbors=i)
    cross_val_scores = cross_val_score(estimator = knn_model,X = x_scaled,y=y,cv=
    print(i,'th Iteration:\n',cross_val_scores.mean().round(4))
    cv_scores.append(cross_val_scores.mean().round(4))
```

```
1 th Iteration:
0.96
3 th Iteration:
0.9505
5 th Iteration:
0.8905
7 th Iteration:
0.861
9 th Iteration:
0.8114
11 th Iteration:
0.8019
13 th Iteration:
0.8019
15 th Iteration:
0.7919
17 th Iteration:
0.7924
19 th Iteration:
0.7924
21 th Iteration:
0.7824
23 th Iteration:
0.7824
25 th Iteration:
0.7624
27 th Iteration:
0.7433
29 th Iteration:
0.7143
31 th Iteration:
0.6652
33 th Iteration:
0.6552
35 th Iteration:
0.6352
37 th Iteration:
0.6252
39 th Iteration:
0.6152
41 th Iteration:
0.5852
43 th Iteration:
0.5552
45 th Iteration:
```

```
0.5052
47 th Iteration:
0.4552
49 th Iteration:
0.4552
```

```
In [81]: cv_scores
```

```
Out[81]: [0.96,
0.9505,
0.8905,
0.861,
0.8114,
0.8019,
0.8019,
0.7919,
0.7924,
0.7924,
0.7824,
0.7824,
0.7624,
0.7433,
0.7143,
0.6652,
0.6552,
0.6352,
0.6252,
0.6152,
0.5852,
0.5552,
0.5052,
0.4552,
0.4552]
```

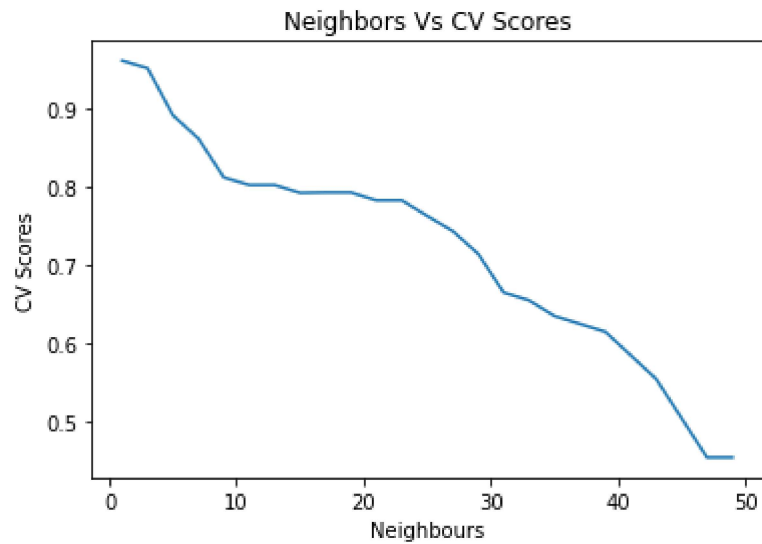
```
In [82]: max(cv_scores)
```

```
Out[82]: 0.96
```

```
In [83]: cv_scores.index(max(cv_scores))
```

```
Out[83]: 0
```

```
In [84]: plt.plot(range(1,50,2),cv_scores)
plt.xlabel('Neighbours')
plt.ylabel('CV Scores')
plt.title('Neighbors Vs CV Scores')
plt.show()
```



```
In [85]: knn.score(x_train,y_train)
```

```
Out[85]: 0.84
```

```
In [86]: knn.score(x_test,y_test)
```

```
Out[86]: 0.9230769230769231
```

```
In [ ]:
```