

Project

December 5, 2025

1 MAIN OBJECTIVE

1.1 USING UNSUPERVISED AND SUPERVISED LEARNING MODELS TO SEGREGATE AND PREDICT THE CLASS OF PUMPKIN SEED

2 DATASET USED = PUMPKIN SEED DATASET

Pumpkin seeds are frequently consumed as confection worldwide because of their adequate amount of protein, fat, carbohydrate, and mineral contents. This study was carried out on the two most important and quality types of pumpkin seeds, ‘‘Urgup_Sivrisi’’ and ‘‘Cercevelik’’, generally grown in Urgup and Karacaoren regions in Turkey. However, morphological measurements of 2500 pumpkin seeds of both varieties were made possible by using the gray and binary forms of threshold techniques. Considering morphological features, all the data were modeled with five different machine learning methods: Logistic Regression (LR), Multilayer Perceptrons (MLP), Support Vector Machine (SVM) and Random Forest (RF), and k-Nearest Neighbor (k-NN), which further determined the most successful method for classifying pumpkin seed varieties. However, the performances of the models were determined with the help of the 10 kfold cross-validation method. The accuracy rates of the classifiers were obtained as LR 87.92 percent, MLP 88.52 percent, SVM 88.64 percent, RF 87.56 percent, and k-NN 87.64 percent. DATASET: https://www.muratkoklu.com/datasets/Pumpkin_Seeds_Dataset.zip

TOTAL ROWS = 2500

FEATURES: |FEATURE|N ROWS| TYPE| |—|—|—| |0 Area | 2500 non-null | int64| 1 Perimeter | 2500 non-null | float64| 2 Major_Axis_Length | 2500 non-null | float64| 3 Minor_Axis_Length | 2500 non-null | float64| 4 Convex_Area | 2500 non-null | int64| 5 Equiv_Diameter | 2500 non-null | float64| 6 Eccentricity | 2500 non-null | float64| 7 Solidity | 2500 non-null | float64| 8 Extent | 2500 non-null | float64| 9 Roundness | 2500 non-null | float64| 10 Aspect_Ration | 2500 non-null | float64| 11 Compactness | 2500 non-null | float64| 12 Class | 2500 non-null | object | 13 LR | 2500 non-null | float64|

```
[40]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, \
    classification_report
from sklearn.cluster import KMeans, DBSCAN, HDBSCAN, MeanShift
```

```

from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV

```

```

[7]: dataset = pd.read_excel('Pumpkin_Seeds_Dataset.xlsx')
dataset.head()

```

```

[7]:
   Area  Perimeter  Major_Axis_Length  Minor_Axis_Length  Convex_Area  \
0  56276    888.242         326.1485         220.2388        56831
1  76631   1068.146         417.1932         234.2289        77280
2  71623   1082.987         435.8328         211.0457        72663
3  66458    992.051         381.5638         222.5322        67118
4  66107    998.146         383.8883         220.4545        67117

   Equiv_Diameter  Eccentricity  Solidity  Extent  Roundness  Aspect_Ration  \
0         267.6805         0.7376   0.9902  0.7453    0.8963         1.4809
1         312.3614         0.8275   0.9916  0.7151    0.8440         1.7811
2         301.9822         0.8749   0.9857  0.7400    0.7674         2.0651
3         290.8899         0.8123   0.9902  0.7396    0.8486         1.7146
4         290.1207         0.8187   0.9850  0.6752    0.8338         1.7413

   Compactness  Class
0         0.8207  Çerçvelik
1         0.7487  Çerçvelik
2         0.6929  Çerçvelik
3         0.7624  Çerçvelik
4         0.7557  Çerçvelik

```

```

[8]: dataset.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Area                  2500 non-null  int64
1   Perimeter             2500 non-null  float64
2   Major_Axis_Length     2500 non-null  float64
3   Minor_Axis_Length     2500 non-null  float64
4   Convex_Area           2500 non-null  int64
5   Equiv_Diameter        2500 non-null  float64
6   Eccentricity          2500 non-null  float64
7   Solidity              2500 non-null  float64
8   Extent                2500 non-null  float64
9   Roundness             2500 non-null  float64
10  Aspect_Ration         2500 non-null  float64
11  Compactness           2500 non-null  float64
12  Class                 2500 non-null  object

```

```
dtypes: float64(10), int64(2), object(1)
memory usage: 254.0+ KB
```

```
[9]: dataset.isna().sum()
```

```
[9]: Area          0
     Perimeter     0
     Major_Axis_Length  0
     Minor_Axis_Length  0
     Convex_Area    0
     Equiv_Diameter  0
     Eccentricity   0
     Solidity       0
     Extent         0
     Roundness      0
     Aspect_Ration  0
     Compactness    0
     Class          0
     dtype: int64
```

```
[10]: dataset.describe()
```

```
[10]:
```

	Area	Perimeter	Major_Axis_Length	Minor_Axis_Length	\
count	2500.000000	2500.000000	2500.000000	2500.000000	
mean	80658.220800	1130.279015	456.601840	225.794921	
std	13664.510228	109.256418	56.235704	23.297245	
min	47939.000000	868.485000	320.844600	152.171800	
25%	70765.000000	1048.829750	414.957850	211.245925	
50%	79076.000000	1123.672000	449.496600	224.703100	
75%	89757.500000	1203.340500	492.737650	240.672875	
max	136574.000000	1559.450000	661.911300	305.818000	

	Convex_Area	Equiv_Diameter	Eccentricity	Solidity	Extent	\
count	2500.000000	2500.000000	2500.000000	2500.000000	2500.000000	
mean	81508.084400	319.334230	0.860879	0.989492	0.693205	
std	13764.092788	26.891920	0.045167	0.003494	0.060914	
min	48366.000000	247.058400	0.492100	0.918600	0.468000	
25%	71512.000000	300.167975	0.831700	0.988300	0.658900	
50%	79872.000000	317.305350	0.863700	0.990300	0.713050	
75%	90797.750000	338.057375	0.897025	0.991500	0.740225	
max	138384.000000	417.002900	0.948100	0.994400	0.829600	

	Roundness	Aspect_Ration	Compactness
count	2500.000000	2500.000000	2500.000000
mean	0.791533	2.041702	0.704121
std	0.055924	0.315997	0.053067
min	0.554600	1.148700	0.560800
25%	0.751900	1.801050	0.663475

50%	0.797750	1.984200	0.707700
75%	0.834325	2.262075	0.743500
max	0.939600	3.144400	0.904900

3 FEATURE ENGINEERING

TAKE LATUS RECTUM EQUAL TO $2 * (\text{MINOR_AXIS_LENGTH})^2 / \text{MAJOR_AXIS_LENGTH}$
 # DATA CLEANING REMOVING SOLIDITY AS VARIANCE IN SOLIDITY VERY LITTLE
 NOT PROVIDING VALUABLE INFO

```
[11]: dataset['LR'] = 2*dataset['Major_Axis_Length']**2 /
↳dataset['Minor_Axis_Length']
```

```
[12]: dataset.head()
```

```
[12]:
```

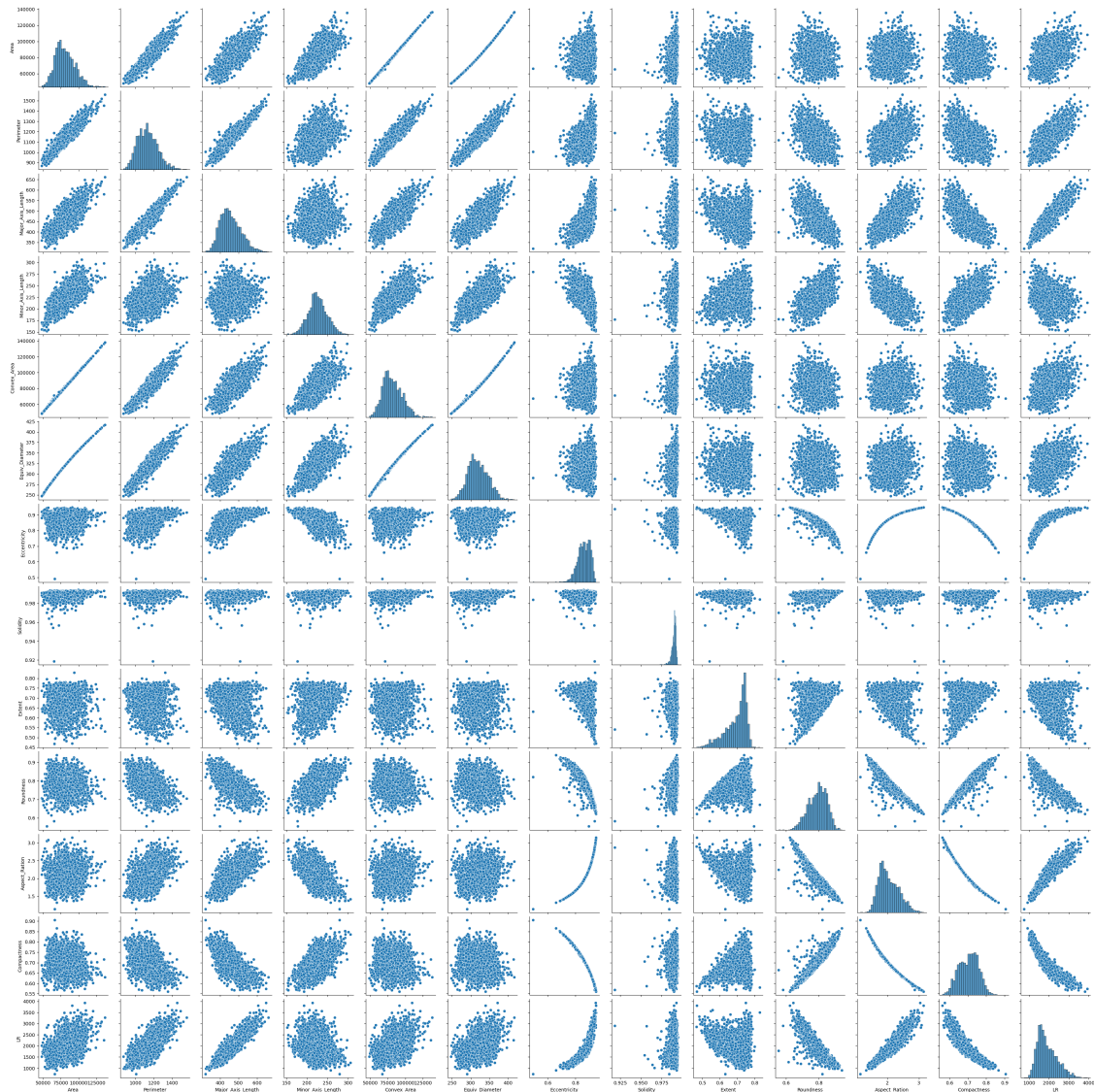
	Area	Perimeter	Major_Axis_Length	Minor_Axis_Length	Convex_Area	\
0	56276	888.242	326.1485	220.2388	56831	
1	76631	1068.146	417.1932	234.2289	77280	
2	71623	1082.987	435.8328	211.0457	72663	
3	66458	992.051	381.5638	222.5322	67118	
4	66107	998.146	383.8883	220.4545	67117	

	Equiv_Diameter	Eccentricity	Solidity	Extent	Roundness	Aspect_Ration	\
0	267.6805	0.7376	0.9902	0.7453	0.8963	1.4809	
1	312.3614	0.8275	0.9916	0.7151	0.8440	1.7811	
2	301.9822	0.8749	0.9857	0.7400	0.7674	2.0651	
3	290.8899	0.8123	0.9902	0.7396	0.8486	1.7146	
4	290.1207	0.8187	0.9850	0.6752	0.8338	1.7413	

	Compactness	Class	LR
0	0.8207	Çerçvelik	965.977331
1	0.7487	Çerçvelik	1486.154494
2	0.6929	Çerçvelik	1800.086233
3	0.7624	Çerçvelik	1308.493184
4	0.7557	Çerçvelik	1336.967282

```
[32]: import seaborn as sns
sns.pairplot(dataset)
```

```
[32]: <seaborn.axisgrid.PairGrid at 0x70e765b76f90>
```



```
[13]: x = dataset.drop(['Major_Axis_Length', 'Class', "Solidity"],
    ↪, "Minor_Axis_Length"], axis=1)
y = dataset['Class']
```

```
[24]: np.unique(y)
```

```
[24]: array([0, 1])
```

ENCODING CLASS

```
[15]: from sklearn.preprocessing import LabelEncoder
```

```
[17]: le = LabelEncoder()  
      y = le.fit_transform(y)
```

```
[18]: y
```

```
[18]: array([0, 0, 0, ..., 1, 1, 1], shape=(2500,))
```

```
[28]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

```
[20]: svc = SVC()
```

4 SVM

Achieved Accuracy of 87.6% on test dataset

```
[86]: from sklearn.pipeline import Pipeline  
      pipe = Pipeline([  
          ('scaler', StandardScaler()),  
          ('classifier', SVC())  
      ])
```

```
[87]: pipe.fit(x_train, y_train)
```

```
[87]: Pipeline(steps=[('scaler', StandardScaler()), ('classifier', SVC())])
```

```
[88]: accuracy_score(pipe.predict(x_test), y_test)
```

```
[88]: 0.876
```

5 Random Forest Classifier

Accuracy: 87.6

```
[35]: from sklearn.ensemble import RandomForestClassifier
```

```
[71]: pipe2= Pipeline([  
      ('scaler', StandardScaler()),  
      ('tree', RandomForestClassifier())  
  ])
```

```
[72]: pipe2.fit(x_train, y_train)  
      accuracy_score(pipe2.predict(x_test), y_test)*100
```

```
[72]: 87.6
```

6 Decision Tree

Accuracy 84.2

```
[79]: from sklearn.tree import DecisionTreeClassifier
pipe3 = Pipeline([
    ('scaler', StandardScaler()),
    ('tree', DecisionTreeClassifier())
])
pipe3.fit(x_train, y_train)
accuracy_score(pipe3.predict(x_test), y_test)*100
```

[79]: 84.2

```
[74]: from sklearn.mixture import GaussianMixture
from sklearn.decomposition import PCA, KernelPCA
```

6.0.1 USING DIMENSIONALITY REDUCTION

PCA WITH RANDOM TREE CLASSIFIER Accuracy 85.4

```
[99]: pipe4 = Pipeline([
    ('scaler', StandardScaler()),
    ('pca', PCA(n_components=2)),
    ('tree', RandomForestClassifier())
])
pipe4.fit(x_train, y_train)
accuracy_score(pipe4.predict(x_test), y_test)*100
```

[99]: 85.39999999999999

7 Model Evaluation

Random Forest and SVM are better than Decision Tree classifier PCA is not helping improving the model performance. For improving accuracy we can shift to Deep Neural Networks

8

8.1 UNSUPERVISED IS NOT RECOMMENDED ON THIS DATASET

ACCURACY IS AROUND 50 - 55%

```
[132]: km = KMeans(n_clusters=2)
```

```
[133]: km.fit(x_train_transformed, y_train)
```

```
[133]: KMeans(n_clusters=2)
```

```
[134]: pca = PCA(n_components=3)  
pca.fit(x_train)
```

```
[134]: PCA(n_components=3)
```

```
[135]: preds = km.predict(pca.transform(x_test))
```

```
[136]: accuracy_score(preds, y_test)
```

```
[136]: 0.566
```

8.1.1 INSIGHTS

MODEL CAN BE DEPLOYED AT LARGE SCALE FARM IN SEGREGATING PUMPKIN SEEDS