RAISIN BINARY CLASSIFICATION MODELS

Prediction with Logistic Regression + KNN + SVM + DTC

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Introduction

This project aims to classify two different varieties of raisins (Besni and Keçimen) grown in Turkey using their morphological features. By performing Exploratory Data Analysis (EDA) and implementing logistic regression models, the goal is to build effective classification models for raisin variety prediction. the aim is to enhance the understanding of raisin varieties and improve classification accuracy.

Objectives

- Understand the dataset and its features.
- Clean and prepare the data for modelling.
- Feature engineering.
- Implement logistic regression algorithms to classify raisin varieties.
- Optimize model performance by tuning hyperparameters and focusing on important features.
- Compare the performance of logistic regression with other classification algorithms.

*The dataset and results are used for educational purposes, demonstrating the application of advanced machine learning techniques on real-world data. We aim to build an effective classification model to predict the type of raisin grains and gain a deeper understanding of machine learning techniques.

About the Dataset

The dataset contains two types of raisins (Keçimen and Besni) grown in Turkey. Images of Kecimen and Besni raisin varieties were obtained with CVS. A total of 900 raisin grains were used, including 450 pieces from both varieties. These images were subjected to various stages of pre-processing and 7 morphological features were extracted.

Dataset: Raisin Grain

- **Content:** 2 type of raisins (Besni(0) and Keçimen(1)).
- **Number of Rows:** 900
- **Number of Columns:** 8

INPUTS

- `Area` : The number of pixels within the boundaries of the raisin grain.
- `Perimeter` : The distance between the boundaries of the raisin grain and the surrounding pixels.
- `MajorAxisLength` : The length of the longest line that can be drawn on the raisin grain.

- `MinorAxisLength` : The length of the shortest line that can be drawn on the raisin grain.
- `Eccentricity` : A measure of the eccentricity of the ellipse which has the same moments as the raisins.
- `ConvexArea` : The number of pixels in the smallest convex shell of the region formed by the raisin grain.
- `Extent` : The ratio of the region formed by the raisin grain to the total pixels in the bounding box.

Reference

- CINAR I., KOKLU M. and TASDEMIR S., (2020). Classification of Raisin Grains Using Machine Vision and Artificial Intelligence Methods, Gazi Journal of Engineering Sciences, vol. 6, no. 3, pp. 200-209, December, 2020, DOI: https://doi.org/10.30855/gmbd.2020.03.03

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EXPLORATORY DATA ANALYSIS (EDA)

In [121…

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats

from sklearn.model_selection import train_test_split,cross_validate, GridSearchCV, StratifiedKFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler, LabelEncoder

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline

from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, log_loss
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay
from sklearn.metrics import RocCurveDisplay, PrecisionRecallDisplay, roc_auc_score, auc, roc_curve, average_precision_score, precisio

plt.rcParams["figure.figsize"] = (10,6)
pd.options.display.float_format = '{:.3f}'.format

%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
warnings.warn("this will not show")
```

In [2]:

```
df0 = pd.read_excel('/kaggle/input/raisin-dataset/Raisin_Dataset/Raisin_Dataset.xlsx')
df = df0.copy()
```

In [3]:

```
df.shape
```

Out[3]: (900, 8)

In [4]:

```
df.head()
```

Out[4]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
0	87524	442.246	253.291	0.820	90546	0.759	1184.040	Kecimen
1	75166	406.691	243.032	0.802	78789	0.684	1121.786	Kecimen
2	90856	442.267	266.328	0.798	93717	0.638	1208.575	Kecimen
3	45928	286.541	208.760	0.685	47336	0.700	844.162	Kecimen
4	79408	352.191	290.828	0.564	81463	0.793	1073.251	Kecimen

In [5]:
```
df.tail()
```

Out[5]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
895	83248	430.077	247.839	0.817	85839	0.669	1129.072	Besni
896	87350	440.736	259.293	0.809	90899	0.636	1214.252	Besni
897	99657	431.707	298.837	0.722	106264	0.741	1292.828	Besni
898	93523	476.344	254.176	0.846	97653	0.659	1258.548	Besni
899	85609	512.082	215.272	0.907	89197	0.632	1272.862	Besni

Missing Values

In [6]:
```
# Check out the missing values

missing_count = df.isnull().sum()
value_count = df.isnull().count()
missing_percentage = round(missing_count / value_count * 100, 2)
missing_df = pd.DataFrame({"count": missing_count, "percentage": missing_percentage})
missing_df
```

Out[6]:

	count	percentage
Area	0	0.000
MajorAxisLength	0	0.000
MinorAxisLength	0	0.000
Eccentricity	0	0.000
ConvexArea	0	0.000
Extent	0	0.000
Perimeter	0	0.000
Class	0	0.000

Duplicated Values

In [8]:
```
# Checks duplicates and drops them

def duplicate_values(df):
    print("Duplicate check...")
    num_duplicates = df.duplicated(subset=None, keep='first').sum()
    if num_duplicates > 0:
        print("There are", num_duplicates, "duplicated observations in the dataset.")
        df.drop_duplicates(keep='first', inplace=True)
        print(num_duplicates, "duplicates were dropped!")
        print("No more duplicate rows!")
    else:
        print("There are no duplicated observations in the dataset.")

duplicate_values(df)
```

```
Duplicate check...
There are no duplicated observations in the dataset.
```

Basic Statistics

In [9]:
```
df.describe().T
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
Area	900.000	87804.128	39002.111	25387.000	59348.000	78902.000	105028.250	235047.000
MajorAxisLength	900.000	430.930	116.035	225.630	345.443	407.804	494.187	997.292
MinorAxisLength	900.000	254.488	49.989	143.711	219.111	247.848	279.889	492.275
Eccentricity	900.000	0.782	0.090	0.349	0.742	0.799	0.843	0.962
ConvexArea	900.000	91186.090	40769.290	26139.000	61513.250	81651.000	108375.750	278217.000
Extent	900.000	0.700	0.053	0.380	0.671	0.707	0.735	0.835
Perimeter	900.000	1165.907	273.764	619.074	966.411	1119.509	1308.390	2697.753

In [10]:
```
df.info()
```

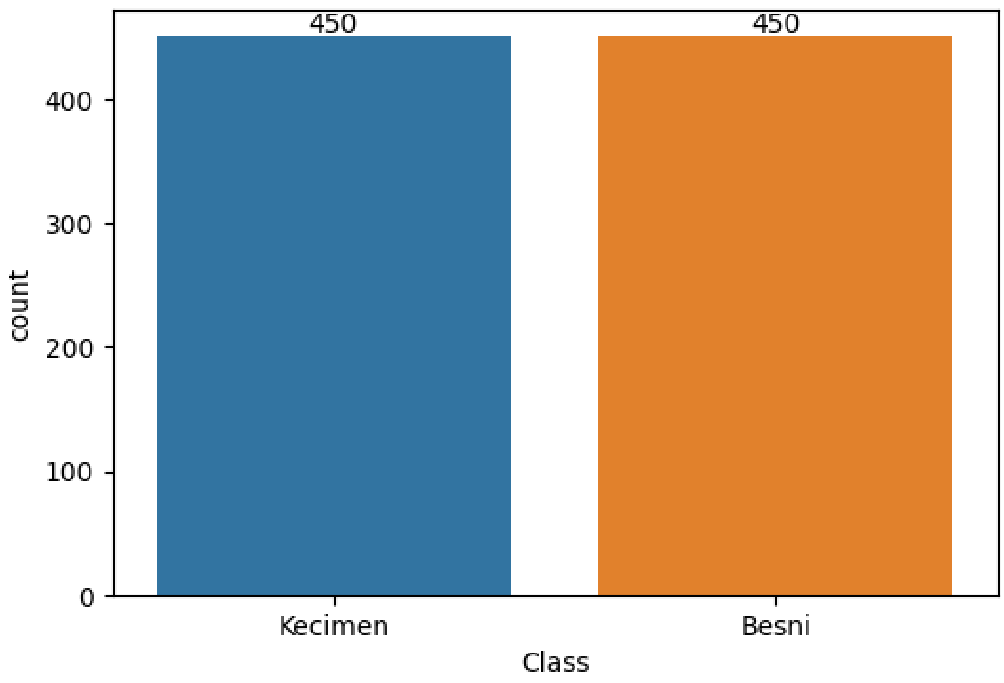
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             900 non-null    int64  
 1   MajorAxisLength  900 non-null    float64
 2   MinorAxisLength  900 non-null    float64
 3   Eccentricity     900 non-null    float64
 4   ConvexArea       900 non-null    int64  
 5   Extent           900 non-null    float64
 6   Perimeter        900 non-null    float64
 7   Class            900 non-null    object 
dtypes: float64(5), int64(2), object(1)
memory usage: 56.4+ KB
```

Categorical Features

In [11]:
```
# Target Feature

df.Class.value_counts() # Balanced Data
```

Out[11]:
```
Class
Kecimen    450
Besni      450
Name: count, dtype: int64
```

In [12]:
```
plt.figure(figsize = (6,4))
ax = sns.countplot(x='Class', data=df)
ax.bar_label(ax.containers[0]);
```



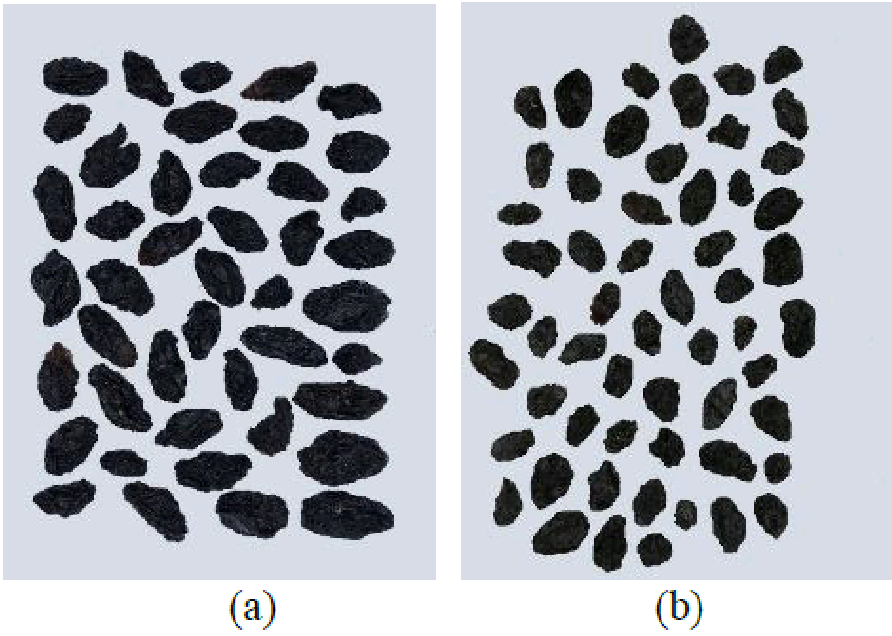
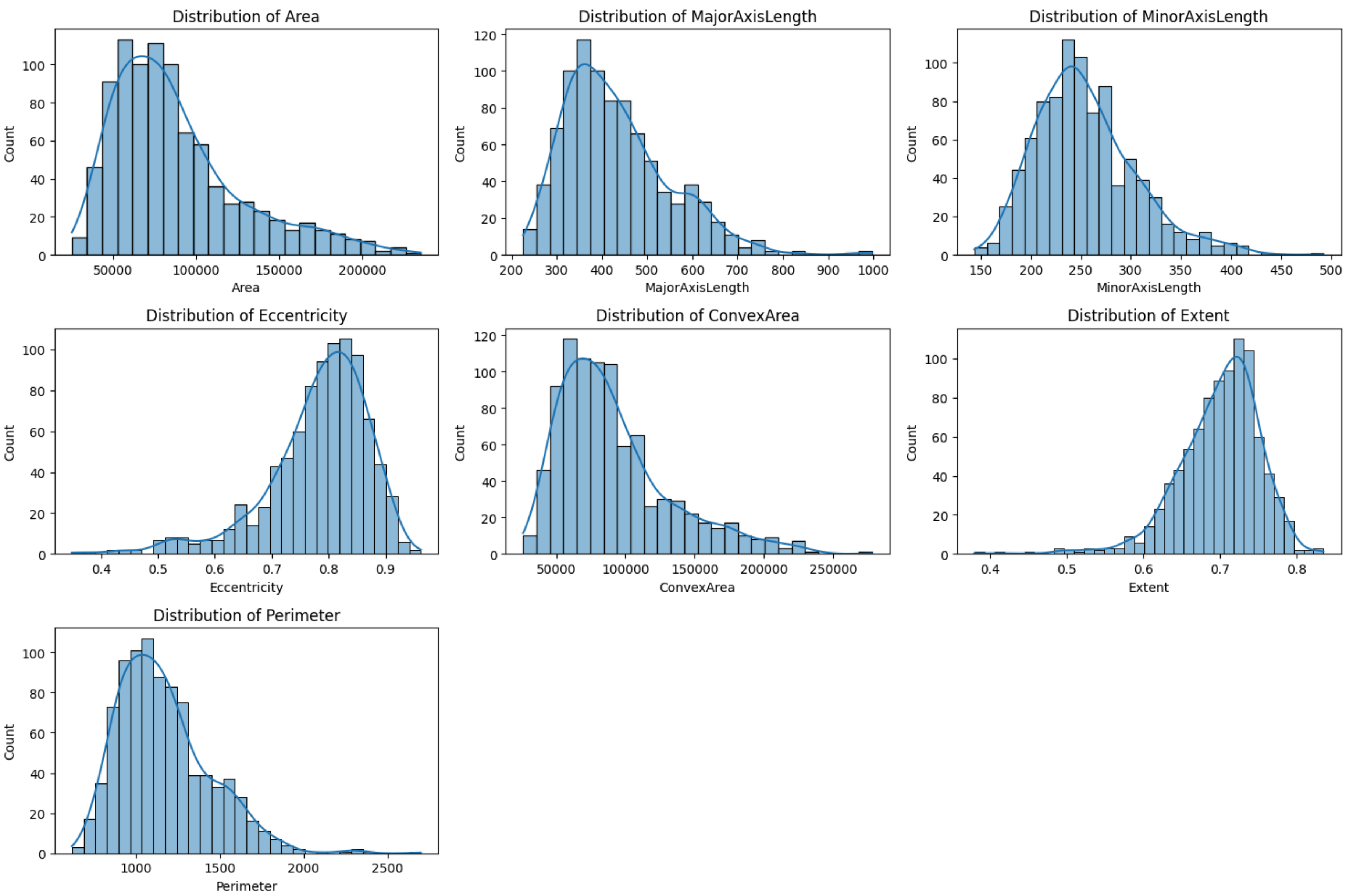


Figure 3. Sample image of raisin varieties used in the study ((a) Besni, (b) Kecimen) *(Çalışmada kullanılan kuru üzüm çeşitlerine ait örnek görüntü ((a) Besni, (b) Keçimen))*

CINAR I., KOKLU M. and TASDEMIR S., (2020). Classification of Raisin Grains Using Machine Vision and Artificial Intelligence Methods, Gazi Journal of Engineering Sciences, vol. 6, no. 3, pp. 200-209, December, 2020, DOI: https://doi.org/10.30855/gmbd.2020.03.03

Numerical Features

In [13]:
```
numerical_df = df.select_dtypes(include=['number'])

plt.figure(figsize=(15, 10))

num_vars = len(numerical_df.columns)

for i, var in enumerate(numerical_df.columns, 1):
    plt.subplot((num_vars // 3) + 1, 3, i)
    sns.histplot(data=df, x=var, kde=True)
    plt.title(f'Distribution of {var}')

plt.tight_layout()
plt.show()
```



Feature Engineering

Label the Target Feature

- 0: Besni
- 1: Kecimen

In [14]:
```
labelencoder = LabelEncoder()
df["target"] = labelencoder.fit_transform(df["Class"])
```

In [15]:
```
besni_count = df[df['target'] == 0].shape[0]
kecimen_count = df[df['target'] == 1].shape[0]

print(f"Besni (0) count: {besni_count}")
print(f"Keçimen (1) count: {kecimen_count}")
```

```
Besni (0) count: 450
Keçimen (1) count: 450
```

In [16]:
```
print(df.shape)
df.sample(3)
```

```
(900, 9)
```

Out[16]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class	target
694	172783	820.724	352.194	0.903	219952	0.497	2289.889	Besni	0
649	113164	486.766	297.110	0.792	116531	0.740	1313.092	Besni	0
616	199015	615.417	413.927	0.740	201464	0.769	1687.866	Besni	0

In [17]:
```
df=df.drop(['Class'], axis=1)
```

In [18]:
```
print(df.shape)
df.head(3)
```

```
(900, 8)
```

Out[18]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	target
0	87524	442.246	253.291	0.820	90546	0.759	1184.040	1
1	75166	406.691	243.032	0.802	78789	0.684	1121.786	1
2	90856	442.267	266.328	0.798	93717	0.638	1208.575	1

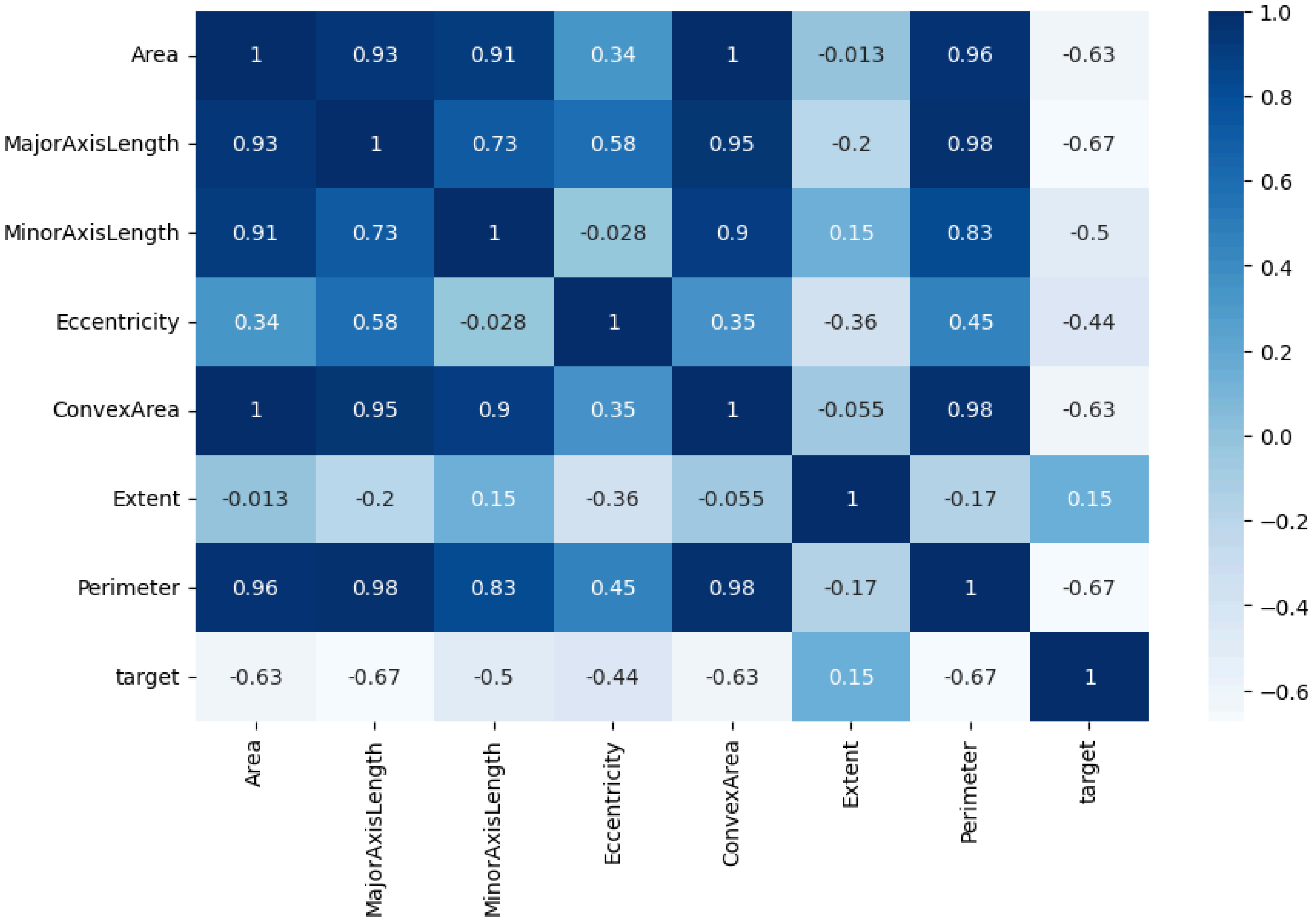
In [19]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             900 non-null    int64  
 1   MajorAxisLength  900 non-null    float64
 2   MinorAxisLength  900 non-null    float64
 3   Eccentricity     900 non-null    float64
 4   ConvexArea       900 non-null    int64  
 5   Extent           900 non-null    float64
 6   Perimeter        900 non-null    float64
 7   target           900 non-null    int64  
dtypes: float64(5), int64(3)
memory usage: 56.4 KB
```

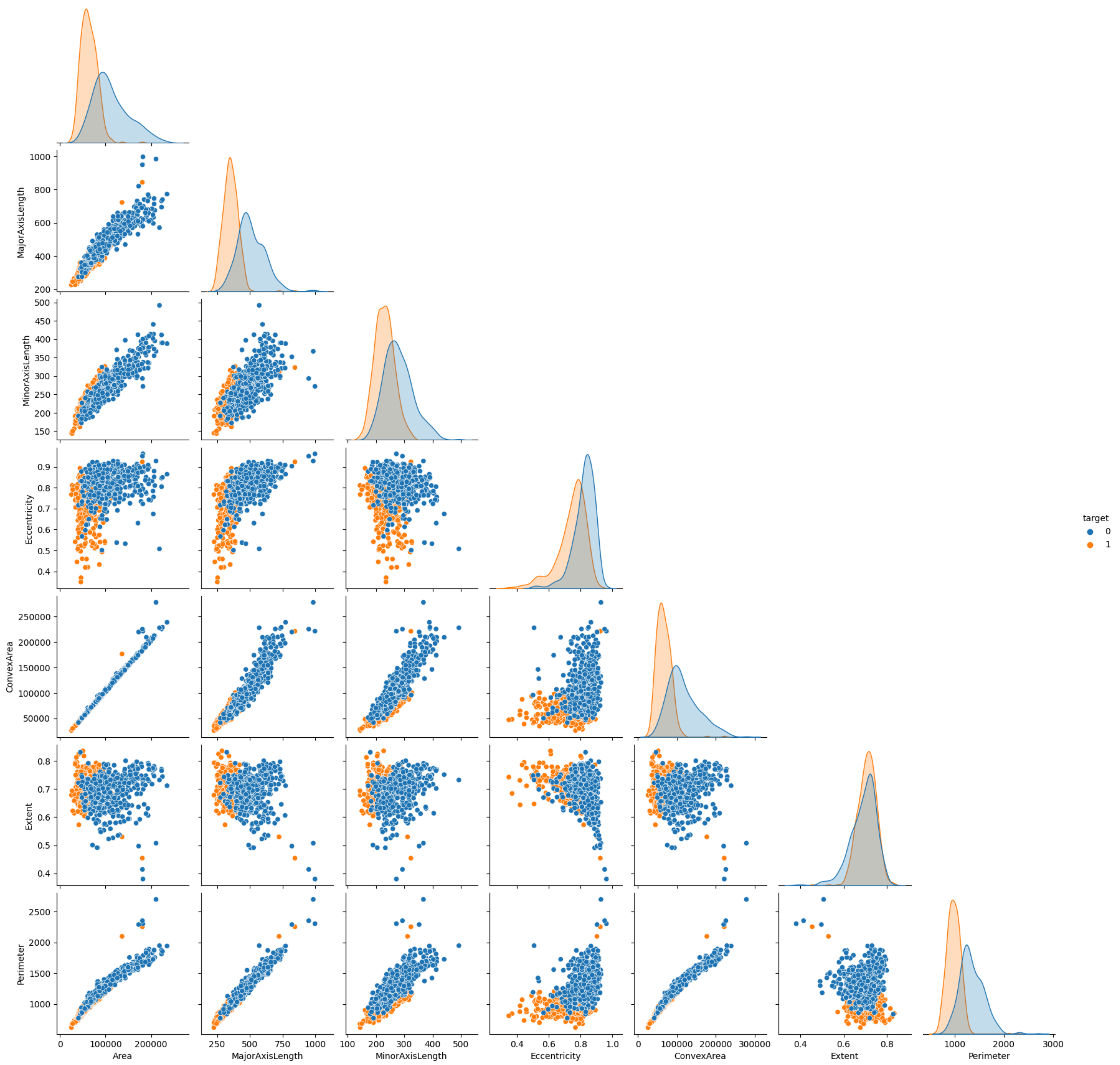
Correlations

In [20]:
```
# 0: Besni
# 1: Kecimen

sns.heatmap(df.corr(), cmap='Blues', annot= True)
```

Out[20]: <Axes: >



In [21]:
```
# 0: Besni
# 1: Kecimen

sns.pairplot(data=df, corner=True, hue='target');
```

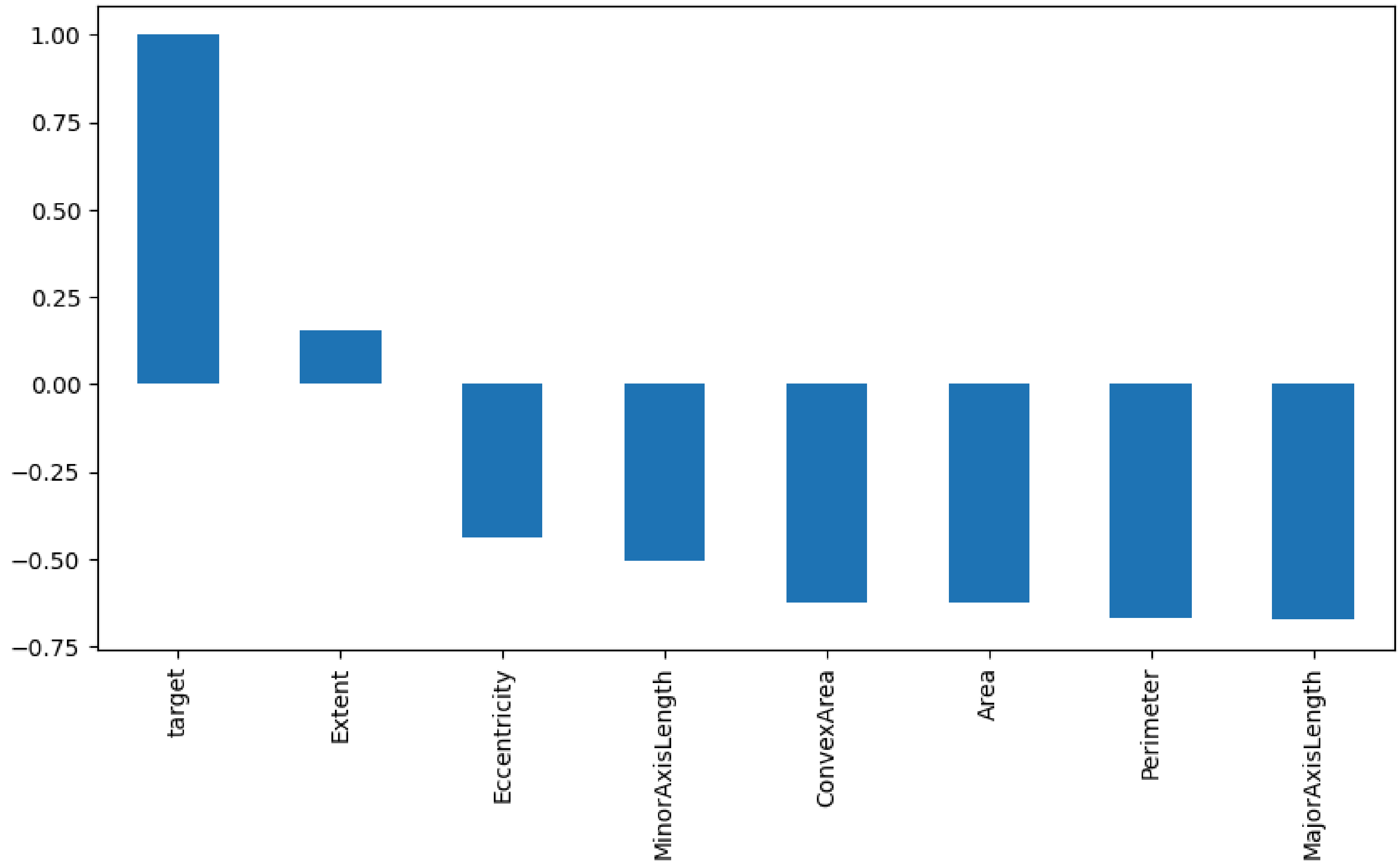


In [22]:
```
corr = df.corr()['target'].sort_values(ascending=False)
corr
```

Out[22]:
```
target             1.000
Extent             0.155
Eccentricity      -0.438
MinorAxisLength   -0.503
ConvexArea        -0.626
Area              -0.626
Perimeter         -0.666
MajorAxisLength   -0.673
Name: target, dtype: float64
```

In [23]:
```
# 0: Besni
# 1: Kecimen

corr.plot(kind='bar',figsize=(10,5))
```

Out[23]: <Axes: >



In [24]:
```
# Check Multicolinarty between features

def color_custom(val):
    if val > 0.90 and val < 0.99:
        color = 'red'
    elif val >= 1:
        color = 'blue'
    else:
        color = 'black'
    return f'color: {color}'

df.corr().style.map(color_custom)
```

Out[24]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	target
Area	1.000000	0.932774	0.906650	0.336107	0.995920	-0.013499	0.961352	-0.625715
MajorAxisLength	0.932774	1.000000	0.728030	0.583608	0.945031	-0.203866	0.977978	-0.673194
MinorAxisLength	0.906650	0.728030	1.000000	-0.027683	0.895651	0.145322	0.827417	-0.503102
Eccentricity	0.336107	0.583608	-0.027683	1.000000	0.348210	-0.361061	0.447845	-0.438500
ConvexArea	0.995920	0.945031	0.895651	0.348210	1.000000	-0.054802	0.976612	-0.625567
Extent	-0.013499	-0.203866	0.145322	-0.361061	-0.054802	1.000000	-0.173449	0.154689
Perimeter	0.961352	0.977978	0.827417	0.447845	0.976612	-0.173449	1.000000	-0.665981
target	-0.625715	-0.673194	-0.503102	-0.438500	-0.625567	0.154689	-0.665981	1.000000

Correlation Analysis

1. **Intercorrelated Features:**
    - **Area, MajorAxisLength, ConvexArea, and Perimeter:** These features are highly correlated with each other (above 0.9), indicating redundancy.

2. **Correlations with Target (0: Besni, 1: Keçimen):**
    - **Area, MajorAxisLength, ConvexArea, and Perimeter:** Strong negative correlations with the target variable (-0.63 to -0.67).
    - Higher values of these features make it more likely that the raisin is Besni.
    - **Eccentricity and MinorAxisLength:** Moderate negative correlations with the target (-0.44 and -0.5).
    - Higher values of these features also suggest the raisin is more likely to be Besni.
    - **Extent:** Displays a low positive correlation with the target (0.15),
    - indicating it may slightly increase the likelihood of the raisin being Keçimen, but it is not a strong predictor.

Managing the multicollinearity among highly correlated features is crucial for building a stable and accurate classification model.

Outlier Analysis

Logistic Regression and Outliers

- Logistic regression models can be sensitive to outliers, which can affect the performance and stability of the model.
- Outliers can have a disproportionate influence on the model coefficients, leading to suboptimal decision boundaries and predictions.
- Therefore, it is often advisable to address outliers before fitting a logistic regression model.

- However, Outliers should be carefully considered when preparing data for logistic regression.
- The decision to remove or retain outliers should be based on the specific context, nature of the data, and the goals of the analysis.
- Addressing outliers appropriately can lead to more accurate and reliable logistic regression models.

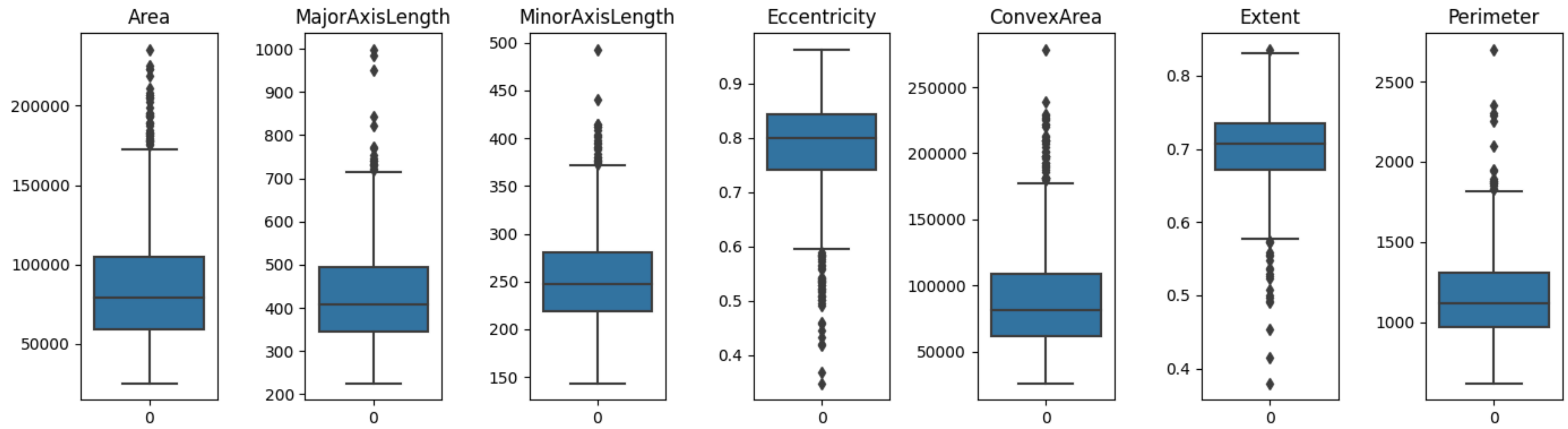
When to Remove Outliers

1. **Skewed Data**: If outliers skew the data distribution significantly, removing them can help in normalizing the distribution, leading to better model performance.
2. **Influence on Model Coefficients**: If outliers have a large influence on the estimated coefficients, it may distort the model. Removing such outliers can help in achieving more robust coefficients.
3. **Error Reduction**: In cases where outliers are due to data entry errors or anomalies not representative of the underlying distribution, removing them can reduce noise and improve model accuracy.
4. **Improving Model Fit**: When diagnostics and residual analysis indicate that outliers adversely affect model fit and prediction accuracy, it's beneficial to remove them.

When Not to Remove Outliers

1. **Genuine Data Points**: If outliers are genuine observations that reflect real variability in the data, they should not be removed, as they provide important information about the data distribution.
2. **Informative Outliers**: Sometimes outliers may carry valuable information about specific conditions or factors that should be modeled. Retaining them ensures the model captures these effects.
3. **Small Sample Size**: In datasets with a small number of observations, removing outliers can lead to loss of valuable data and reduce the model's generalizability.

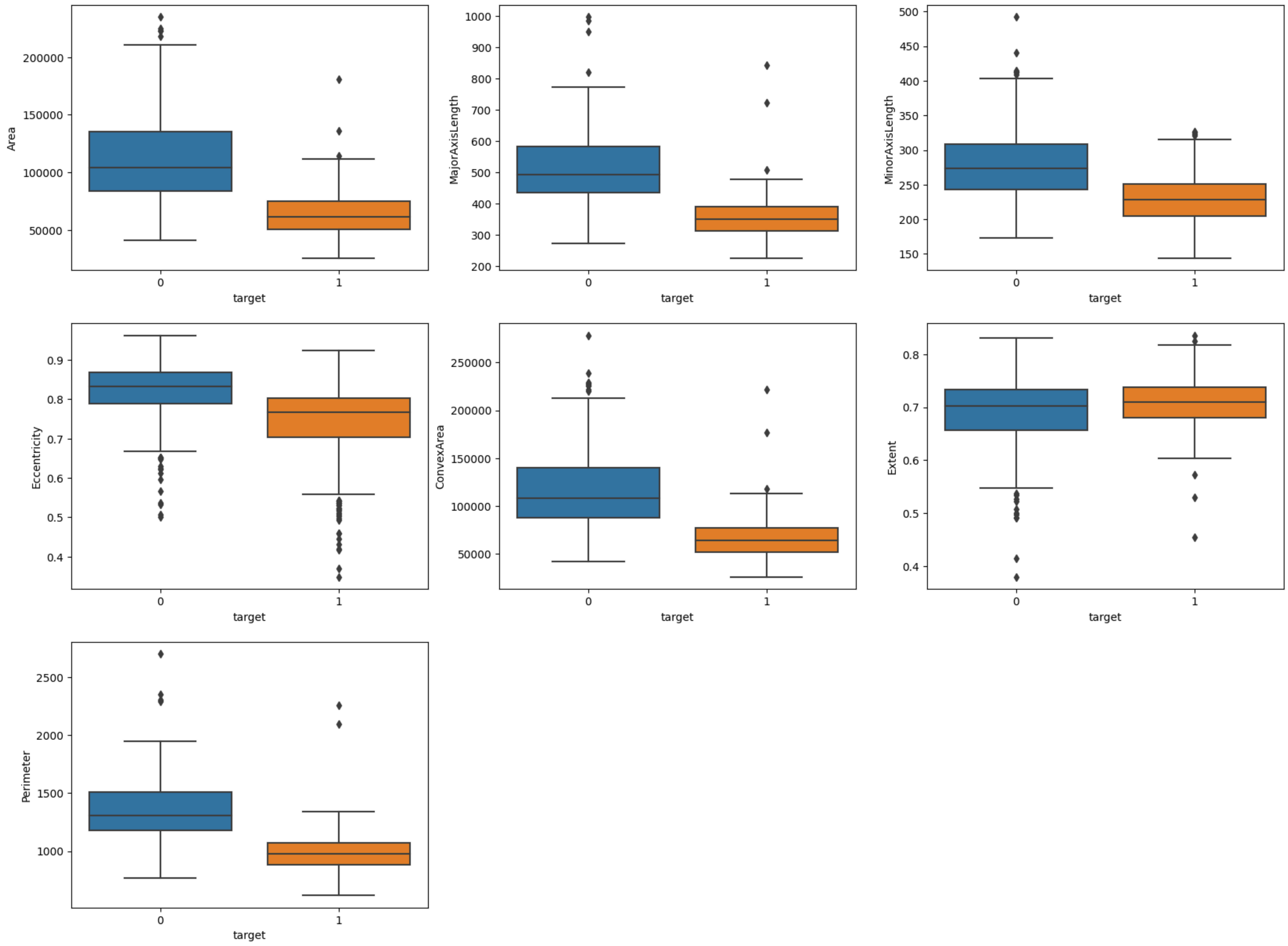
In [25]:
```
# Checking Outliers in Individual Features

x = 0
#Numerical features;
numerical_columns = ['Area', 'MajorAxisLength', 'MinorAxisLength', 'Eccentricity',
       'ConvexArea', 'Extent', 'Perimeter']

# Create a figure with specified size
plt.figure(figsize=(16, 4))

for col in numerical_columns:
    x += 1
    plt.subplot(1, 8, x)
    sns.boxplot(data=df[col])
    plt.title(col)

plt.tight_layout()
plt.show()
```



In [26]:
```
# 0: Besni | 1: Kecimen

df.target.value_counts()
```

Out[26]:
```
target
1    450
0    450
Name: count, dtype: int64
```

In [27]:
```
# Checking Outliers by the Target; 0: Besni | 1: Kecimen

index = 0
plt.figure(figsize=(20,15))
for feature in df.columns:
    if feature != "target":
        index += 1
        plt.subplot(3,3,index)
        sns.boxplot(x='target',y=feature,data=df)
plt.show()
```



Analysis

- The result reveals outliers in almost all features in the dataset except for Extent, indicating considerable variability in the morphological characteristics of the raisins.
- The Besni variety (target = 0) shows more outliers compared to the Keçimen variety (target = 1).
- **Most Effective Features:** Area, MajorAxisLength, ConvexArea, Perimeter, and Eccentricity are the most effective features for distinguishing between Besni and Keçimen varieties.
- **Less Effective Features:** MinorAxisLength shows moderate effectiveness, while Extent is the least effective feature for class separation.

However, I will not intervene with outliers at the moment, but could take an action later according to the model's forecasting performance.

MACHINE LEARNING MODELS

Splitting Train-Test

In [28]:
```
X= df.drop(columns="target")
y= df['target']
```

In [29]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Logistic Regression with Pipeline

Model

In [30]:
```
# Set the model and Scale in the Pipeline

logistic_model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression())])

logistic_model.fit(X_train, y_train)
```

Out[30]:

```
Pipeline
  MinMaxScaler
  LogisticRegression
```

In [31]:
```
logistic_model["logistic"].coef_
```

Out[31]:
```
array([[-2.73295414, -3.00314467, -1.14065412, -2.96268963, -2.77951842,
         1.35628873, -3.17332199]])
```

In [32]:
```
logistic_model.named_steps['scaler'].get_feature_names_out()
```

Out[32]:
```
array(['Area', 'MajorAxisLength', 'MinorAxisLength', 'Eccentricity',
       'ConvexArea', 'Extent', 'Perimeter'], dtype=object)
```

In [33]:
```
logistic_model["logistic"].intercept_
```

Out[33]:
```
array([4.67125606])
```

Prediction

In [107…
```
y_pred = logistic_model.predict(X_test)
y_pred
```

Out[107…
```
array([0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1,
       0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0,
       0, 0, 1, 1])
```

In [35]:
```
y_pred_proba = logistic_model.predict_proba(X_test) #returns the probability estimates for each class label
y_pred_proba[:5,:]
```

Out[35]:
```
array([[0.71304677, 0.28695323],
       [0.23501451, 0.76498549],
       [0.04214933, 0.95785067],
       [0.89483378, 0.10516622],
       [0.0524295 , 0.9475705 ]])
```

In [36]:
```
test_data = pd.concat([X_test, y_test], axis=1)
test_data.head()
```

Out[36]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	target
70	95347	451.526	280.226	0.784	99256	0.675	1255.245	1
827	61861	345.944	235.430	0.733	67390	0.702	1063.621	0
231	52693	283.504	242.114	0.520	54860	0.738	895.745	1
588	112808	542.505	267.202	0.870	116961	0.743	1390.400	0
39	49882	287.264	222.186	0.634	50880	0.766	843.764	1

In [37]:
```
# Create new column for 'predicted' classes to compore with actual target classes

test_data["pred"] = y_pred
test_data.head()
```

Out[37]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	target	pred
70	95347	451.526	280.226	0.784	99256	0.675	1255.245	1	0
827	61861	345.944	235.430	0.733	67390	0.702	1063.621	0	1
231	52693	283.504	242.114	0.520	54860	0.738	895.745	1	1
588	112808	542.505	267.202	0.870	116961	0.743	1390.400	0	0
39	49882	287.264	222.186	0.634	50880	0.766	843.764	1	1

In [38]:
```
# Filtering incorrect predicted class labels of a data points in one df

wrong_pred = test_data[((test_data["target"] == 1) & (test_data["pred"] == 0)) |
                       ((test_data["target"] == 0) & (test_data["pred"] == 1))]


print(wrong_pred.shape)
wrong_pred

# The model has predicted 26 observations incorrectly.
```

```
(26, 9)
```

Out[38]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	target	pred
70	95347	451.526	280.226	0.784	99256	0.675	1255.245	1	0
827	61861	345.944	235.430	0.733	67390	0.702	1063.621	0	1
731	84383	403.909	271.252	0.741	87629	0.675	1140.605	0	1
139	110616	461.145	306.899	0.746	112150	0.752	1252.875	1	0
168	92735	436.986	271.579	0.783	94693	0.704	1183.447	1	0
67	89235	443.516	258.947	0.812	91201	0.655	1179.694	1	0
688	57999	311.022	243.476	0.622	61519	0.656	968.697	0	1
30	88745	429.770	265.690	0.786	90715	0.752	1162.877	1	0
298	105020	440.390	306.105	0.719	107423	0.715	1228.366	1	0
744	53077	327.288	212.231	0.761	55532	0.646	934.708	0	1
396	75431	433.671	222.999	0.858	78125	0.723	1103.236	1	0
44	77310	436.530	228.280	0.852	80138	0.632	1141.189	1	0
826	47609	331.894	184.213	0.832	49720	0.748	874.091	0	1
136	97026	455.972	273.054	0.801	99561	0.671	1212.667	1	0
218	72915	414.718	229.556	0.833	76912	0.680	1131.096	1	0
545	68231	394.647	228.161	0.816	71591	0.665	1099.228	0	1
398	82886	424.823	253.172	0.803	85879	0.648	1163.528	1	0
338	74612	430.865	229.287	0.847	79297	0.665	1140.399	1	0
481	75173	365.803	267.583	0.682	78359	0.680	1087.034	0	1
465	67579	402.310	217.059	0.842	70809	0.703	1051.553	0	1
807	78632	407.940	245.821	0.798	79715	0.689	1068.727	0	1
885	54502	346.458	204.081	0.808	56464	0.636	927.283	0	1
363	103377	460.670	287.993	0.780	105569	0.727	1230.233	1	0
518	64303	442.745	187.029	0.906	67199	0.686	1081.680	0	1
693	49371	320.643	200.246	0.781	52692	0.675	921.059	0	1
54	111450	478.311	298.631	0.781	113256	0.690	1298.188	1	0

In [131…

```
log_y_pred = logistic_model.predict(X_test)
LR = accuracy_score(y_test, log_y_pred)
LR
```

Out[131…

```
0.8555555555555555
```

Model Performance

In [39]:

```
# Function to Evaluate the Model Performans using Classification Confusion_matrix()

def eval_metric(model, X_train, y_train, X_test, y_test):
    y_train_pred = model.predict(X_train)
    y_pred = model.predict(X_test)

    print("Test_Set")
    print(confusion_matrix(y_test, y_pred))
    print(classification_report(y_test, y_pred))
    print()
    print("Train_Set")
    print(confusion_matrix(y_train, y_train_pred))
    print(classification_report(y_train, y_train_pred))
```

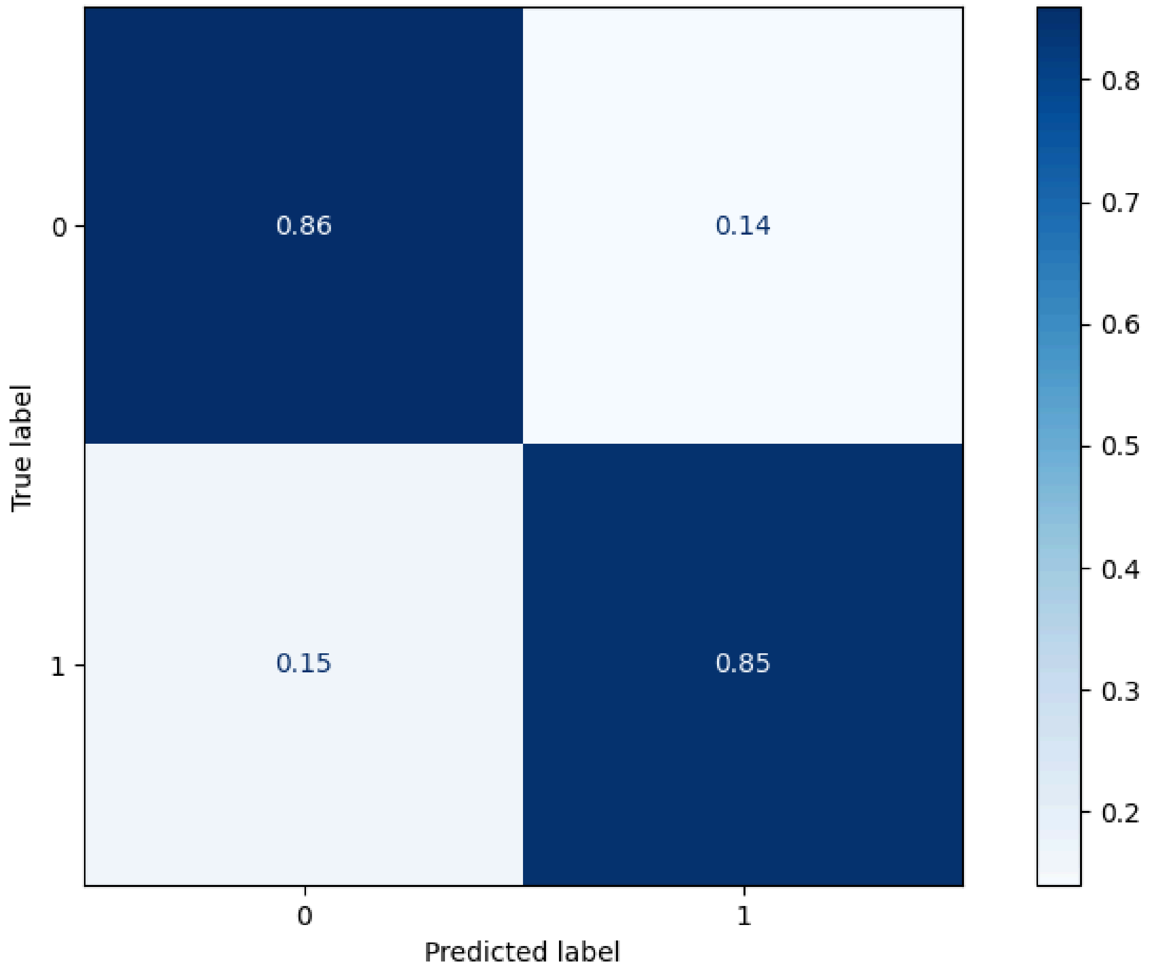
In [40]:

```
# Evaluating the Model Performance using Classification Metrics

log_scores = eval_metric(logistic_model, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[74 12]
 [14 80]]
              precision    recall  f1-score   support

           0       0.84      0.86      0.85        86
           1       0.87      0.85      0.86        94

    accuracy                           0.86       180
   macro avg       0.86      0.86      0.86       180
weighted avg       0.86      0.86      0.86       180


Train_Set
[[303  61]
 [ 37 319]]
              precision    recall  f1-score   support

           0       0.89      0.83      0.86       364
           1       0.84      0.90      0.87       356

    accuracy                           0.86       720
   macro avg       0.87      0.86      0.86       720
weighted avg       0.87      0.86      0.86       720
```

In [41]:
```
ConfusionMatrixDisplay.from_estimator(logistic_model, X_test,y_test, normalize='true', cmap='Blues' )
```

Out[41]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7ca7b93f4160>
```



- True Negative (TN): top left
- False Positive (FP): top right
- False Negative (FN): bottom left
- True Positive (TP): bottom right

Model Validation

In [42]:
```
operations = [("scaler", MinMaxScaler()), ("logistic", LogisticRegression())]

model = Pipeline(steps=operations)

scores = cross_validate(model,
                        X_train,
                        y_train,
                        scoring=['accuracy', 'precision', 'recall', 'f1'],
                        cv=5, # 5-folded
                        return_train_score=True)

df_scores = pd.DataFrame(scores, index=range(1, 6)) # CV has 5 iteration.
df_scores
```

Out[42]:

	fit_time	score_time	test_accuracy	train_accuracy	test_precision	train_precision	test_recall	train_recall	test_f1	train_f1
1	0.011	0.010	0.868	0.865	0.853	0.841	0.889	0.894	0.871	0.867
2	0.009	0.010	0.882	0.863	0.875	0.837	0.887	0.898	0.881	0.866
3	0.013	0.009	0.868	0.863	0.833	0.841	0.915	0.891	0.872	0.865
4	0.010	0.011	0.799	0.885	0.769	0.857	0.845	0.923	0.805	0.889
5	0.009	0.011	0.903	0.854	0.861	0.834	0.958	0.881	0.907	0.857

In [43]:
```
df_scores.mean()[2:]
```

Out[43]:
```
test_accuracy     0.864
train_accuracy    0.866
test_precision    0.838
train_precision   0.842
test_recall       0.899
train_recall      0.897
test_f1           0.867
train_f1          0.869
dtype: float64
```

Hyperparameter Optimization:

In [44]:
```
logistic_model.get_params()
```

Out[44]:
```
{'memory': None,
 'steps': [('scaler', MinMaxScaler()), ('logistic', LogisticRegression())],
 'verbose': False,
 'scaler': MinMaxScaler(),
 'logistic': LogisticRegression(),
 'scaler__clip': False,
 'scaler__copy': True,
 'scaler__feature_range': (0, 1),
 'logistic__C': 1.0,
 'logistic__class_weight': None,
 'logistic__dual': False,
 'logistic__fit_intercept': True,
 'logistic__intercept_scaling': 1,
 'logistic__l1_ratio': None,
 'logistic__max_iter': 100,
 'logistic__multi_class': 'auto',
 'logistic__n_jobs': None,
 'logistic__penalty': 'l2',
 'logistic__random_state': None,
 'logistic__solver': 'lbfgs',
 'logistic__tol': 0.0001,
 'logistic__verbose': 0,
 'logistic__warm_start': False}
```

In [45]:
```
# Hyperparameters Tuning with GridSearchSV

# Define the pipeline steps
model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression())])

# Define hyperparameters for tuning
penalty = ["l1", "l2"]       # Regularization terms: L1 (Lasso) and L2 (Ridge)
C = np.logspace(-1, 5, 20)   # Regularization strength; inverse of regularization parameter
solver = ["lbfgs", "liblinear", "sag", "saga"]  # Optimization algorithms

# Create the parameter grid
param_grid = {"logistic__penalty" : penalty,
              "logistic__C" : C,
              "logistic__solver":solver}

grid_model = GridSearchCV(estimator=model,
                          param_grid=param_grid,
                          cv=5,
                          scoring = "accuracy",
                          n_jobs = -1,            # Use all available cores
                          return_train_score=True) # Return training scores
```

In [ ]:
```
grid_model.fit(X_train, y_train)
```

In [47]:
```
grid_model.best_params_
```

Out[47]:
```
{'logistic__C': 1.8329807108324356,
 'logistic__penalty': 'l2',
 'logistic__solver': 'liblinear'}
```

In [48]:
```
grid_model.best_score_
```

Out[48]:
```
0.8694444444444445
```

Prediction with Grid_Model

In [114…
```
# Prediction with Test Data

y_pred = grid_model.predict(X_test)
y_pred_proba = grid_model.predict_proba(X_test)
```

In [109…
```
# Prediction with Train Data
y_train_pred = grid_model.predict(X_train)
y_train_pred_proba = grid_model.predict_proba(X_train)
```

In [110…
```
average_precision_score(y_train, y_train_pred_proba[:,1]) # Accuracy score for balanced data
```

Out[110…
```
0.9044538542126601
```

In [140…
```
grid_y_pred = grid_model.predict(X_test)
GLR = accuracy_score(y_test, grid_y_pred)
GLR
```

Out[140…
```
0.8722222222222222
```

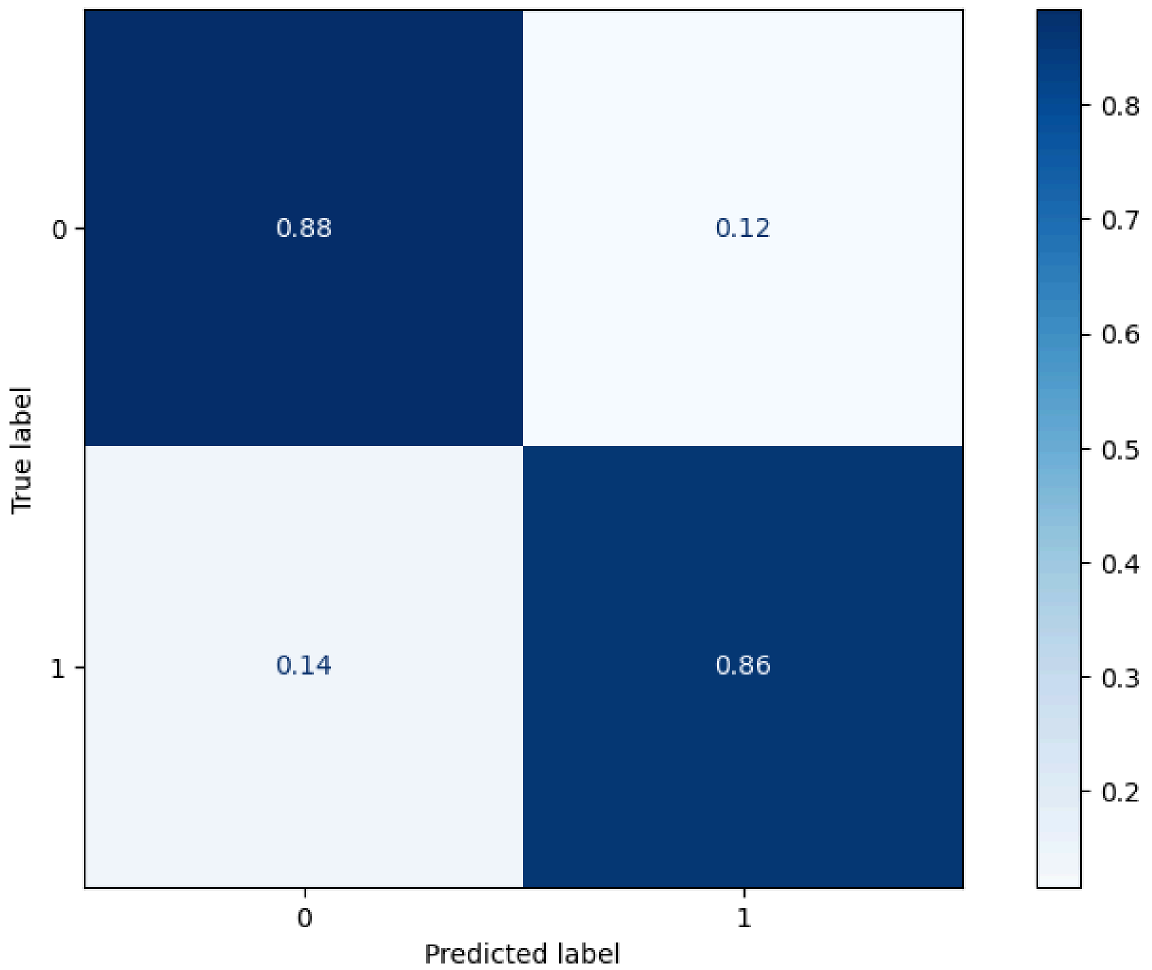
Evaluating the Model Performance

In [111…
```
# Evaluating the Model Performance using Classification Metrics

grid_scores = eval_metric(grid_model, X_train, y_train, X_test, y_test)
```

```
Test_Set
[[76 10]
 [13 81]]
              precision    recall  f1-score   support

           0       0.85      0.88      0.87        86
           1       0.89      0.86      0.88        94

    accuracy                           0.87       180
   macro avg       0.87      0.87      0.87       180
weighted avg       0.87      0.87      0.87       180


Train_Set
[[307  57]
 [ 38 318]]
              precision    recall  f1-score   support

           0       0.89      0.84      0.87       364
           1       0.85      0.89      0.87       356

    accuracy                           0.87       720
   macro avg       0.87      0.87      0.87       720
weighted avg       0.87      0.87      0.87       720
```

In [50]:
```
ConfusionMatrixDisplay.from_estimator(grid_model, X_test,y_test, normalize='true', cmap='Blues' )
```

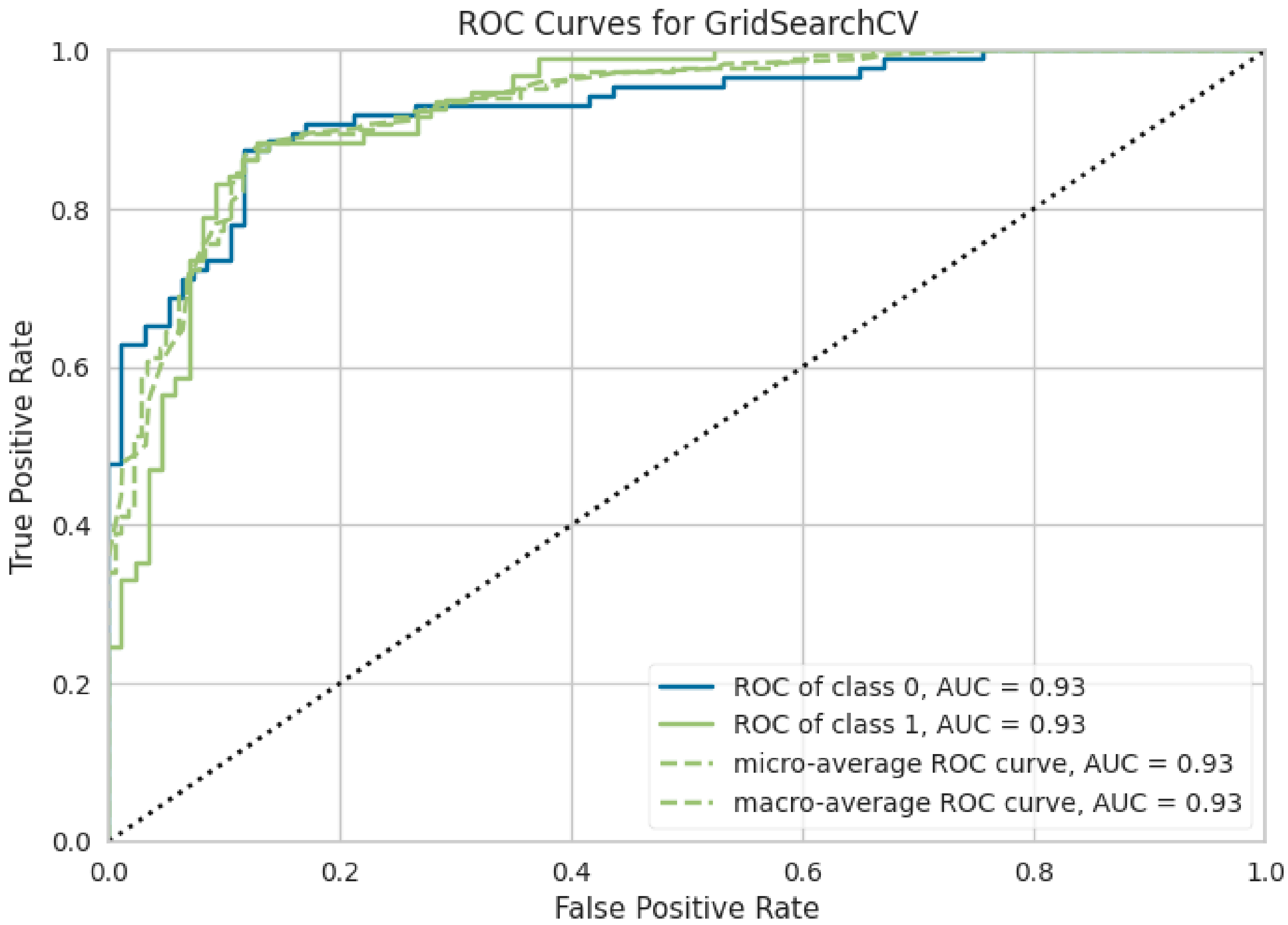
Out[50]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7ca7bb233670>
```



ROC (Receiver Operating Curve) & AUC (Area Under Curve)

In [112…

```
#Finding Best Thresholds

from yellowbrick.classifier import ROCAUC

model = grid_model
visualizer = ROCAUC(model)
visualizer.fit(X_train, y_train)        # Fit the training data to the visualizer
visualizer.score(X_test, y_test)        # Evaluate the model on the test data
visualizer.show();
```



In [113…

```
# Let's see the best thresholds

precisions, recalls, thresholds = precision_recall_curve(y_train, y_train_pred_proba[:, 1])


dict = {
    "precisions": precisions[:-1],
    "recalls": recalls[:-1],
    "threshold": thresholds
}
df_metric = pd.DataFrame(dict).sort_values(by=["recalls", "precisions"],
                                           ascending=False)
df_metric.head(12)

# The purpose is identifying the optimal threshold value that maximizes recall while achieving the highest possible precision.

#The best threshold value could be 0.103 because it provides a high recall (0.994) along with a higher precision (0.633).
# This helps the model make more balanced and accurate predictions.
# The best threshold (0.103) is on the 161st index row. After that, recall remains stable but precision decreases!
```

Out[113…

	precisions	recalls	threshold
2	0.496	1.000	0.000
1	0.495	1.000	0.000
0	0.494	1.000	0.000
8	0.499	0.997	0.001
7	0.498	0.997	0.001
6	0.497	0.997	0.001
5	0.497	0.997	0.001
4	0.496	0.997	0.000
3	0.495	0.997	0.000
161	0.633	0.994	0.103
160	0.632	0.994	0.098
159	0.631	0.994	0.097

In [97]:

```
optimal_threshold = 0.103

predict_proba = grid_model.predict_proba(X_train)[:,1]

prediction = [1 if i >= optimal_threshold else 0 for i in predict_proba]
```

```
print(confusion_matrix(y_train, prediction))
print(classification_report(y_train, prediction))
```

```
[[159 205]
 [  2 354]]
              precision    recall  f1-score   support

           0       0.99      0.44      0.61       364
           1       0.63      0.99      0.77       356

    accuracy                           0.71       720
   macro avg       0.81      0.72      0.69       720
weighted avg       0.81      0.71      0.69       720
```

In [99]:
```
# Prediction on test data with optimal threshold;

def pred_bestTreshold(model, X_test, optimal_threshold = 0.103):
    predict_proba = model.predict_proba(X_test)
    prediction = [1 if i >= optimal_threshold else 0 for i in predict_proba[:,1]]
    return prediction
```

In [100…
```
predictions = pred_bestTreshold(grid_model, X_test)

print(confusion_matrix(y_test, predictions))
print(classification_report(y_test, predictions))
```

```
[[34 52]
 [ 0 94]]
              precision    recall  f1-score   support

           0       1.00      0.40      0.57        86
           1       0.64      1.00      0.78        94

    accuracy                           0.71       180
   macro avg       0.82      0.70      0.68       180
weighted avg       0.81      0.71      0.68       180
```

Support Vector Machine

In [139…
```
# creating an instance of SVM class
svm_model = SVC()
svm_model.fit(X_train, y_train)

# maing predictions
svm_y_pred = svm_model.predict(X_test)

# checking score
SVM = accuracy_score(y_test, svm_y_pred)

SVM
# printing Classification Report
print(classification_report(y_test, svm_y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.79      0.83        86
           1       0.83      0.90      0.86        94

    accuracy                           0.85       180
   macro avg       0.85      0.85      0.85       180
weighted avg       0.85      0.85      0.85       180
```

K-Nearest Neighbours

In [123…
```
# building a function to test best neighbour
def KNN(k):
    # building a KNN model (default k=5)
    knn_model = KNeighborsClassifier(n_neighbors=k)

    # fitting the model to the training data
    knn_model.fit(X_train, y_train)

    # making predictions on the test set
    y_pred_knn = knn_model.predict(X_test)

    # evaluating the model's accuracy
    accuracy_knn = accuracy_score(y_test, y_pred_knn)
    return accuracy_knn
```

In [136…
```
# finding the best n value
k_values = [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]

best_accuracy = 0
best_k = None
```

```
for k in k_values:
    accuracy = KNN(k)
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k

print("Best Accuracy: {0:0.5f} for K = {1}".format(best_accuracy, best_k))

KNN = best_accuracy
KNN
```

```
Best Accuracy: 0.85556 for K = 10
```

Out[136…

```
0.8555555555555555
```

Decision Tree Classifier

In [125…

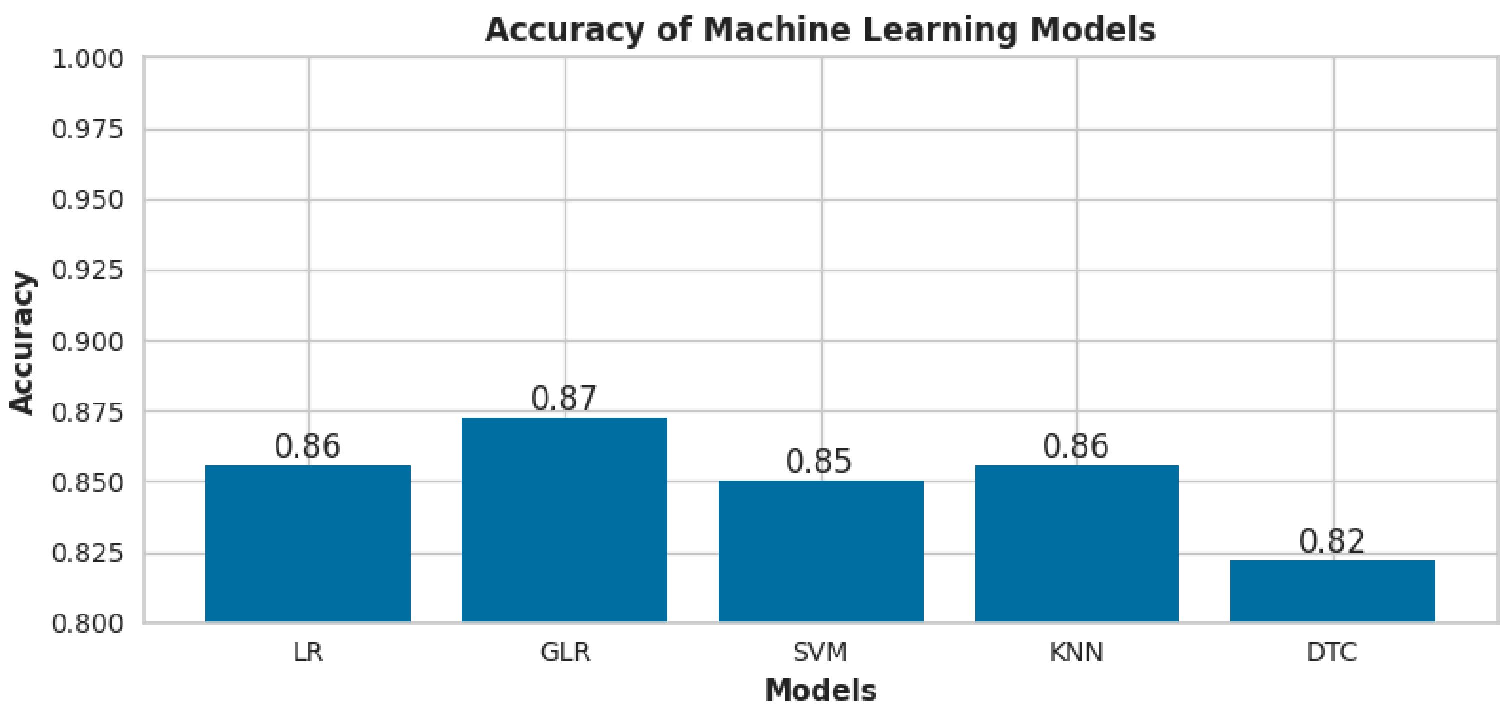
```
# Creating an instance of Decision Tree Classifier
dt_model = DecisionTreeClassifier(max_depth = 10)

# Fitting the model to the training data
dt_model.fit(X_train, y_train)

# Making predictions
dt_y_pred = dt_model.predict(X_test)

# Checking accuracy
DTC = accuracy_score(y_test, dt_y_pred)

# Printing Classification Report
print(classification_report(y_test, dt_y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.84      0.82        86
           1       0.84      0.81      0.83        94

    accuracy                           0.82       180
   macro avg       0.82      0.82      0.82       180
weighted avg       0.82      0.82      0.82       180
```

Comparing the Models

In [145…

```
# Accuracy dictionary
accuracy_dict = {"LR": LR, "GLR": GLR, "SVM": SVM, "KNN": KNN, "DTC": DTC}

# Plotting accuracy scores
plt.figure(figsize=(8,4))
bars = plt.bar(list(accuracy_dict.keys()), list(accuracy_dict.values()))

# Adding annotations
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, round(height, 2), ha='center', va='bottom')

plt.xlabel('Models', fontweight='bold')
plt.ylabel('Accuracy', fontweight='bold')
plt.title('Accuracy of Machine Learning Models', fontweight='bold')
plt.tight_layout()
plt.ylim(0.8, 1)
plt.show()
```



Based on the evaluation metrics, the **Grid Logistic Regression (GLR)** model should be selected as the final model. Here are the reasons:

1. **Highest Accuracy**: The GLR model has the highest accuracy at 0.87, meaning it makes the most correct predictions overall.
2. **Balanced Performance**:
   - **Precision and Recall**: The GLR model shows balanced precision and recall for both classes. For class 0, precision is 0.85 and recall is 0.88. For class 1, precision is 0.89 and recall is 0.86. This balance indicates the model is effective at identifying both classes.
   - **F1-Score**: High F1-scores (0.87 for class 0 and 0.88 for class 1) demonstrate the model's strength in balancing precision and recall.
3. **Consistency**:
   - The GLR model performs consistently on the training set with an accuracy of 0.87, showing it is well-fitted and not overfitting the data.
4. **Comparison with Other Models**:
   - **Logistic Regression**: Slightly lower accuracy at 0.86 and less balanced precision and recall.
   - **SVM**: Lower accuracy at 0.85 with less balanced precision and recall.
   - **Decision Tree**: Lowest accuracy at 0.82, making it less reliable.
5. **Generalization Capability**: The GLR model generalizes well to new data, ensuring reliability in real-world applications.

In summary, the GLR model's superior accuracy, balanced performance, and consistency make it the best choice for the final model.

Final Model

Best Parameters from the Grid Logistic Model

In [124…
```
grid_model.best_params_
```

Out[124…
```
{'logistic__C': 1.8329807108324356,
 'logistic__penalty': 'l2',
 'logistic__solver': 'liblinear'}
```

In [101…
```
final_model = Pipeline([("scaler", MinMaxScaler()), ("logistic", LogisticRegression(C=0.1,penalty='l2', solver='lbfgs'))])

final_model.fit(X, y)
```

Out[101…
```
Pipeline
  MinMaxScaler
  LogisticRegression
```

In [102…
```
import pickle

pickle.dump(final_model, open('final_model','wb')) # export the final model in local -> serilarization
```

In [ ]:
```
final_model = pickle.load(open('final_model','rb')) # import the final model to use -> deserilization
```

Prediction with a new sample

In [103…
```
new_data_sample = {
    "Area": [87524, 61600, 52266, 51180, 55787, 83248, 87350, 99657, 93523, 85609],
    "MajorAxisLength": [442.2460114, 350.1827545, 320.4425614, 288.6310651, 333.7034529, 430.0773077, 440.7356978, 431.7069809, 476.34
    "MinorAxisLength": [253.291155, 225.8427713, 213.8574996, 226.6304906, 226.9512079, 247.8386945, 259.2931487, 298.8373229, 254.176
    "Eccentricity": [0.819738392, 0.764243075, 0.744715834, 0.619253764, 0.733120775, 0.817262582, 0.802682995, 0.721864076, 0.845738
    "ConvexArea": [90546, 63397, 54116, 52396, 59520, 85839, 90899, 106264, 97653, 89197],
    "Extent": [0.758650579, 0.746829611, 0.684289081, 0.737442725, 0.688592377, 0.66879293, 0.636476246, 0.741098519, 0.658798253, 0.6
    "Perimeter": [1184.04, 972.472, 923.19, 855.997, 977.425, 1129.072, 1214.252, 1292.828, 1258.548, 1272.862]
}
```

In [104…
```
new_test_data = pd.DataFrame(new_data_sample)
new_test_data
```

Out[104…

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
0	87524	442.246	253.291	0.820	90546	0.759	1184.040
1	61600	350.183	225.843	0.764	63397	0.747	972.472
2	52266	320.443	213.857	0.745	54116	0.684	923.190
3	51180	288.631	226.630	0.619	52396	0.737	855.997
4	55787	333.703	226.951	0.733	59520	0.689	977.425
5	83248	430.077	247.839	0.817	85839	0.669	1129.072
6	87350	440.736	259.293	0.803	90899	0.636	1214.252
7	99657	431.707	298.837	0.722	106264	0.741	1292.828
8	93523	476.344	254.176	0.846	97653	0.659	1258.548
9	85609	512.082	215.272	0.907	89197	0.632	1272.862

In [86]:
```
# Prediction

predictions = final_model.predict(new_test_data)
```

In [87]:
```
# Probability of the Positive class (1)
positive_class_proba = final_model.predict_proba(new_test_data)[:, 1]
positive_class_proba
```

Out[87]:
```
array([0.47085013, 0.67938162, 0.72790826, 0.80112732, 0.70181434,
       0.48450128, 0.4421438 , 0.42930943, 0.38275814, 0.37703478])
```

In [88]:
```
results = pd.DataFrame({
    'Prediction': predictions,
    'Positive Probability': positive_class_proba
})

results
```

Out[88]:

	Prediction	Positive Probability
0	0	0.471
1	1	0.679
2	1	0.728
3	1	0.801
4	1	0.702
5	0	0.485
6	0	0.442
7	0	0.429
8	0	0.383
9	0	0.377

In [89]:
```
new_test_data["pred"] = predictions
new_test_data['Positive Probability'] = positive_class_proba
new_test_data
```

Out[89]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	pred	Positive Probability
0	87524	442.246	253.291	0.820	90546	0.759	1184.040	0	0.471
1	61600	350.183	225.843	0.764	63397	0.747	972.472	1	0.679
2	52266	320.443	213.857	0.745	54116	0.684	923.190	1	0.728
3	51180	288.631	226.630	0.619	52396	0.737	855.997	1	0.801
4	55787	333.703	226.951	0.733	59520	0.689	977.425	1	0.702
5	83248	430.077	247.839	0.817	85839	0.669	1129.072	0	0.485
6	87350	440.736	259.293	0.803	90899	0.636	1214.252	0	0.442
7	99657	431.707	298.837	0.722	106264	0.741	1292.828	0	0.429
8	93523	476.344	254.176	0.846	97653	0.659	1258.548	0	0.383
9	85609	512.082	215.272	0.907	89197	0.632	1272.862	0	0.377

Conclusion

In this project, we performed a comprehensive analysis to classify raisin varieties using their morphological features. Here are the key steps and findings:

1. **Exploratory Data Analysis (EDA)**:
    - Conducted thorough EDA to understand the dataset.
    - Identified and handled missing and duplicated values.
    - Analyzed basic statistics, categorical and numerical features.
    - Performed feature engineering, correlation analysis, and outlier detection.
2. **Machine Learning Models**:
    - Implemented several machine learning models:
        - **Logistic Regression**
        - **Support Vector Machine (SVM)**
        - **K-Nearest Neighbors (KNN)**
        - **Decision Tree Classifier**
3. **Model Comparison and Selection**:
    - Among all models, the **Grid Logistic Regression (GLR)** model demonstrated the highest accuracy and balanced performance.
    - **GLR Model Performance**:

    - Accuracy: 0.87
    - Balanced precision and recall values.
- This indicates that the GLR model is robust and reliable for accurately identifying both raisin varieties.

The structured approach and thorough analysis ensured the selection of the most effective model for raisin classification.

If you find this work helpful, don't forget to give it an 👍 UPVOTE! and join the discussion on Kaggle!

Thank you...

Duygu Jones | Data Scientist | 2024
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