CA 3 - Banana Classification

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Imports

In [52]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import itertools

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatri

from sklearn.linear_model import LogisticRegression, Perceptron
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
```

Reading data

In [53]:
```
df = pd.read_csv('train.csv')
df
```

Out[53]:

	Size	Weight	Sweetness	Softness	HarvestTime	Ripeness	A
0	-1.825734	-0.883754	-2.423530	-1.198136	-4.286523	1.585792	-0.5
1	-0.142286	-0.708374	-2.224219	2.222650	1.896814	-4.284821	1.0
2	-1.957254	-4.293733	-1.073703	-1.405019	-0.729812	3.930497	-0.3
3	-2.168043	3.095472	1.707717	-0.584218	-0.564767	0.014740	-0.1
4	-3.149338	3.058402	2.173671	-0.265609	-2.563220	0.376015	1.4
...	...	...	...	...	...	...	
2795	-3.558241	2.238072	3.659291	-2.009616	-1.182283	2.644585	0.9
2796	-0.674817	0.356224	-2.063503	-2.002749	-1.169246	0.710731	-2.7
2797	0.734057	-0.521849	-2.398139	3.082185	1.961583	-0.136754	-1.4
2798	-0.292535	1.418799	1.135584	-2.608716	-0.497932	2.589713	1.1
2799	-1.626098	2.229498	3.856501	0.652745	-1.943957	-0.638567	2.5

2800 rows × 10 columns

Comments: The dataset has 9 features and target variable "Quality" for the banana

Data exploration and visualisation

In [54]:

```
# Statiscal summary:
df.describe()
```

Out[54]:

	Size	Weight	Sweetness	Softness	HarvestTime	R
count	2800.000000	2800.000000	2800.000000	2800.000000	2800.000000	2800
mean	-0.764652	-0.751050	-0.751005	-0.019557	-0.700683	0
std	2.114313	2.006590	1.955109	2.076865	2.029916	2
min	-7.998074	-7.103426	-6.434022	-6.959320	-7.570008	-7
25%	-2.249285	-2.238843	-2.104742	-1.593816	-2.112747	-0
50%	-0.922448	-0.882387	-0.997902	0.220174	-0.856858	0
75%	0.638570	0.853566	0.334989	1.542899	0.628895	2
max	5.806328	5.679692	6.438196	8.241555	5.942060	7

Comment: All features are numerical so no need for encoding. Only 'Banana Density' has a significantly diffferent scale than the other features.

In [55]:
```
# Missing values:
df.isnull().any()
```

Out[55]:
```
Size              False
Weight            False
Sweetness         False
Softness          False
HarvestTime       False
Ripeness          False
Acidity           False
Peel Thickness    False
Banana Density    False
Quality           False
dtype: bool
```

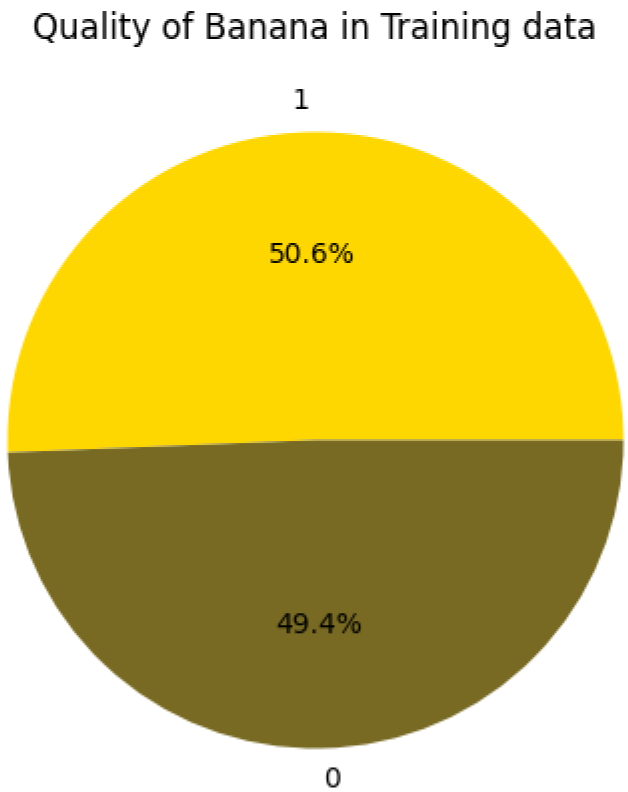
In [56]:
```
# Check for duplicates:
df.duplicated().any()
```

Out[56]:
```
np.False_
```

Comment: There is no missing values or duplicated samples in the dataset.

In [57]:
```
# Initialize colors to be used in this notebook.
banana_colors = {0: "#786A23", 1: "#FFD700"}
```

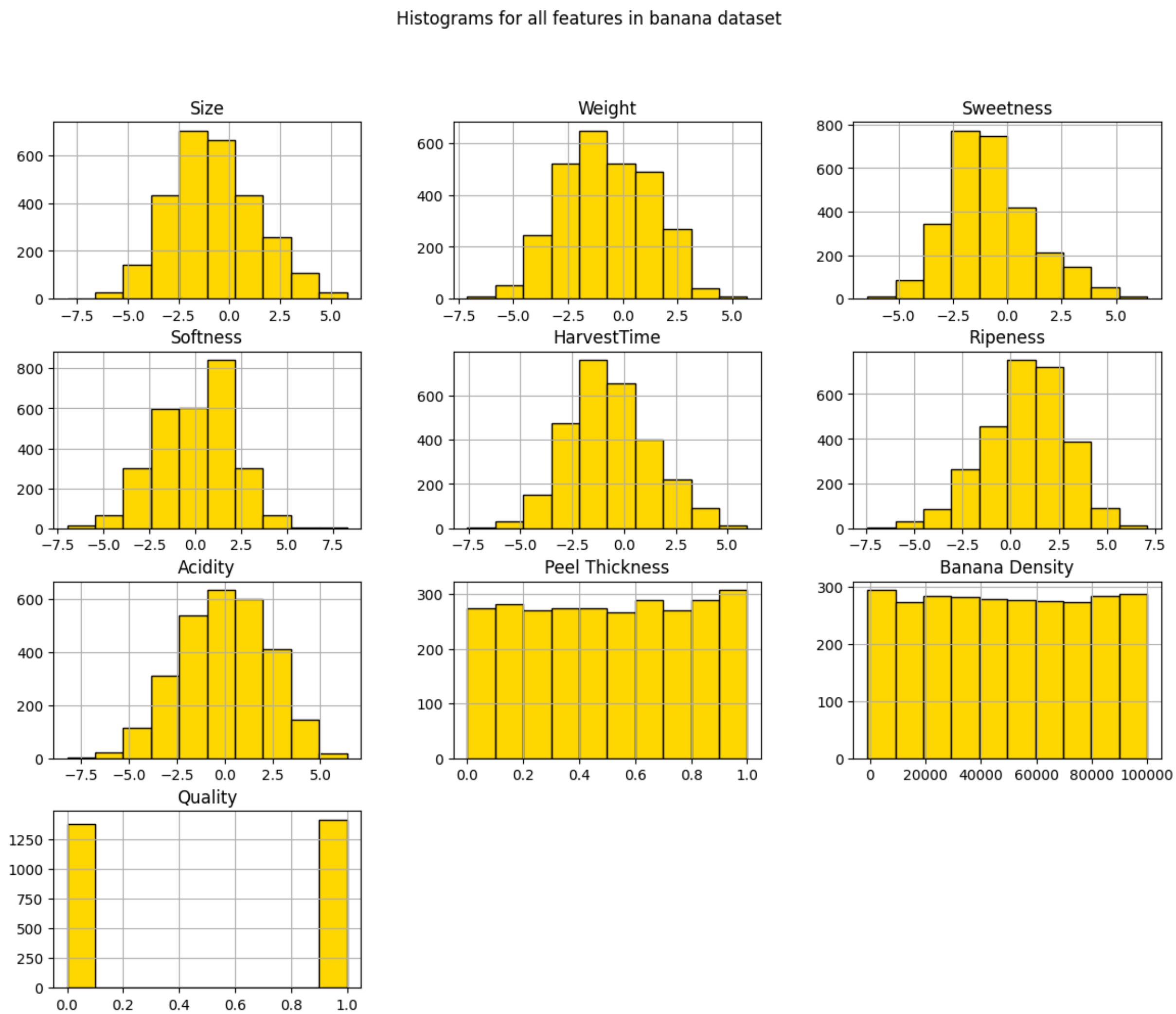
In [58]:
```
# Check the class proportion of the target
target_counts = df['Quality'].value_counts()
plt.figure(figsize=(5,5))
plt.pie(target_counts, autopct='%1.1f%%', labels=target_counts.index,
        colors=list(reversed(banana_colors.values())))
plt.title('Quality of Banana in Training data')
plt.show()

print(target_counts)
```




```
Quality
1    1418
0    1382
Name: count, dtype: int64
```

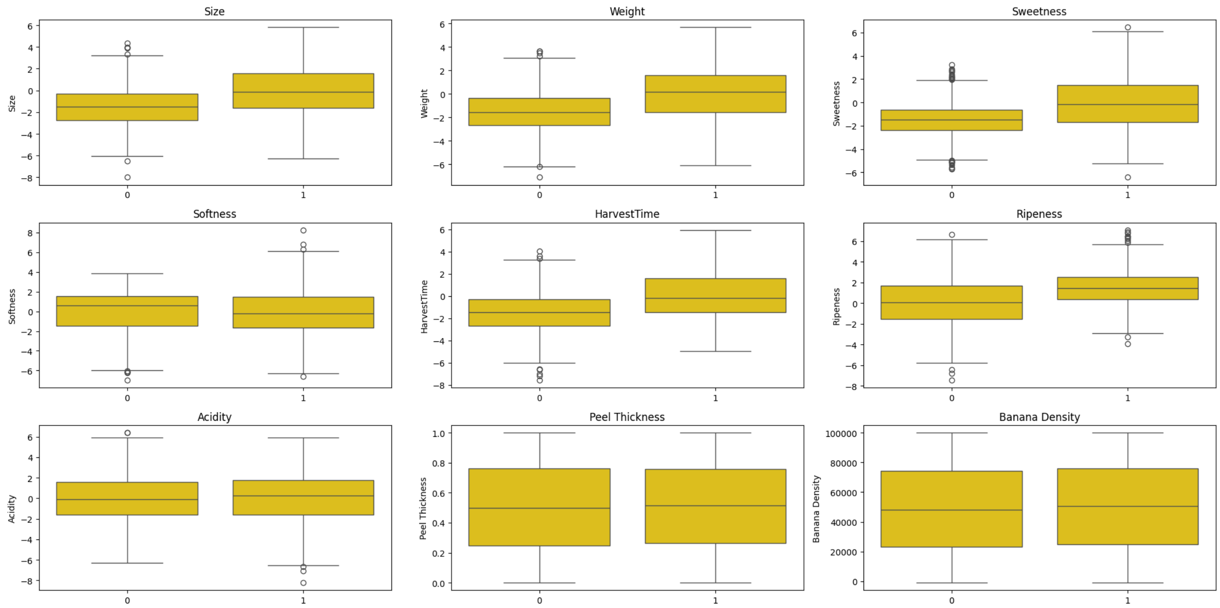
Comment: The proportion of each class in Quality is nearly the half, good banana - 50.6% while bad banana - 49.4%.

In [59]:
```
# Histograms to observe how the data is distributed
df.hist(figsize=(14, 11), bins=10, color = banana_colors[1], edgecolor ='bla
plt.suptitle("Histograms for all features in banana dataset")
plt.show()
```



Comments: The first 7 features has approximate normal distribution with the mean closes to 0. The last two have almost have equal bins for their flt distribution.

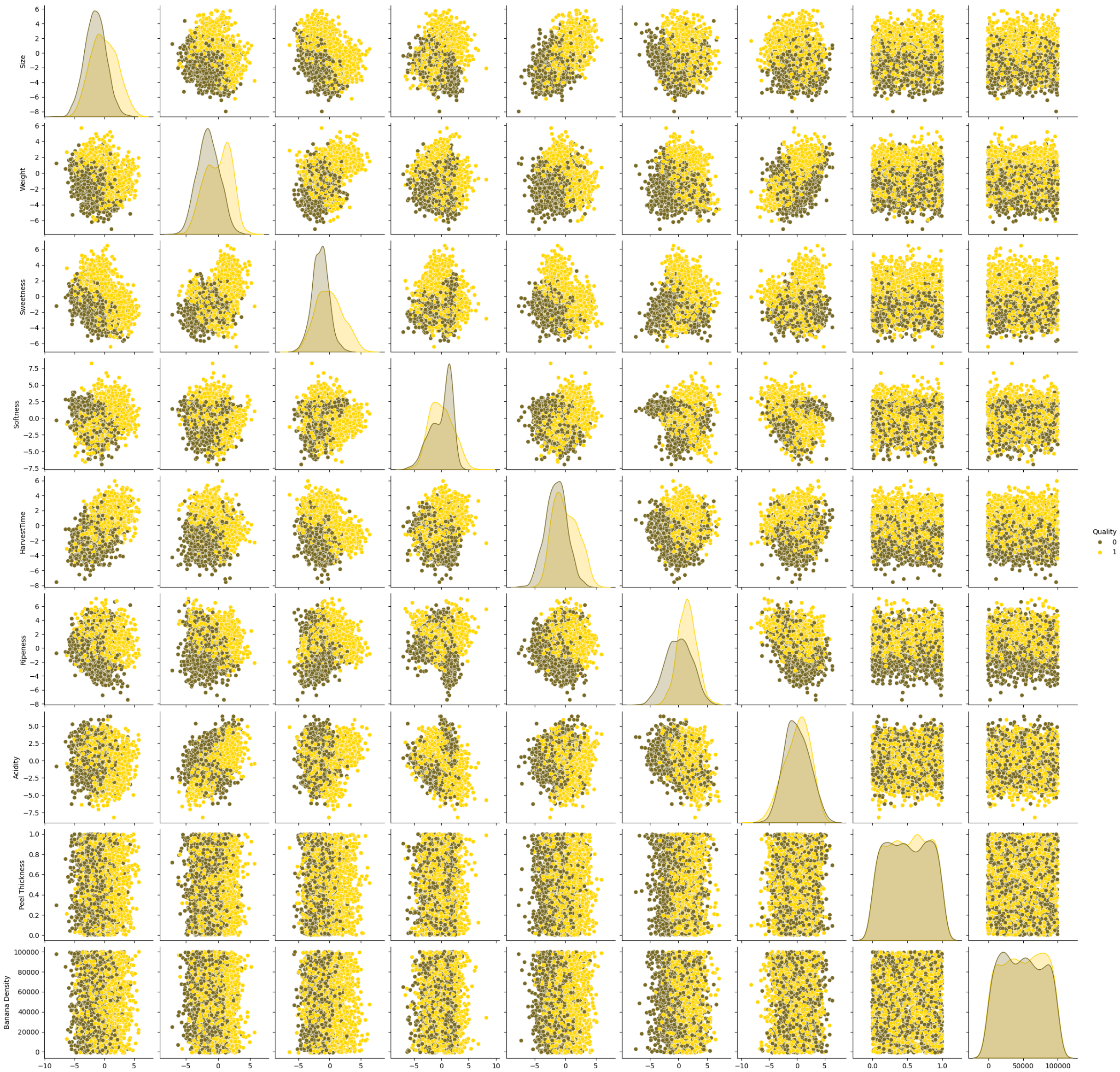
In [60]:
```
# Box plots to observe how bad and good bananas distributed on each feature
features = df.columns[:-1]
num_features = len(features)

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(20, 10))
axes = axes.flatten()

# Create individual box plots for each feature
for i, feature in enumerate(features):
    sns.boxplot(x='Quality', y=feature, data=df, ax=axes[i], color=banana_co
    axes[i].set_title(feature)
    axes[i].set_xlabel("")

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



Comment: Overall it seems quite difficult to distinguish two classes at each feature. Some features like 'Sweetness', 'HarvestTime', 'Ripeness' have noticable amount of outliers.

In [61]:
```
# Scatterplot with distinguishing colors to see if there is possible linearl
sns.pairplot(df, hue='Quality', palette=banana_colors)
```

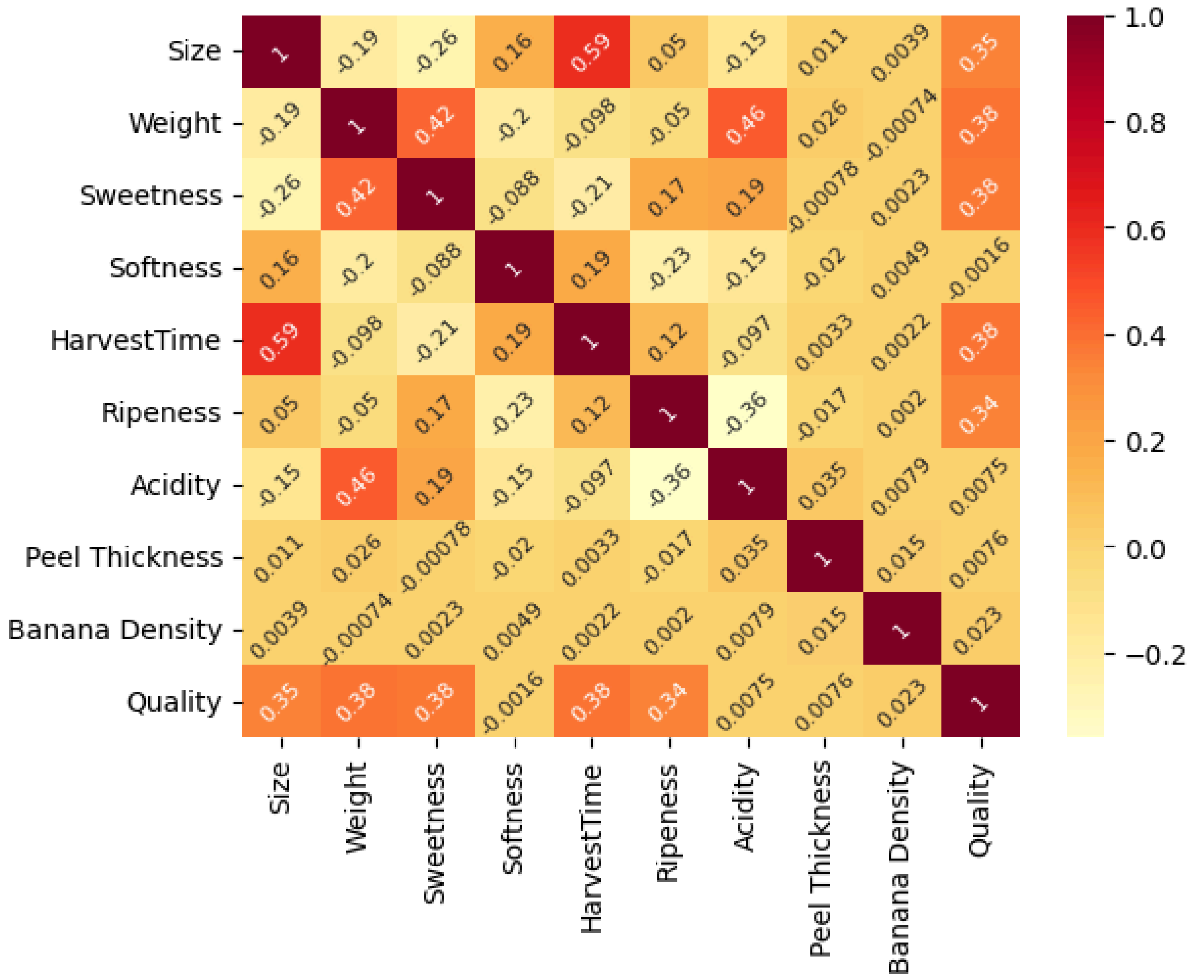
Out[61]: <seaborn.axisgrid.PairGrid at 0x28e8a0e10>



Comment: Marking quality of banana on pair-wise plots shows us that it appear unlikely the target can be classified by a linear separating line. This could suggest that linear models like Perceptron, Adaline or Logistic Regression may not perform well on this dataset.

In [62]:
```
# Correlation matrix of the dataset:
sns.heatmap(df.corr(), annot=True,
            annot_kws={'size': 8,'rotation': 45}, cmap="YlOrRd")
```

Out[62]: <Axes: >

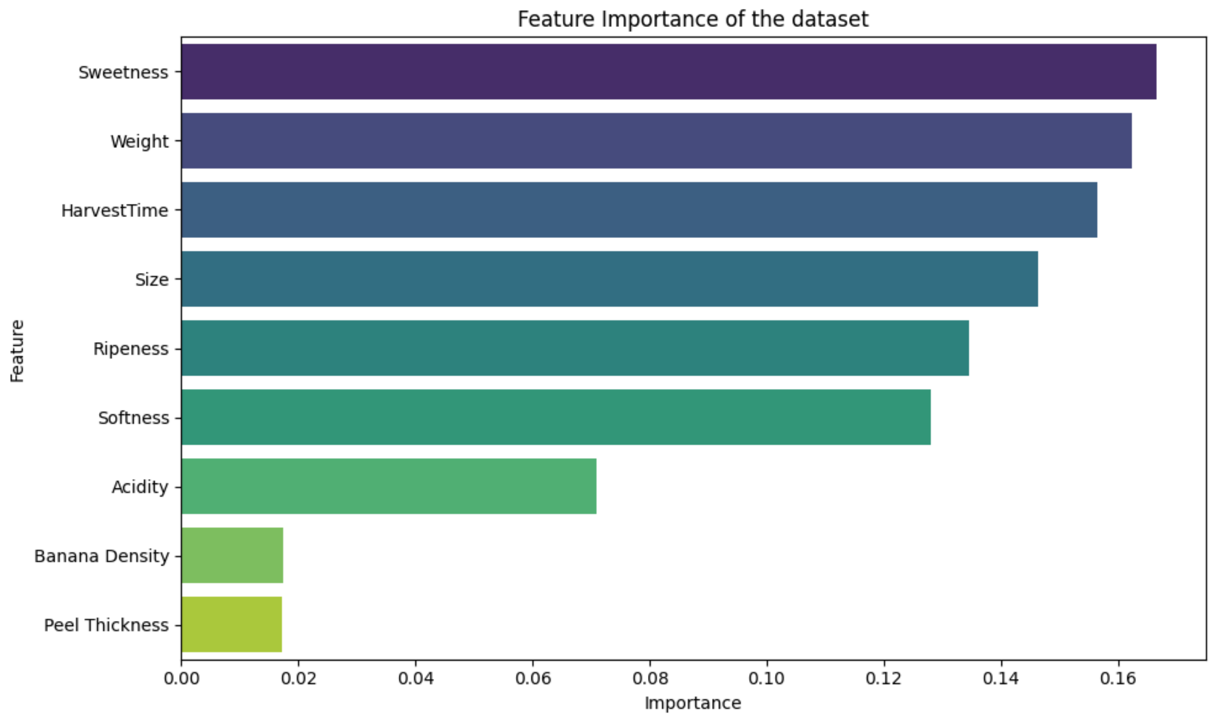


Comment: The dataset generally have very low correlation between pairs of feature. The most significant ones are ('Size' vs 'HarvestTime'), ('Weight' vs 'Acidity') og ('Weight' vs 'Sweetness')

In [63]:
```
# Analysis the feature importance

# Train Random Forest:
X = df.drop(['Quality'], axis=1)
y = df['Quality']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

rf = RandomForestClassifier(n_estimators=500, random_state=42)
rf.fit(X_train, y_train)

# Get feature importance
feature_importance = rf.feature_importances_
importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_im
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plot feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df, palette='viridi
plt.title('Feature Importance of the dataset')
```

```
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
/var/folders/tb/4p7pqq7j23n681mj_tfj2wl40000gn/T/ipykernel_7892/2647690016.p
y:19: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(x='Importance', y='Feature', data=importance_df, palette='viri
dis')
```



Comment: 'Acidity', 'Banana density' and 'Peel Thickness' are the least important features. They could be removed from the training data.

Data cleaning and visualization

Analysing if we should remove outliers

In [64]:
```
#Function to evaluate general models without hyperparameters
def evaluate_models(model_list, df, remove_columns = None):
    if remove_columns == None:
        X = df.drop(['Quality'], axis = 1)
    else:
        X = df.drop(['Quality'] + remove_columns, axis=1)

    y = df['Quality']

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
```

```python
    model_accuracies = {}

    for model_class in model_list:
        model = model_class()                # Instantiate model
        model.fit(X_train, y_train)          # Train model
        y_pred = model.predict(X_test)       # Predict
        accuracy = accuracy_score(y_test, y_pred)  # Calculate accuracy

        model_name = model.__class__.__name__
        model_accuracies[model_name] = accuracy  # Store name and accuracy

        print(f"{model_name} accuracy: {accuracy:.3f}\n")

    return model_accuracies

model_list = [Perceptron, LogisticRegression, SVC,
              RandomForestClassifier, DecisionTreeClassifier,
              KNeighborsClassifier]
```

In [65]:
```python
#First, train and fit to see the models' performance without removing anythi
sc = StandardScaler()
df.iloc[:,:-1] = sc.fit_transform(df.iloc[:,:-1])

original_models = evaluate_models(model_list, df)
```

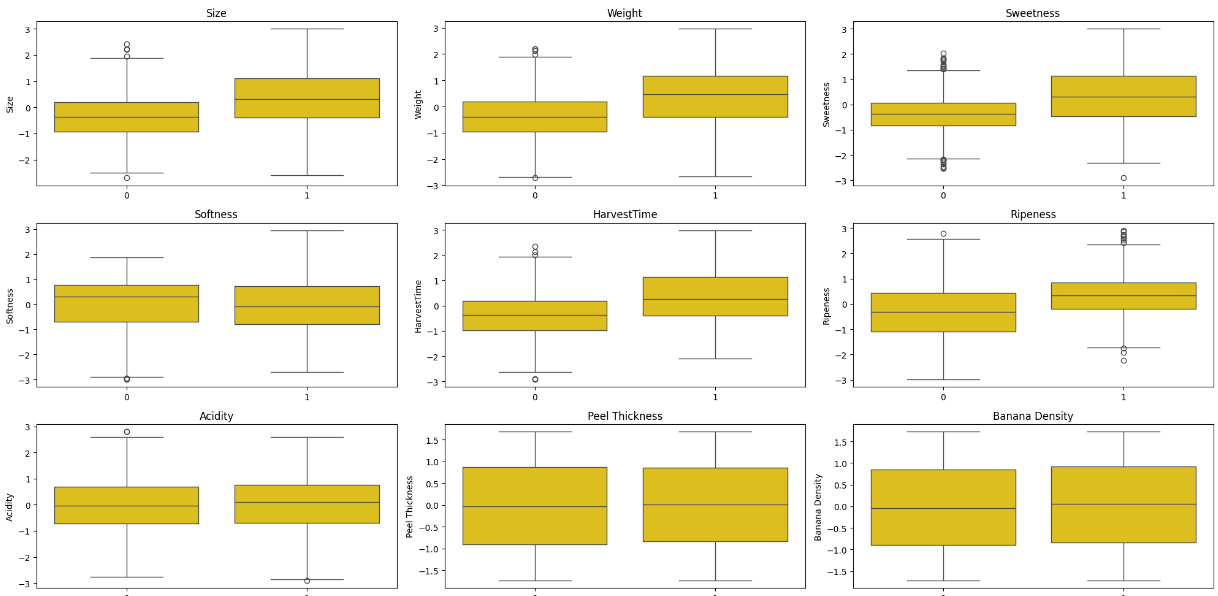
```
Perceptron accuracy: 0.806

LogisticRegression accuracy: 0.886

SVC accuracy: 0.969

RandomForestClassifier accuracy: 0.961

DecisionTreeClassifier accuracy: 0.924

KNeighborsClassifier accuracy: 0.963
```

Comment: SVC yields the highest of 96.9% while RandomForestClassifier and KNN yields the same of 96.3%.

In [66]:
```python
# Function removing outliers using Z_score:
def remove_outliers(df, threshold=3):
    df_clean = df.copy()
    numerical_cols = df_clean.select_dtypes(include=['number']).columns

    for col in numerical_cols:
        mean = df_clean[col].mean()
        std = df_clean[col].std()

        # Compute Z-score
        df_clean['Z_score'] = (df_clean[col] - mean) / std

        # Filter out outliers
        df_clean = df_clean[abs(df_clean['Z_score']) < threshold]
```

```
    df_clean = df_clean.drop(columns=['Z_score'])
    return df_clean

df_no_outliers = remove_outliers(df)
```

In [67]:
```
# Box plots after removing outliers:
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(20, 10))
axes = axes.flatten()

# Create individual box plots for each feature
for i, feature in enumerate(features):
    sns.boxplot(x='Quality', y=feature, data=df_no_outliers,
                ax=axes[i], color=banana_colors[1])
    axes[i].set_title(feature)
    axes[i].set_xlabel("")

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



Comments: With threshold of 3 standard deviation, a few of outliers have been remove. We have tested the models with lower threshold, they results in lower accuracy. So threshold of 3 is not too strict but it can remove extreme outliers that led to fail in classification.

In [68]:
```
no_outliers_models = evaluate_models(model_list, df_no_outliers)
```

```
Perceptron accuracy: 0.787

LogisticRegression accuracy: 0.875

SVC accuracy: 0.983

RandomForestClassifier accuracy: 0.963

DecisionTreeClassifier accuracy: 0.909

KNeighborsClassifier accuracy: 0.972
```

Comment: SVC yields higher at now 98.3 % and both RandomForest and KNN increase in accuracy.

Then we are curious of if the models perform better if we remove some features has small importance (noise to the dataset).

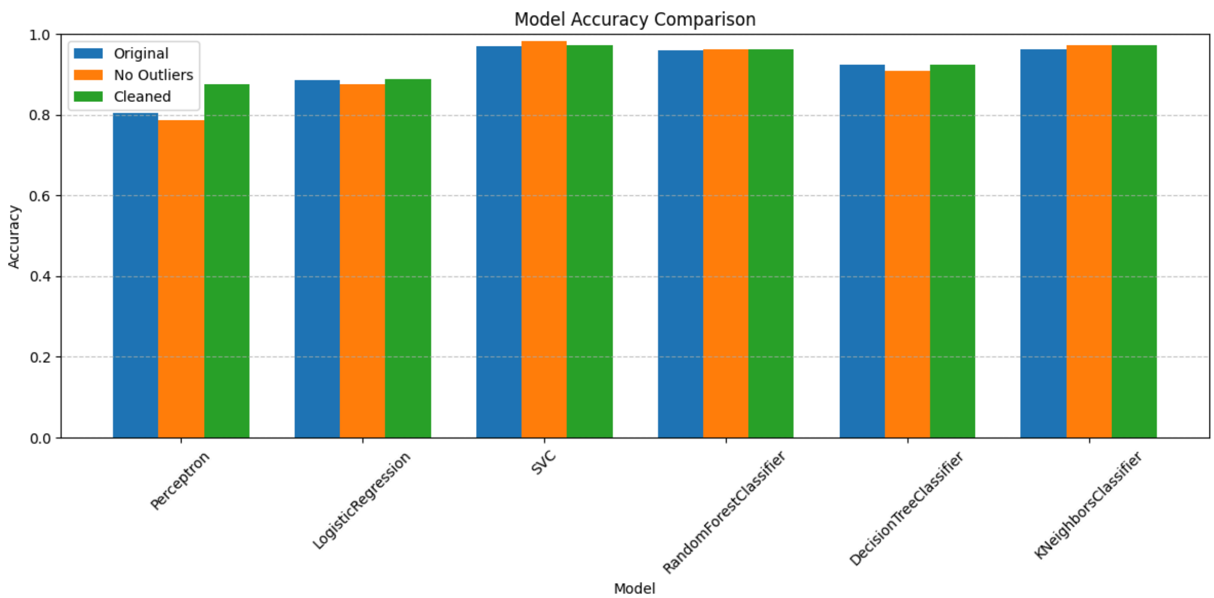
In [69]:
```
# Models performance when the two least important removed:
cleaned_models = evaluate_models(model_list, df,
                                 ['Peel Thickness', 'Banana Density'])
```

```
Perceptron accuracy: 0.876

LogisticRegression accuracy: 0.888

SVC accuracy: 0.974

RandomForestClassifier accuracy: 0.963

DecisionTreeClassifier accuracy: 0.925

KNeighborsClassifier accuracy: 0.973
```

Comment: The accuracy drops when we removed some columns. We tried removing from 1 to 4 columns and all results in lower accuracy.

In [70]:
```
# Convert dictionaries to lists of model names and their accuracies
model_names = list(original_models.keys())
original_acc = [original_models[model] for model in model_names]
no_outliers_acc = [no_outliers_models[model] for model in model_names]
cleaned_acc = [cleaned_models[model] for model in model_names]

# Bar width and positions
x = np.arange(len(model_names))
bar_width = 0.25

# Create the bar plot
plt.figure(figsize=(12, 6))
plt.bar(x - bar_width, original_acc, width=bar_width, label='Original')
plt.bar(x, no_outliers_acc, width=bar_width, label='No Outliers')
plt.bar(x + bar_width, cleaned_acc, width=bar_width, label='Cleaned')
```

```
# Labels and titles
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.xticks(x, model_names, rotation=45)
plt.ylim(0, 1)  # since accuracy is between 0 and 1
plt.legend()
plt.tight_layout()
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



Comment: From exploration and this graph, we would focus on Support Vector Machine, Random Forest and KNNeighbors as effective models. We will also just remove extreme outliers that lies out of 3 standard deviations.

DATA PREPROCESSING

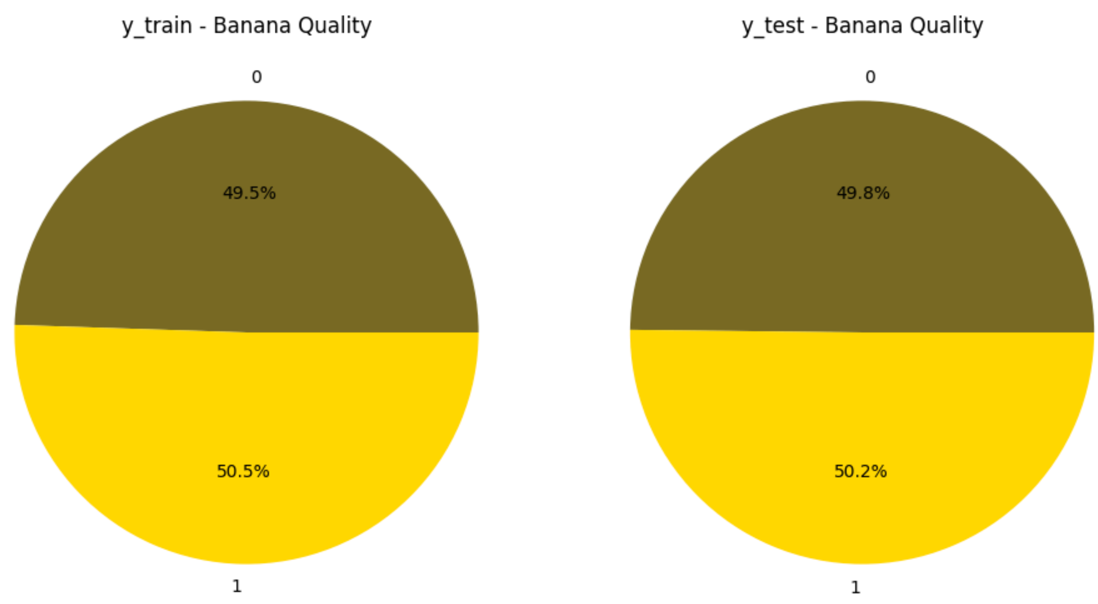
This will include:

- Scaling: StandardScaler()
- Remove outliers
- Splitting training and test sets
- Remove 'Peel Thickness' and 'Banana Density': We have done the whole process without this step but received lower accuracy score so we decided to remove them.

In [71]:
```
# df was scaled before
df = remove_outliers(df, threshold=3)

X = df.drop(['Quality', 'Peel Thickness', 'Banana Density'], axis = 1)
y = df['Quality']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [72]:
```
# Check the class proportions in both training and test sets
train_dist = y_train.value_counts(normalize=True).sort_index()
test_dist = y_test.value_counts(normalize=True).sort_index()
fig, axes = plt.subplots(1, 2, figsize=(10, 5))

# Pie chart for y_train
axes[0].pie(train_dist, autopct='%1.1f%%', labels=train_dist.index,
            colors=list(banana_colors.values()))
axes[0].set_title('y_train - Banana Quality')

# Pie chart for y_test
axes[1].pie(test_dist, autopct='%1.1f%%', labels=test_dist.index,
            colors=list(banana_colors.values()))
axes[1].set_title('y_test - Banana Quality')

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



EVALUATING MODELS AND PARAMETERS

In [73]:
```
def manual_search_evaluate(model_class, param_grid, X_train, X_test,
                               y_train, y_test, scoring='accuracy', cv=5):
    # Initialize variables to store values after each iteration
    best_score = 0
    best_params = None
    best_model = None

    # Generate all combinations of parameters
    keys, values = zip(*param_grid.items())
    param_combinations = [dict(zip(keys, v)) for v in itertools.product(*val

    # Loop over each combination of parameters
```

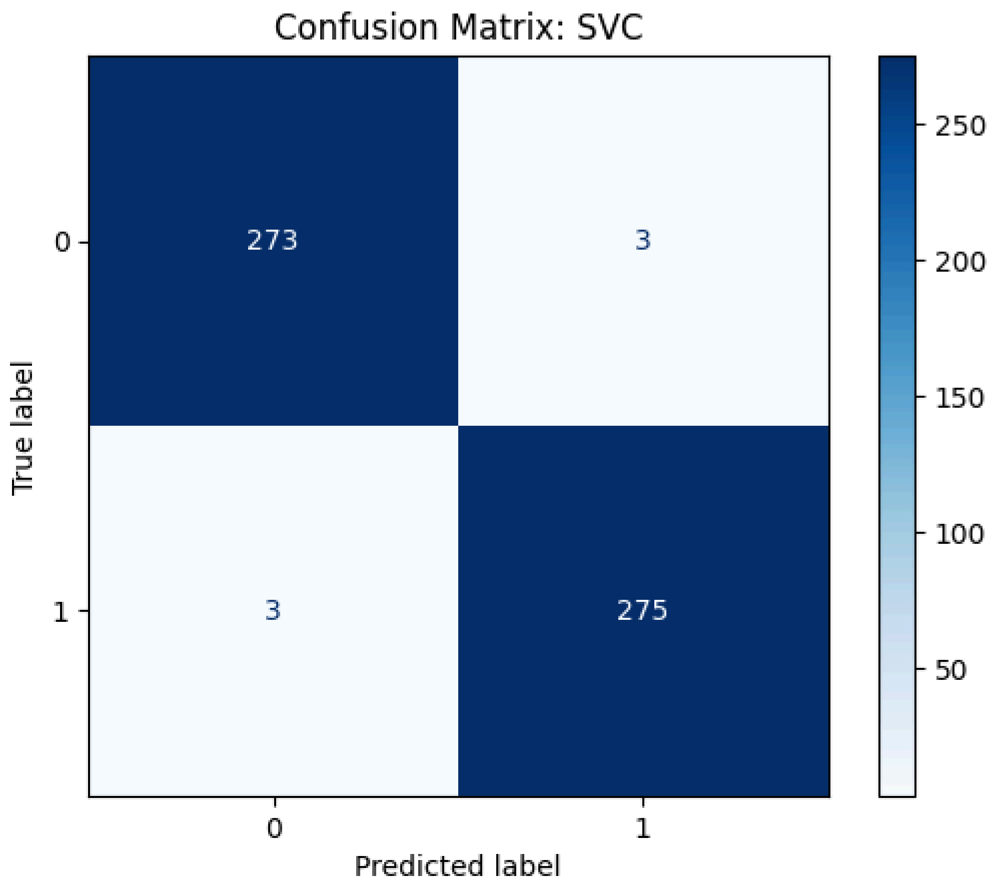
```
    for params in param_combinations:
        scores = []
        # Cross-validation
        skf = StratifiedKFold(n_splits=cv, shuffle=True, random_state=42)

        # Perform cross-validation
        for train_idx, val_idx in skf.split(X_train, y_train):
            # Split training data into training and validation folds
            X_fold_train, X_fold_val = X_train.iloc[train_idx], X_train.iloc
            y_fold_train, y_fold_val = y_train.iloc[train_idx], y_train.iloc

            # Train model with parameter combination:
            model = model_class(**params)
            model.fit(X_fold_train, y_fold_train)

            # Predict on validation set and compute accuracy
            y_val_pred = model.predict(X_fold_val)
            score = accuracy_score(y_fold_val, y_val_pred)
            scores.append(score)

        # Average cross-validation score for the param combination
        avg_score = np.mean(scores)

        # Update best score and best params
        if avg_score > best_score:
            best_score = avg_score
            best_params = params

    # Train best model on full training set
    best_model = model_class(**best_params)
    best_model.fit(X_train, y_train)

    # Predict on the test set
    y_pred = best_model.predict(X_test)

    # Compute accuracy
    acc = accuracy_score(y_test, y_pred)
    print(f"Best Parameters: {best_params}")
    print(f"Test Accuracy: {acc:.3f}")

    # Plot confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm)
    disp.plot(cmap='Blues', values_format='d')
    plt.title(f"Confusion Matrix: {model_class.__name__}")
    plt.show()

    return best_model, acc, cm
```

SUPPORT VECTOR MACHINE

Observed from the scatterplot that it seems very difficult to classify classes from linear separating line so we do not use Linear SVC

In [74]:
```
# RBF KERNEL SVM
param_grid_rbf = {
    'kernel': ['rbf'],
    'C': [0.1, 1, 10],
    'gamma': ['scale', 'auto', 0.01, 0.1]
}

rbf_SVC = manual_search_evaluate(SVC, param_grid_rbf, X_train, X_test, y_tra
```

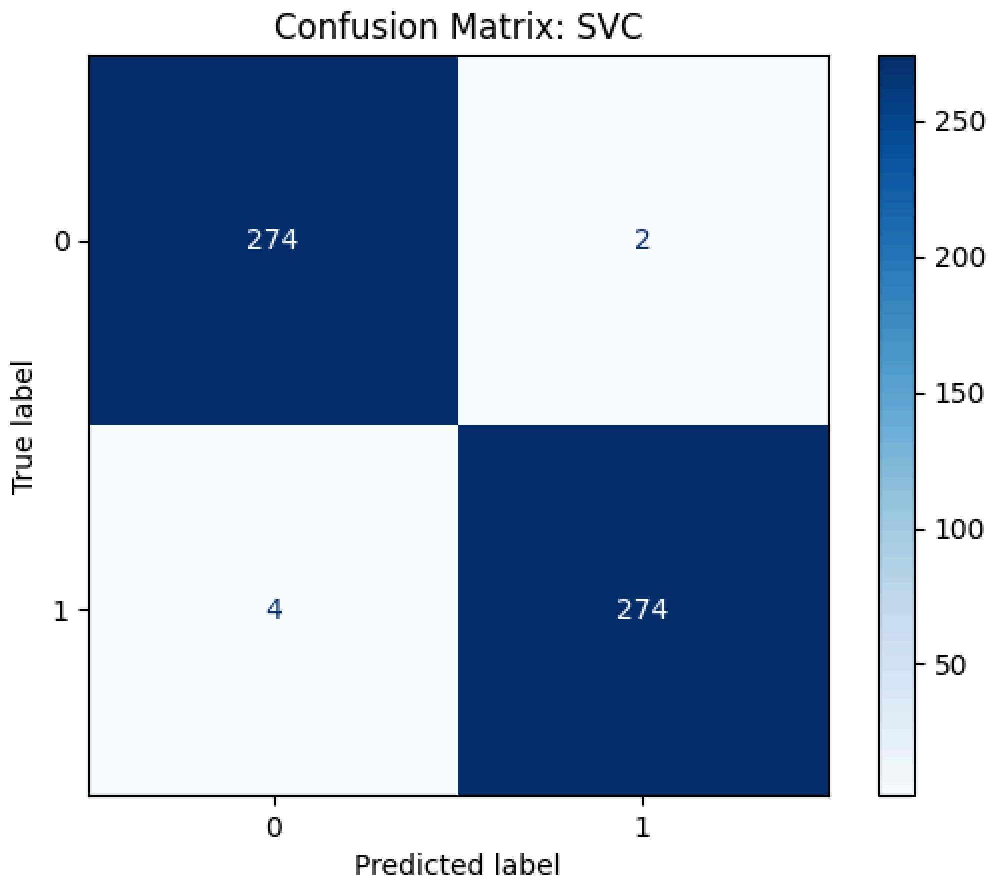
```
Best Parameters: {'kernel': 'rbf', 'C': 10, 'gamma': 0.1}
Test Accuracy: 0.989
```



Comment: Submission score on Kaggle: 0.98541 - a bit overfitting.

In [75]:
```
param_grid_poly = {
    'kernel': ['poly'],
    'C': [0.1, 1],
    'degree': [2, 3],
    'gamma': ['scale', 0.01],
    'coef0': [0.0, 0.1]
}
poly_SVC = manual_search_evaluate(SVC, param_grid_poly, X_train, X_test, y_t
```

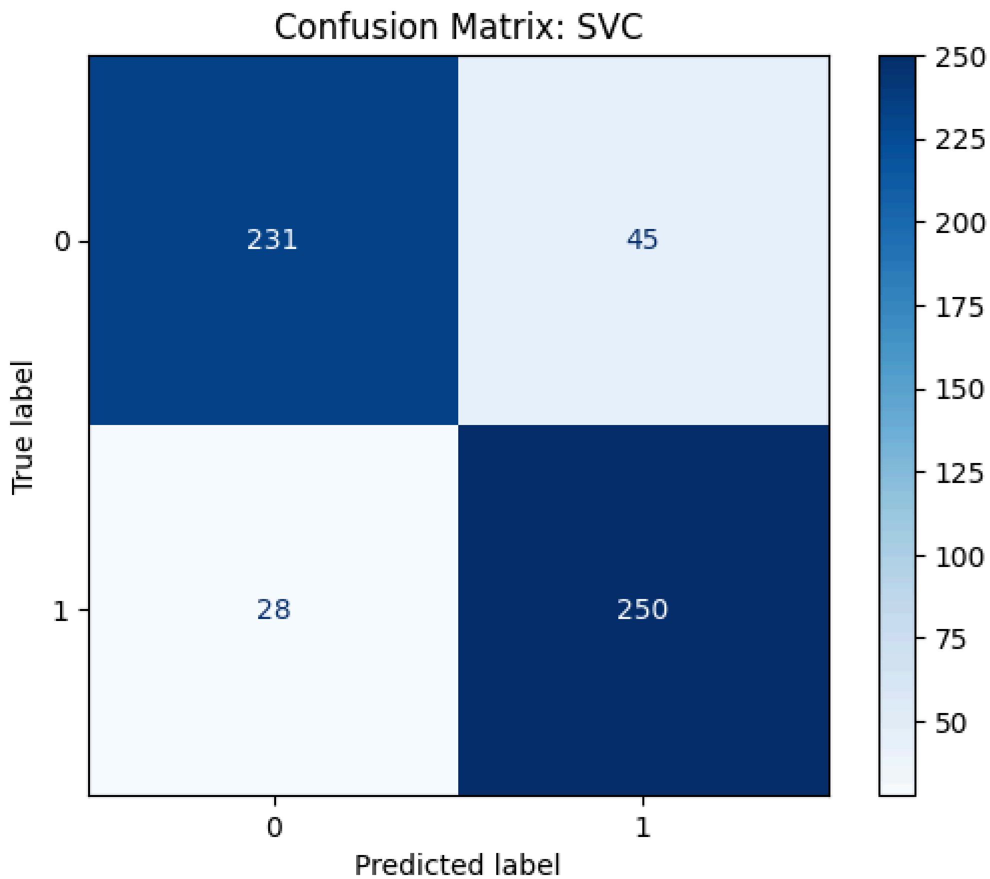
```
Best Parameters: {'kernel': 'poly', 'C': 1, 'degree': 3, 'gamma': 'scale',
'coef0': 0.1}
Test Accuracy: 0.989
```



Comment: Submission score on Kaggle: 0.98541

In [76]:
```
param_grid_sigmoid = {
    'kernel': ['sigmoid'],
    'C': [0.1, 1, 10],
    'gamma': ['scale', 0.01],
    'coef0': [0.0, 0.1]
}
sigmoid_SVC = manual_search_evaluate(SVC, param_grid_sigmoid, X_train, X_tes
```

```
Best Parameters: {'kernel': 'sigmoid', 'C': 1, 'gamma': 0.01, 'coef0': 0.0}
Test Accuracy: 0.868
```

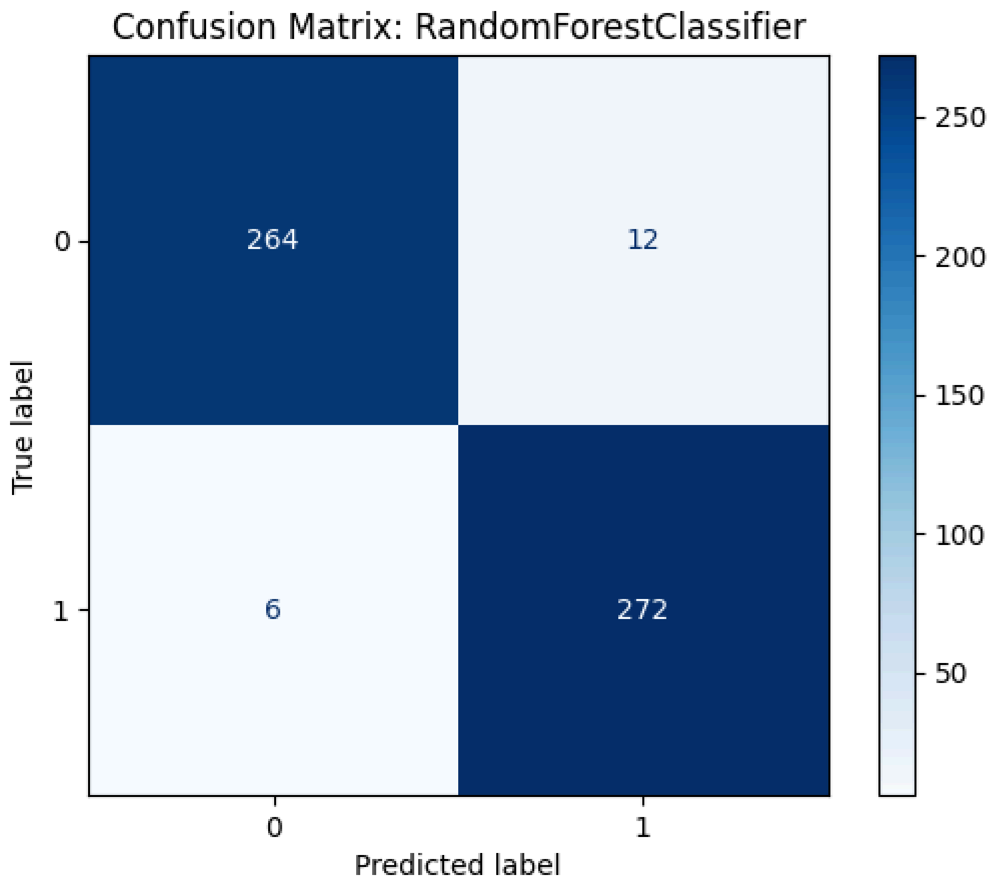


Comment: Submission score on Kaggle - 0.84811

RANDOM FOREST

In [77]:
```
param_grid_rf = {
    'max_depth': [None, 10, 20],       # Maximum depth of the tree
    'min_samples_split': [2, 5],       # Min samples to split an internal no
    'min_samples_leaf': [1, 2],        # Min samples required at a leaf node
    'max_features': ['sqrt', 'log2'],  # Number of features to consider at e
}

best_rf = manual_search_evaluate(RandomForestClassifier, param_grid_rf, X_tr
```

```
Best Parameters: {'max_depth': None, 'min_samples_split': 5, 'min_samples_le
af': 2, 'max_features': 'log2'}
Test Accuracy: 0.968
```

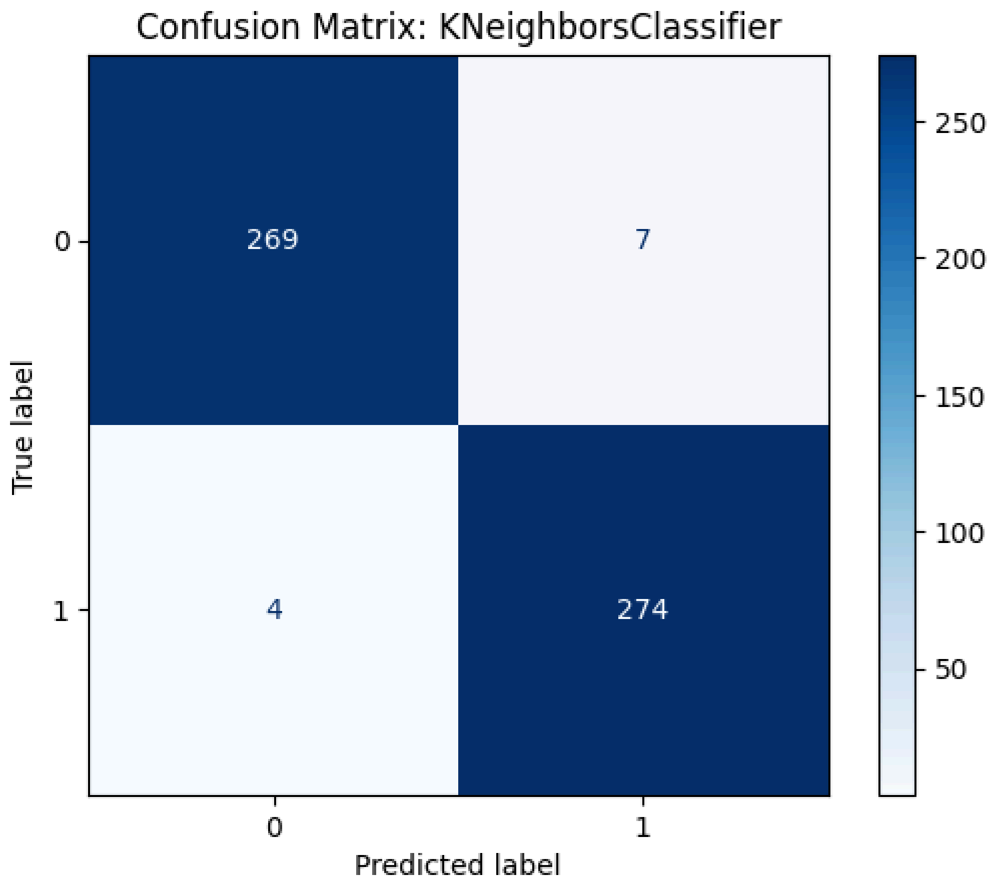


Comment: Submission score on Kaggle: 0.96233

KNN

In [78]:
```
param_grid_knn = {
    'n_neighbors': [3, 4, 5, 6, 7],            # Number of neighbors to use
    'metric': ['euclidean', 'manhattan', 'minkowski'],     # Distance metric
    'p': [1, 2]                                 # Power parameter for Minkowsk
}

best_knn = manual_search_evaluate(KNeighborsClassifier, param_grid_knn, X_tr
```

```
Best Parameters: {'n_neighbors': 7, 'metric': 'euclidean', 'p': 1}
Test Accuracy: 0.980
```



Comment: Submission score on Kaggle: 0.98177

In [80]:
```
df_test = pd.read_csv('test.csv')
df_test = df_test.drop(['Peel Thickness', 'Banana Density'], axis =1)
df_test = sc.fit_transform(df_test)
y_test_kaggle = rbf_SVC[0].predict(df_test)
y_test_kaggle = pd.DataFrame(y_test_kaggle, columns=["Quality"])
y_test_kaggle.index.name = "ID"
y_test_kaggle[['Quality']].to_csv("submission6.csv")
```

```
/Users/dunhul/Library/CloudStorage/OneDrive-NorwegianUniversityofLifeScience
s/VÅR 2025/DAT200/CA3_DAT200/.venv/lib/python3.13/site-packages/sklearn/util
s/validation.py:2739: UserWarning: X does not have valid feature names, but
SVC was fitted with feature names
  warnings.warn(
```

So far RBF-kernel Support Vector Machine is the best model with C=10 and gamma=0.1.