CA3

Imports

In [41]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
```

Reading data

In [42]:
```
df = pd.read_csv("./assets/train.csv", index_col = 0)

df.info()

# Checking for missing values
print(f"\nMissing values inn training data: {df.isnull().sum().sum()}")
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2800 entries, -1.8257343 to -1.6260979
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Weight          2800 non-null   float64
 1   Sweetness       2800 non-null   float64
 2   Softness        2800 non-null   float64
 3   HarvestTime     2800 non-null   float64
 4   Ripeness        2800 non-null   float64
 5   Acidity         2800 non-null   float64
 6   Peel Thickness  2800 non-null   float64
 7   Banana Density  2800 non-null   float64
 8   Quality         2800 non-null   int64  
dtypes: float64(8), int64(1)
memory usage: 218.8 KB

Missing values inn training data: 0
```

Data exploration and visualisation

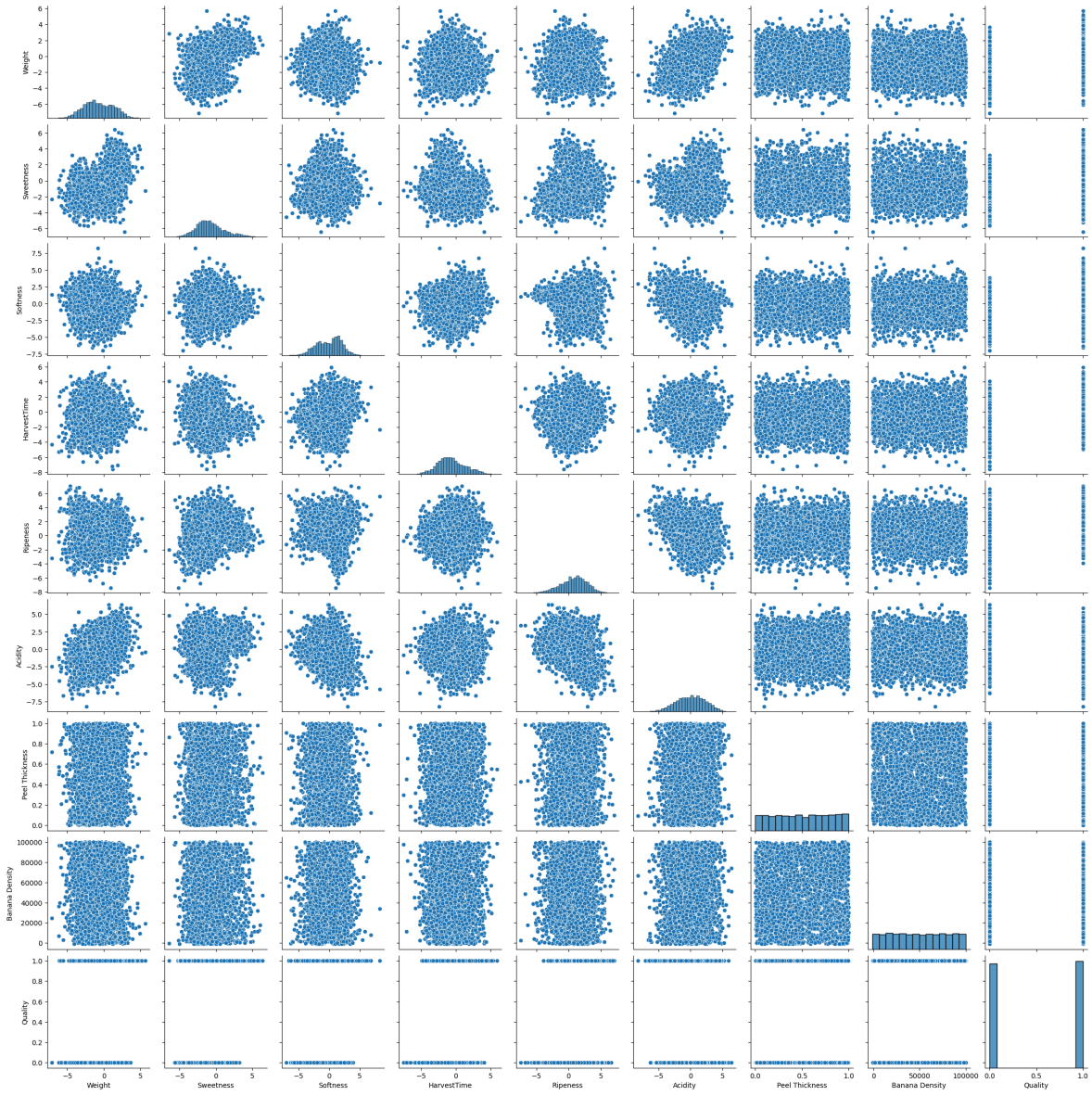
In [43]:
```
print(df.describe()) # Gives a table of the dataset with statistical components

sns.pairplot(df) # Gives a scatter plot for every pair & a histogram for the the
```

	Weight	Sweetness	Softness	HarvestTime	Ripeness
count	2800.000000	2800.000000	2800.000000	2800.000000	2800.000000
mean	-0.751050	-0.751005	-0.019557	-0.700683	0.771011
std	2.006590	1.955109	2.076865	2.029916	2.098275
min	-7.103426	-6.434022	-6.959320	-7.570008	-7.423155
25%	-2.238843	-2.104742	-1.593816	-2.112747	-0.572589
50%	-0.882387	-0.997902	0.220174	-0.856858	0.930927
75%	0.853566	0.334989	1.542899	0.628895	2.229410
max	5.679692	6.438196	8.241555	5.942060	7.077372

	Acidity	Peel Thickness	Banana Density	Quality
count	2800.000000	2800.000000	2800.000000	2800.000000
mean	-0.000989	0.506758	49397.491271	0.506429
std	2.286725	0.291936	29327.077623	0.500048
min	-8.226977	0.000086	-980.343999	0.000000
25%	-1.608385	0.257860	24025.427350	0.000000
50%	0.073963	0.506282	49303.534616	1.000000
75%	1.662417	0.761016	75066.598785	1.000000
max	6.395850	0.999430	99982.761410	1.000000

Out[43]: <seaborn.axisgrid.PairGrid at 0x25d07419b10>

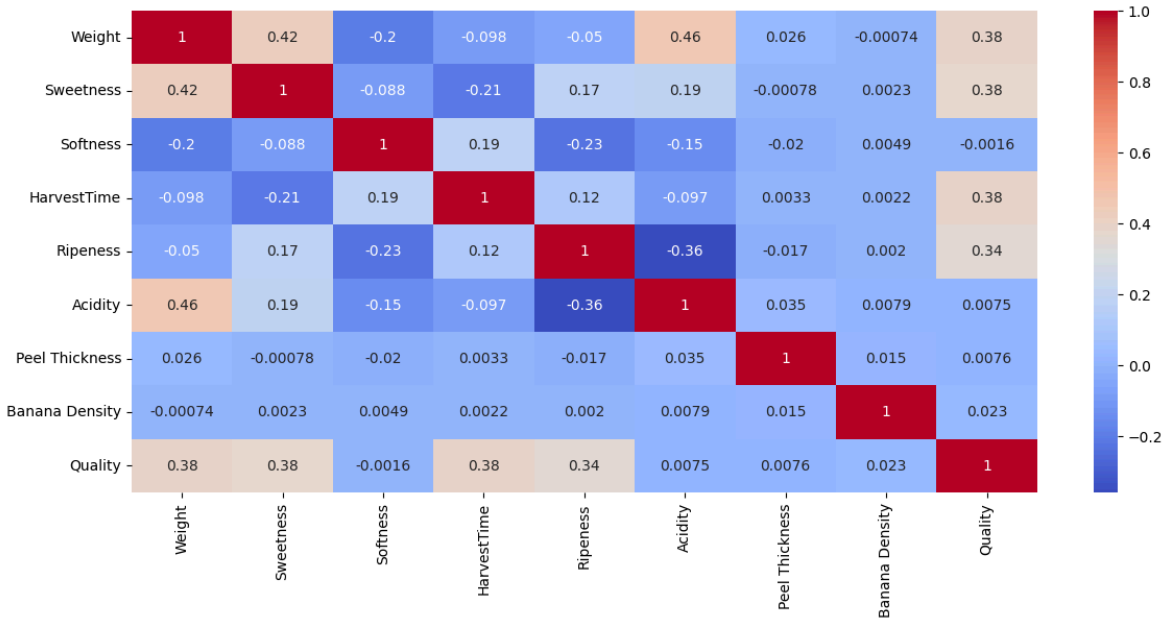


The pairs of different features does not look linear seperable, they have a complex relation.

Therefore, we think models like logistic regression will have low accuracy for theese data.

In [44]:
```
""" Checking correlation with every feature """
fig, axes = plt.subplots(1, 1, figsize=(14, 6)) # To make the values more readab
# annot = true to get value, coolwarm cmap to make sense with correlation
sns.heatmap(df.corr(), annot = True, cmap = "coolwarm")
```

Out[44]: <Axes: >



As we can see: Acidity and Weight, and Weight and Sweetness has the highest positive correlation.
While the Acidity and Ripeness, and Softness and Ripeness has the highest negative correlation.

To conclude:

The pairs of different features have complex relations to each other. The data is not linearly seperable and
therefore, we think models like logistic regression will have low accuracy for theese data.
Acidity and Weight, Weight and Sweetness has the highest positive correlation.
While the Acidity and Ripeness, and Softness and Ripeness has the highest negative correlation.
With this informasjotion we know which features we can focus more on.
We also found out that the banana density values are too high. We want to scale and standardize
the values of the dataset to fit the models better.
We will probably remove the coloumns banana density and peel thickness because of the low correlation
to the other features.
We think that SVC, KNN and Randomforest will be the better models, therefore,
we will only train those models.

Data Preprocessing & Feature Engineering

We found out in the exploration and visualization part that there were not any missing values.
However, we will still drop outliers if we find any.

Feature Selection: We saw that Banana Density and Peel Thickness has low correlation with other features.
Therefore we will drop those features

In [45]:
```
# Feature Selection, we are dropping the features when we're dropping coloumns i
useless_features = ["Banana Density", "Peel Thickness"]

# Including outliers, we found out that our model gets worse by removing outlier

df_clean = df.copy()
X = df_clean.drop(columns = ["Quality"] + useless_features)
y = df_clean["Quality"]
```

Modelling

Finding good parameters

SVC

In [ ]:
```
# Set ranges for C and gamma
params_C = np.arange(-1.6, 2, 0.1)
params_gamma = np.arange(0.1, 0.6, 0.1)

# Collect results in numpy arrays, one for train, one for test
svc_list = np.empty((len(params_C), len(params_gamma)), dtype = object) # Makes
accArr_test = np.zeros((len(params_C), len(params_gamma)))

for c_ind, c in enumerate(params_C):
    for gamma_ind, gamma_val in enumerate(params_gamma):

        accTest_list = []
        for r in range(42, 52):
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size

            sc = StandardScaler()
            sc.fit(X_train)

            X_train_sc = sc.transform(X_train)
            X_test_sc = sc.transform(X_test)

            SVC_rbf = SVC(kernel='rbf', C = 10.**c, gamma = gamma_val, random_st
            SVC_rbf.fit(X_train_sc, y_train)

            test_acc = SVC_rbf.score(X_test_sc, y_test)
            accTest_list.append(test_acc)

        accTest_average = np.mean(accTest_list)

        svc_list[c_ind, gamma_ind] = SVC_rbf
        accArr_test[c_ind, gamma_ind] = accTest_average
```

```
# Calculate and print the best parameters for the test data
best_params = np.unravel_index(accArr_test.argmax(), accArr_test.shape)
best_svc = svc_list[best_params[0], best_params[1]]

print('Best parameters for test data:')
print('c = {0:.2f}'.format(params_C[best_params[0]]))
print('gamma = {0:.2f}'.format(params_gamma[best_params[1]]))
print('with accuracy: {0:.3f}'.format(accArr_test[best_params[0], best_params[1]
```

```
Best parameters for test data:
c = 0.10
gamma = 0.30
with accuracy: 0.974
```

Random Forest

In [77]:

```
params_n_e = np.arange(1, 101, 5)
params_n_j = np.arange(1, 5, 1)
params_depth = np.arange(1, 5, 1)

random_forest_classifiers = np.empty((len(params_n_e), len(params_n_j), len(para
accArr_test = np.zeros((len(params_n_e), len(params_n_j), len(params_depth)))

for n_e_ind, n_e in enumerate(params_n_e):
    for n_j_ind, n_j in enumerate(params_n_j):
        for depth_ind, depth in enumerate(params_depth):
            accTest_list = []

            for r in range(42, 52):

                X_train, X_test, y_train, y_test = train_test_split(X, y, test_s

                sc = StandardScaler()
                sc.fit(X_train)

                X_train_sc = sc.transform(X_train)
                X_test_sc = sc.transform(X_test)

                # Train the model
                clf = RandomForestClassifier(n_estimators = n_e, random_state =
                clf.fit(X_train_sc, y_train)

                test_acc = clf.score(X_test_sc, y_test)
                accTest_list.append(test_acc)

            accTest_average = np.mean(accTest_list)

            random_forest_classifiers[n_e_ind, n_j_ind, depth_ind] = clf
            accArr_test[n_e_ind, n_j_ind, depth_ind] = accTest_average


# Calculate and print the best parameters for the test data

best_params = np.unravel_index(accArr_test.argmax(), accArr_test.shape)
best_rfc = random_forest_classifiers[best_params[0], best_params[1], best_params

print('Best parameters for test data:')
print('n estimatiors = {0:.2f}'.format(params_n_e[best_params[0]]))
print('n jobs = {0:.2f}'.format(params_n_j[best_params[1]]))
```

```
print('max depth = {0:.2f}'.format(params_depth[best_params[2]]))
print('with accuracy: {0:.3f}'.format(accArr_test[best_params[0], best_params[1]
```

```
Best parameters for test data:
n estimatiors = 66.00
n jobs = 1.00
max depth = 4.00
with accuracy: 0.894
```

KNN

In [78]:
```
best_k = 0
best_accuracy = 0

for k in range(1, 15):
    accuracies = []

    for r in range(100):
        X_train, X_val, y_train, y_val = train_test_split(X, y, test_size = 0.25

        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_val_scaled = scaler.transform(X_val)

        knn = KNeighborsClassifier(n_neighbors = k)
        y_pred = knn.fit(X_train_scaled, y_train).predict(X_val_scaled)
        accuracy = accuracy_score(y_pred, y_val)
        accuracies.append(accuracy)

    accuracy = np.mean(accuracies)

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k

print(f"Best k: {best_k}, Best accuracy during optimization: {best_accuracy:.3f}

X_test_scaled = scaler.transform(X_test)
y_pred_final = knn.predict(X_test_scaled)
accuracy = accuracy_score(y_pred_final, y_test)

print(f"Final accuracy of {best_k}-NN on the test set: {accuracy:.3f}")
```

```
Best k: 11, Best accuracy during optimization: 0.970
Final accuracy of 11-NN on the test set: 0.979
```

Final evaluation

SVC

C = 10 ** 0.1, gamma = 0.30,

with an accuracy 97.4%

Kaggle submission

In [81]:
```
# Our best model.
model = best_svc

# Getting our test data and dropping useless features.
```

```
df_test = pd.read_csv("./assets/test.csv", index_col = 0)
df_test = df_test.drop(columns = useless_features)

# Scaling
X_test2_scaled = scaler.transform(df_test)

# Taken from the kaggle submission side.
y_test2 = model.predict(X_test2_scaled)
y_test2 = pd.DataFrame(y_test2, columns=["Quality"])
y_test2.index.name = "ID"
y_test2[['Quality']].to_csv("submission.csv")
```