CA5

Imports

In [545…
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer

from sklearn.model_selection import GridSearchCV, KFold, StratifiedKFold, cross_
from sklearn.linear_model import Ridge
from sklearn.ensemble import HistGradientBoostingClassifier
```

Reading data

In [546…
```
df = pd.read_csv("./assets/train.csv")
```

Data exploration and visualisation

In [547…
```
print(df.shape)
df.describe()
```

```
(1000, 15)
```

Out[547…

	Length (cm)	Width (cm)	Weight (g)	Pericarp Thickness (mm)	Seed Count	Capsaicin Content	Vitam Con (
count	999.000000	999.000000	999.000000	998.000000	999.000000	999.000000	1000.000
mean	15.574675	6.641572	169.346406	4.619499	128.731301	4.215385	142.035
std	6.267303	2.139023	123.779026	2.829503	87.270366	3.163125	72.246
min	0.300000	0.100000	0.560000	0.000000	0.040000	0.010000	0.950
25%	11.290000	5.140000	79.020000	2.400000	55.390000	1.710000	92.290
50%	15.520000	6.600000	147.230000	4.280000	119.490000	3.590000	141.730
75%	19.900000	8.045000	227.625000	6.560000	186.845000	6.115000	192.720
max	35.570000	13.620000	869.970000	14.630000	487.260000	19.020000	450.290

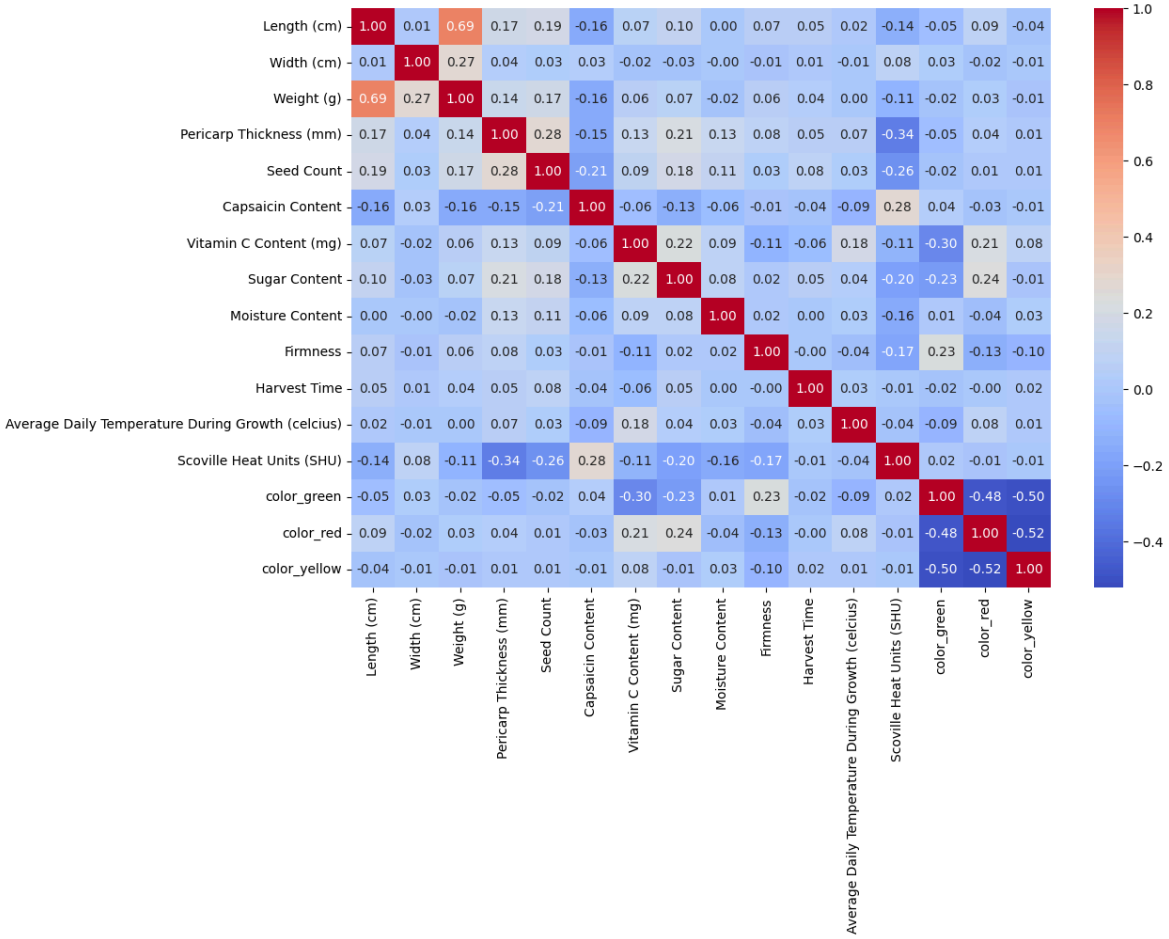
In [548…
```
# Checking the data types to see if i need encoding
```

```
print(df.dtypes)
```

```
Length (cm)                                          float64
Width (cm)                                           float64
Weight (g)                                           float64
Pericarp Thickness (mm)                              float64
Seed Count                                           float64
Capsaicin Content                                    float64
Vitamin C Content (mg)                               float64
Sugar Content                                        float64
Moisture Content                                     float64
Firmness                                             float64
color                                                 object
Harvest Time                                          object
Average Daily Temperature During Growth (celcius)    float64
Average Temperature During Storage (celcius)          object
Scoville Heat Units (SHU)                            float64
dtype: object
```

In [549…

```
# Decoding dataset for visualization
df_decoded = pd.get_dummies(df, columns = ["color"], dtype = int)

mapping = {"Morning": 1, "Midday": 2, "Evening": 3}
df_decoded["Harvest Time"] = df_decoded["Harvest Time"].map(mapping)

# Too many missing values, and it does not make sense for target values
df_decoded = df_decoded.drop(columns = ["Average Temperature During Storage (cel

plt.figure(figsize = (12, 8))
sns.heatmap(df_decoded.corr(), annot = True, cmap = "coolwarm", fmt = ".2f")
plt.show()
```



In [550…
```
print("Missing Values:\n", df.isnull().sum(), "\n")
print("Duplicates:", df.duplicated().sum())
```

```
Missing Values:
 Length (cm)                                          1
Width (cm)                                            1
Weight (g)                                            1
Pericarp Thickness (mm)                               2
Seed Count                                            1
Capsaicin Content                                     1
Vitamin C Content (mg)                                0
Sugar Content                                         1
Moisture Content                                      0
Firmness                                              1
color                                                 1
Harvest Time                                          0
Average Daily Temperature During Growth (celcius)     0
Average Temperature During Storage (celcius)        648
Scoville Heat Units (SHU)                             0
dtype: int64

Duplicates: 0
```

There is alot of missing values we have to deal with,
however there is not any duplicates.
We know too litle too make a conclusion.
In addition, there is alot of cleaning to do before we can visualize the data.
The visualization and conclusion will therefore be made after the data cleaning.

Data cleaning and more visualisation

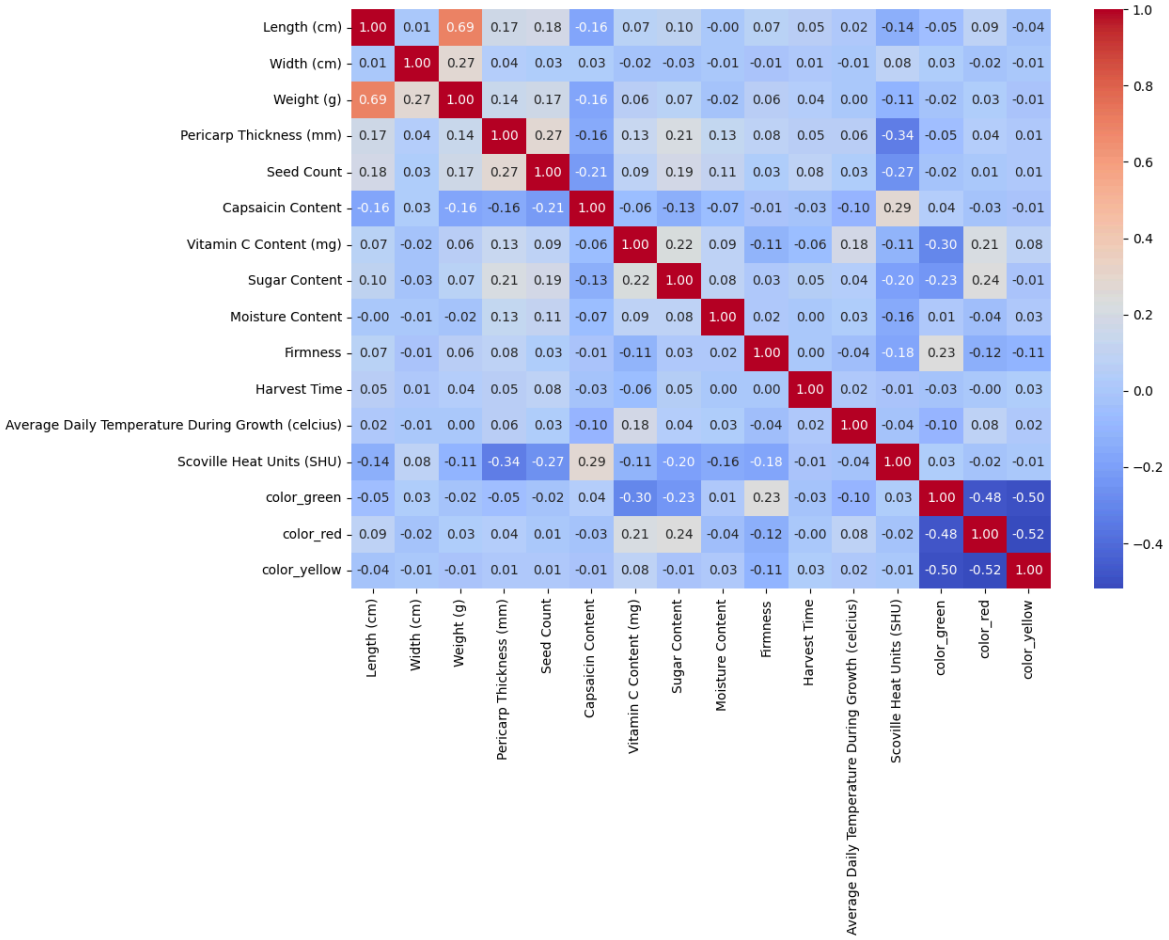
Our plan is to remove the feature "Average Temperature During Storage (celcius)".
The feature seems too unnecessary to imputate the missing data.
We will also remove the data from the other missing values
since there is not many of them.

In [551…
```
# Dealing with missing values: Removal
df = df.drop(columns = ["Average Temperature During Storage (celcius)"])
df = df.dropna()
print(f"Shape: {df.shape}")
```

```
Shape: (990, 14)
```

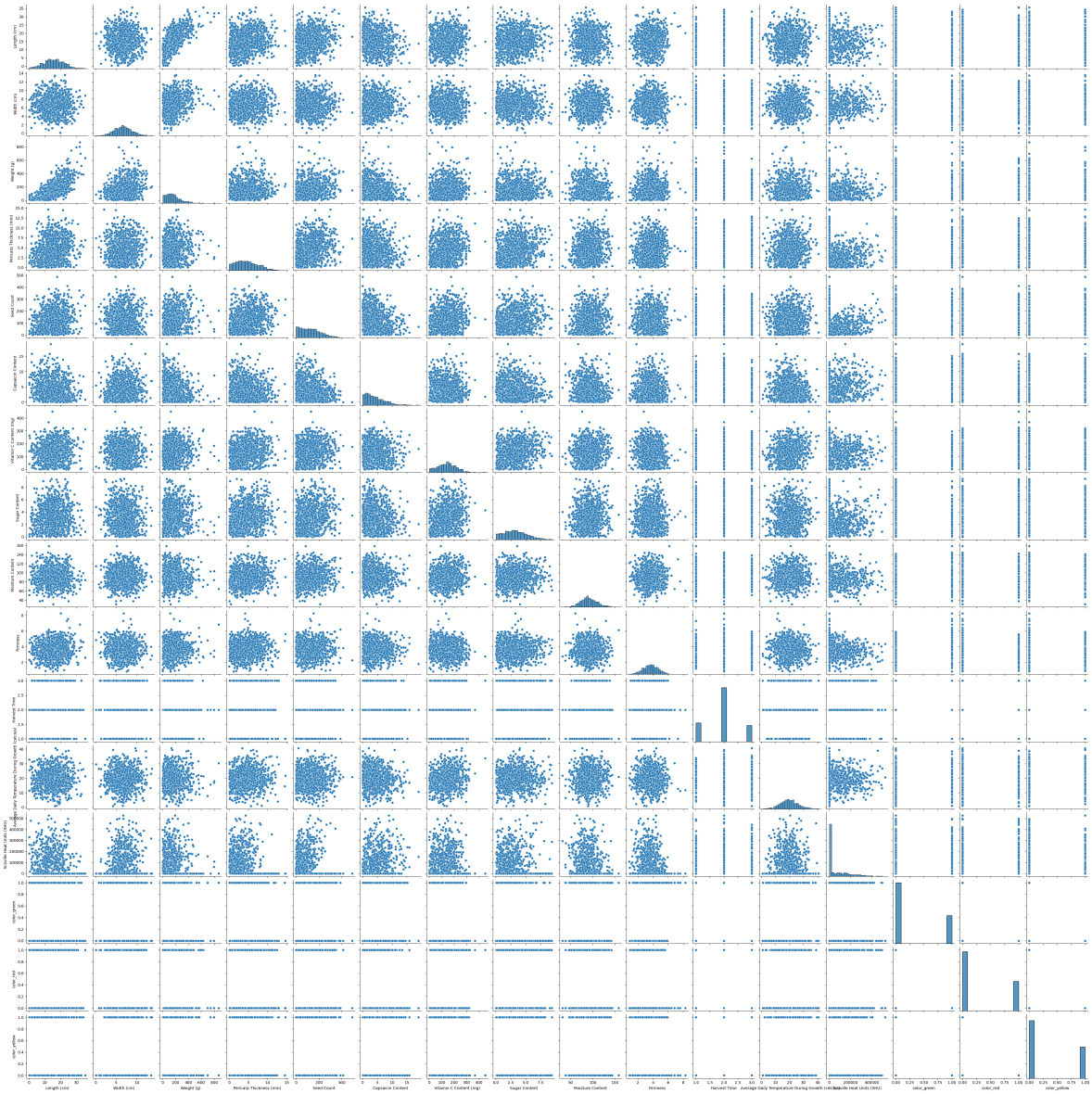
We still have a good amount of data to work with.

In [552…
```
# Decoding again for our main dataset
df = pd.get_dummies(df, columns = ["color"], dtype = int)

mapping = {"Morning": 1, "Midday": 2, "Evening": 3}
df["Harvest Time"] = df["Harvest Time"].map(mapping)

# Revisiting the correlation heatmap
plt.figure(figsize = (12, 8))
sns.heatmap(df.corr(), annot = True, cmap = "coolwarm", fmt = ".2f")
plt.show()
```



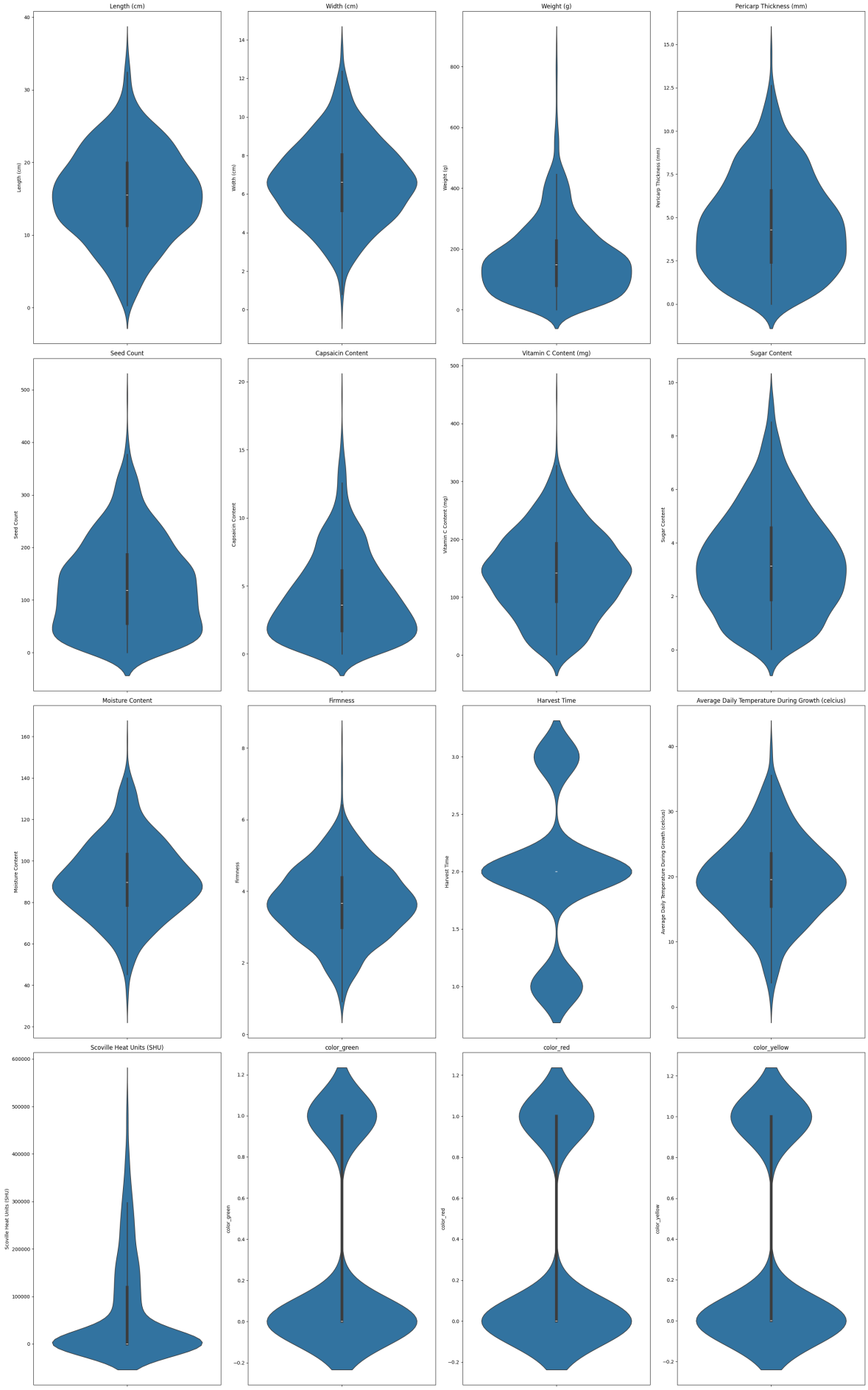
In [553…

```
# Checking patterns with pairplot
sns.pairplot(df)
plt.show()
```



In [557…

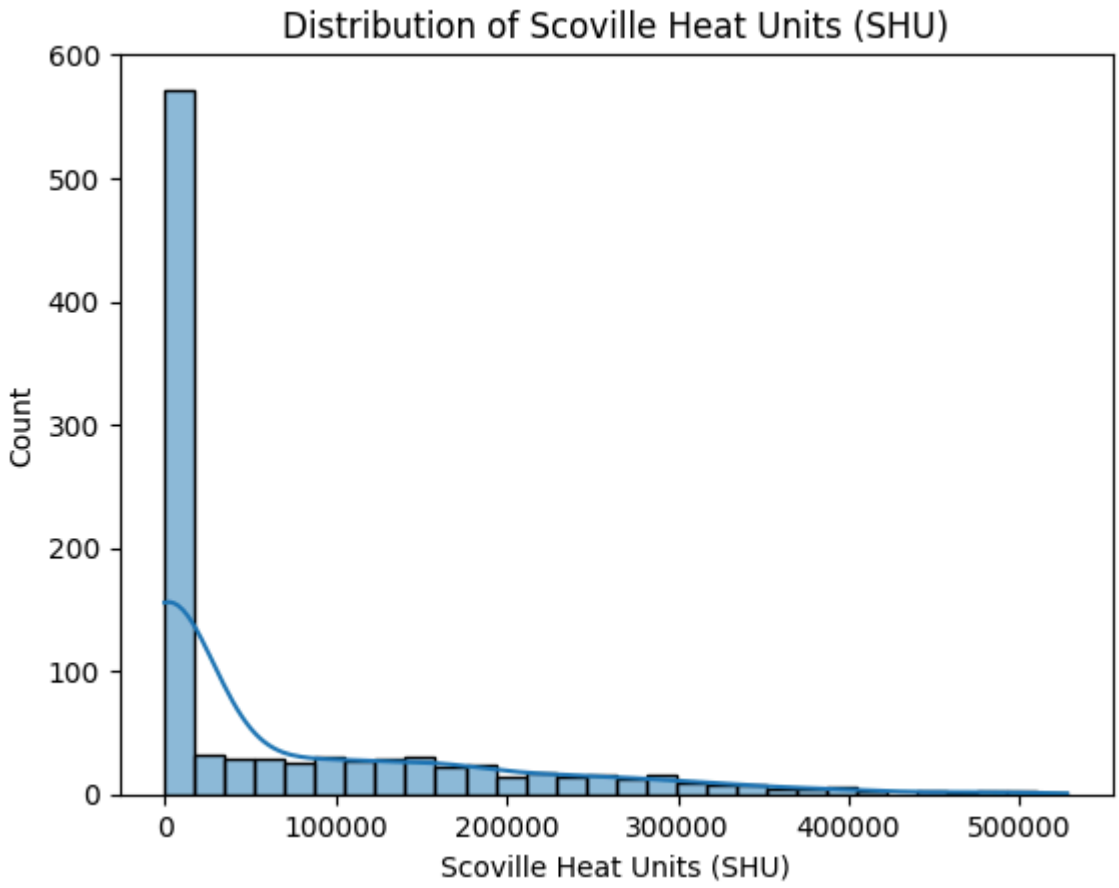
```
# Looking closer for outliers
numeric_features = df.select_dtypes(include = "number").columns

num_features = len(numeric_features)
fig, axes = plt.subplots(4, 4, figsize = (25, 40))
axes = axes.flatten()

for i, feature in enumerate(numeric_features):
    sns.violinplot(y = df[feature], ax = axes[i])
    axes[i].set_title(feature)

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



In [558…

```
# Checking for inbalance
sns.histplot(df["Scoville Heat Units (SHU)"], kde = True, bins = 30)
plt.title("Distribution of Scoville Heat Units (SHU)")
```

```
plt.show()

# Checking for skewness
skew = df["Scoville Heat Units (SHU)"].skew()
print(f"Skewness: {skew:.2f}")
```




```
Skewness: 1.62
```

In [559…

```
# We know that SHU = 0 is bellpeppers
num_zero = (df["Scoville Heat Units (SHU)"] == 0).sum()
num_over_zero = (df["Scoville Heat Units (SHU)"] > 0).sum()

print(f"Bell Peppers: {num_zero}")
print(f"Chilli Peppers: {num_over_zero}")
```

```
Bell Peppers: 537
Chilli Peppers: 453
```

Conclusion

The target value has a skewness of 1.61 and we will therefore consider the dataset inbalanced.
We can use k-fold to cross validate the model. On the other hand, we can use stritified k fold if we work around the data.
We can use some form of dimension reduction that can also reduce noise to help us mitigate outliers.
This dataset is allready small, we do not want discard more data unless it is necessary.
We will also remove outliers by calculating the IQR before the other preprocessing.
There is not any close correlation between the different features,

thus we must use dimension reduction instead of selection, or we can use both.
This task will try out regression analysis and a two step analysis.

In [560…
```
# Dealing with outliers
numeric_cols = df.select_dtypes(include = "number")

# Calculate IQR
Q1 = numeric_cols.quantile(0.25)
Q3 = numeric_cols.quantile(0.75)
IQR = Q3 - Q1

# Filter out outliers
df_filtered = df[~((numeric_cols < (Q1 - 1.5 * IQR)) | (numeric_cols > (Q3 + 1.5

print(df_filtered.shape)
```

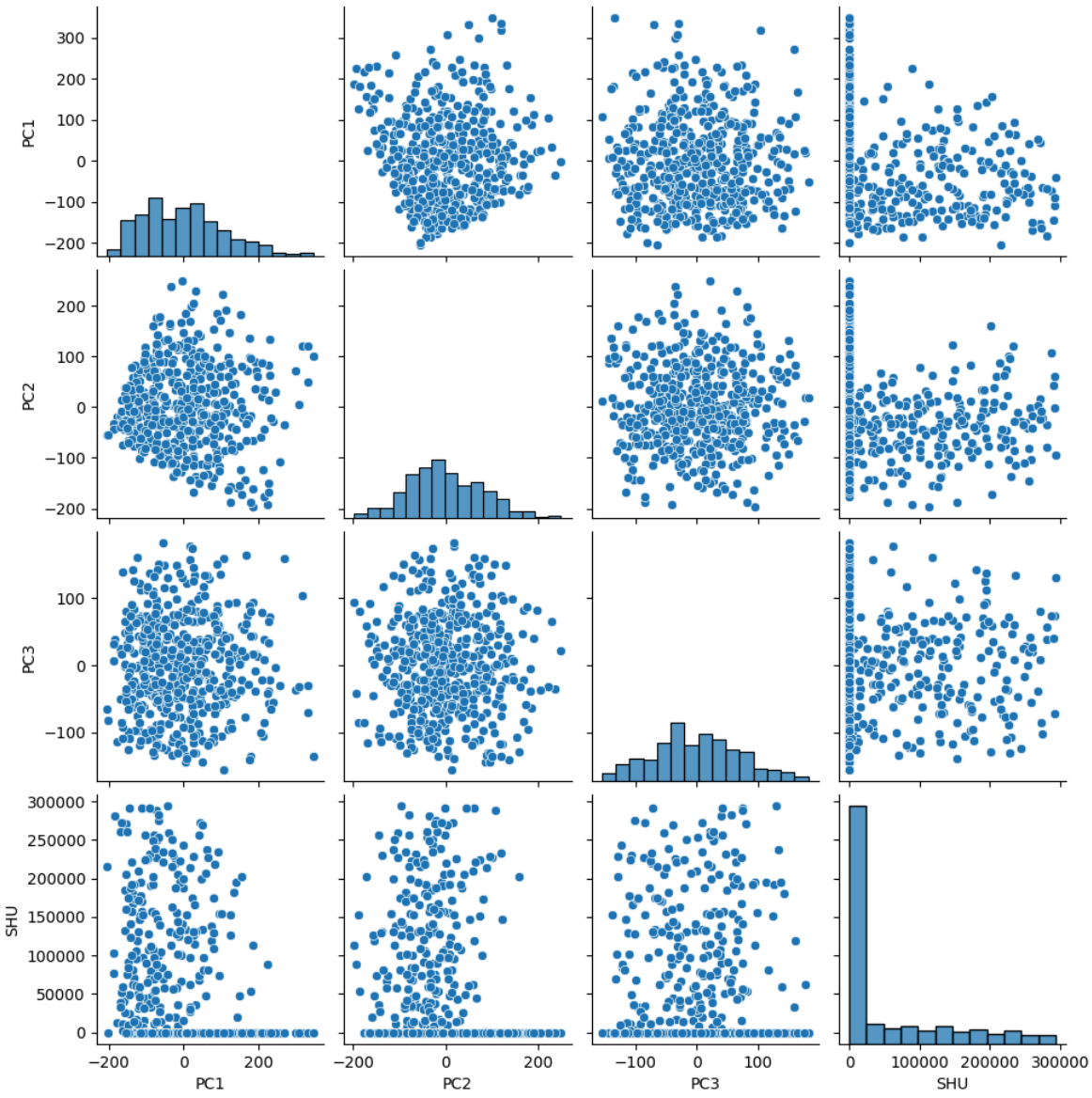
```
(509, 16)
```

In [561…
```
droppes_1 = ["Harvest Time", "Average Daily Temperature During Growth (celcius)"
droppes_2 = ["Moisture Content", "Firmness"]

# Splitting Data
X = df_filtered.drop(columns = ["Scoville Heat Units (SHU)"])
y = df_filtered["Scoville Heat Units (SHU)"]
```

Data preprocessing

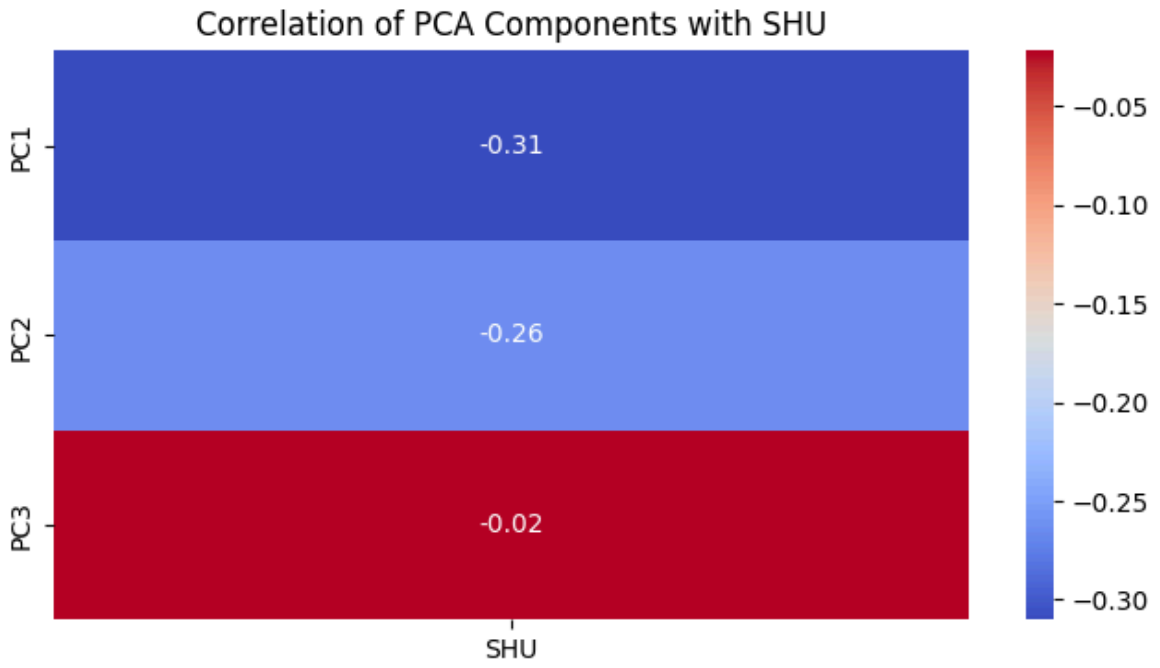
In [630…
```
# Visualizing the n_components for PCA
num_components = 0.85
```

In [631…
```
# Create a pairplot with pca features
pca = PCA(n_components = num_components)
X_pca = pca.fit_transform(X)

columns = [f"PC{i + 1}" for i in range(X_pca.shape[1])]
df_pca = pd.DataFrame(X_pca, columns=columns)
df_pca = df_pca.reset_index(drop=True)
y_clean = y.reset_index(drop=True)
df_pca["SHU"] = y_clean

sns.pairplot(df_pca)
plt.show()
```



In [632…

```
# Heatmap of PCA components vs SHU
pc_corr = df_pca.corr()

plt.figure(figsize=(8, 4))
sns.heatmap(pc_corr[["SHU"]].drop("SHU"), annot = True, cmap = "coolwarm", fmt =
plt.title("Correlation of PCA Components with SHU")
plt.show()
```



In [633…
```
# Prepering for pipeline C
y_is_spicy = (y > 0).astype(int)
X_spicy = X[y_is_spicy == 1]
y_spicy = y[y_is_spicy == 1]
```

In [634…
```
# A
pipeA = Pipeline([
    ('imputer', SimpleImputer(strategy = "median")),
    ("scalar", StandardScaler()),
    ("pca", PCA(n_components = num_components)),
    ("regressor", Ridge())
])


# C
pipeC_clf = Pipeline([
    ("scalar", StandardScaler()),
    ("pca", PCA(n_components = num_components)),
    ("classifier", HistGradientBoostingClassifier(random_state = 42))
])

pipeC_reg = Pipeline([
    ("scalar", StandardScaler()),
    ("pca", PCA(n_components = num_components)),
    ("regressor", Ridge())
])
```

Modelling

In [ ]:
```
# Pipeline A
param_grid_A = {
    "regressor__alpha": np.arange(0, 20, 2)
}

gs_A = GridSearchCV(estimator = pipeA,
                    param_grid = param_grid_A,
                    scoring = "neg_mean_absolute_error",
```

```
                    cv = KFold(n_splits = 10, shuffle = True, random_state = 42)
                    n_jobs = -1)

gs_A.fit(X, y)

print("Best params:", gs_A.best_params_)
print("Best MAE:", gs_A.best_score_)
```

```
Best params: {'regressor__alpha': 18}
Best MAE: -52257.25906284357
```

In [640…

```
# Pipeline C, clf
param_grid_C_clf = {
    "classifier__learning_rate": [0.005, 0.015, 0.002],
    "classifier__max_iter": [300, 400, 500]
}

gs_C_clf = GridSearchCV(estimator = pipeC_clf,
                  param_grid = param_grid_C_clf,
                  cv = StratifiedKFold(n_splits = 10, shuffle = True, random_sta
                  scoring = "accuracy",
                  n_jobs = -1)

gs_C_clf.fit(X, y_is_spicy)

print("params:", gs_C_clf.best_params_)
print("accuracy:", gs_C_clf.best_score_)
```

```
params: {'classifier__learning_rate': 0.015, 'classifier__max_iter': 500}
accuracy: 0.8802352941176471
```

In [637…

```
# Pipeline C, reg
param_grid_C_reg = {
    "regressor__alpha": [0, 0.001, 0.1, 1]
}
gs_C_reg = GridSearchCV(estimator = pipeC_reg,
                    param_grid = param_grid_C_reg,
                    scoring = "neg_mean_absolute_error",
                    cv = KFold(n_splits = 10, shuffle = True, random_state = 42)
                    n_jobs = -1)

gs_C_reg.fit(X_spicy, y_spicy)

print("Best params:", gs_C_reg.best_params_)
print("Best MAE:", gs_C_reg.best_score_)
```

```
Best params: {'regressor__alpha': 0}
Best MAE: -63249.25151733998
```

Final evaluation

In [638…

```
model = gs_A.best_estimator_

cv_scores = cross_val_score(model, X, y, cv = 10, scoring = "neg_mean_absolute_e
print("Mean MAE:", -cv_scores.mean())
```

```
Mean MAE: 52387.99347132634
 52387.99347132634
```

Kaggle submission

In [639…

```
df_test = pd.read_csv("./assets/test.csv")

# Decoding
df_test = pd.get_dummies(df_test, columns = ["color"], dtype = int)

mapping = {"Morning": 1, "Midday": 2, "Evening": 3}
df_test["Harvest Time"] = df_test["Harvest Time"].map(mapping)

df_test = df_test.drop(columns = ["Average Temperature During Storage (celcius)"

submission = model.predict(df_test)
submission = pd.DataFrame(submission, columns = ["Scoville Heat Units (SHU)"])
submission.index = df_test.index
submission.index.name = "index"

submission.to_csv("submission.csv", index = True)
```