# CA3 - Lumifruit Edibility Classification

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### Imports

```
# Importing Libaries
# =======================
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.impute import SimpleImputer

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

### Reading data

```
# Loading the dataset
# =======================
df_train = pd.read_csv('train.csv', index_col=0)
df_test = pd.read_csv('test.csv', index_col=0)
```

### Data exploration and visualisation

```
#Cheking for missing data
# ========================
null_counts = df_train.isnull().sum().sum()
print(f'Total Missing values: {null_counts}' )
```

```
Total Missing values: 37
```

```
# Checking the info
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1248 entries, 0 to 1247
Data columns (total 17 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Acoustic Firmness Index             1245 non-null   float64
 1   Atmospheric Pressure at Harvest (Pa)  1248 non-null   float64
 2   Bitterness Scale                    1244 non-null   float64
```

```
 3   Circumference (mm)                       1246 non-null   float64
 4   Color Intensity (a.u.)                   1248 non-null   float64
 5   Find Distance from Main Vulcano (km)     1246 non-null   float64
 6   Length (mm)                              1244 non-null   float64
 7   Luminescence Intensity (a.u.)            1247 non-null   float64
 8   Magnetic orientation (degree)            1245 non-null   float64
 9   Odor index (a.u.)                        1246 non-null   float64
 10  Seed Count                               1247 non-null   float64
 11  Skin Thickness (mm)                      1247 non-null   float64
 12  Soil pH where Grown                      1245 non-null   float64
 13  Sugar Content (mg)                       1245 non-null   float64
 14  Weight (mg)                              1244 non-null   float64
 15  pH                                       1244 non-null   float64
 16  Edible                                   1248 non-null   float64
dtypes: float64(17)
memory usage: 175.5 KB
```

```
df_train.describe()
```

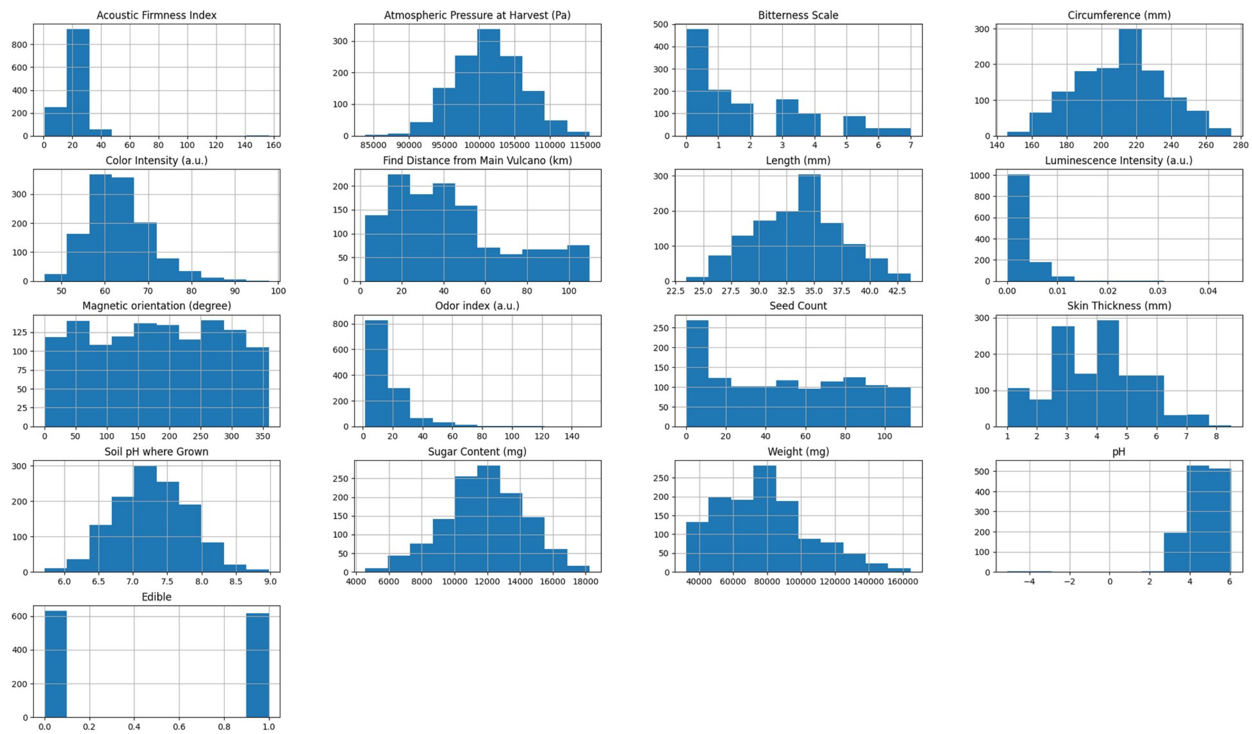
```
       Acoustic Firmness Index  Atmospheric Pressure at Harvest
(Pa)  \
count                1245.000000                                1248.000000

mean                   21.570077                              101327.543269

std                     8.131888                                4772.582203

min                     0.600000                               83825.000000

25%                    17.300000                               98095.750000

50%                    21.300000                              101357.000000

75%                    25.300000                              104470.750000

max                   156.520701                              115636.000000


       Bitterness Scale  Circumference (mm)  Color Intensity (a.u.)  \
count       1244.000000         1246.000000             1248.000000
mean           1.808682          211.046062               63.300962
std            1.960279           24.652278                7.118135
min            0.000000          145.867667               46.060000
25%            0.000000          192.982222               58.577500
50%            1.000000          212.429730               62.390000
75%            3.000000          226.313333               67.202500
max            7.000000          274.719407               97.810000

       Find Distance from Main Vulcano (km)  Length (mm)  \
count                           1246.000000  1244.000000
mean                              44.188204    33.589646
```

```
std                                  28.331532    3.874355
min                                   2.550790   23.451799
25%                                  21.203453   30.777936
50%                                  38.880858   33.784401
75%                                  60.680816   36.049083
max                                 109.952511   43.691515

       Luminescence Intensity (a.u.)  Magnetic orientation (degree)  \
count                    1247.000000                    1245.000000
mean                        0.002850                     178.933737
std                         0.003607                     102.113321
min                         0.000004                       0.085357
25%                         0.000627                      90.582930
50%                         0.001757                     180.043851
75%                         0.003767                     266.481765
max                         0.044624                     359.443812

       Odor index (a.u.)   Seed Count  Skin Thickness (mm)  \
count        1246.000000  1247.000000          1247.000000
mean           16.602442    48.926812             3.839615
std            14.882420    35.871733             1.483029
min             1.722825     0.000000             1.000000
25%             7.615908    15.852008             3.000000
50%            12.258785    47.932723             4.000000
75%            20.302048    80.413165             5.000000
max           152.041780   112.968004             8.500000

       Soil pH where Grown  Sugar Content (mg)    Weight (mg)
pH  \
count          1245.000000         1245.000000    1244.000000
1244.000000
mean              7.278739        11835.978313   78446.779224
4.614780
std               0.529815         2417.733775   26637.766132
0.993407
min               5.710000         4566.000000   32352.182600    -
5.120000
25%               6.910000        10353.000000   57087.682600
4.174979
50%               7.280000        11807.000000   77440.682600
4.910000
75%               7.660000        13534.000000   92664.102600
5.080000
max               8.980000        18246.000000  164679.342600
6.081918

            Edible
count  1248.000000
mean      0.494391
std       0.500169
```

```
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        1.000000
```

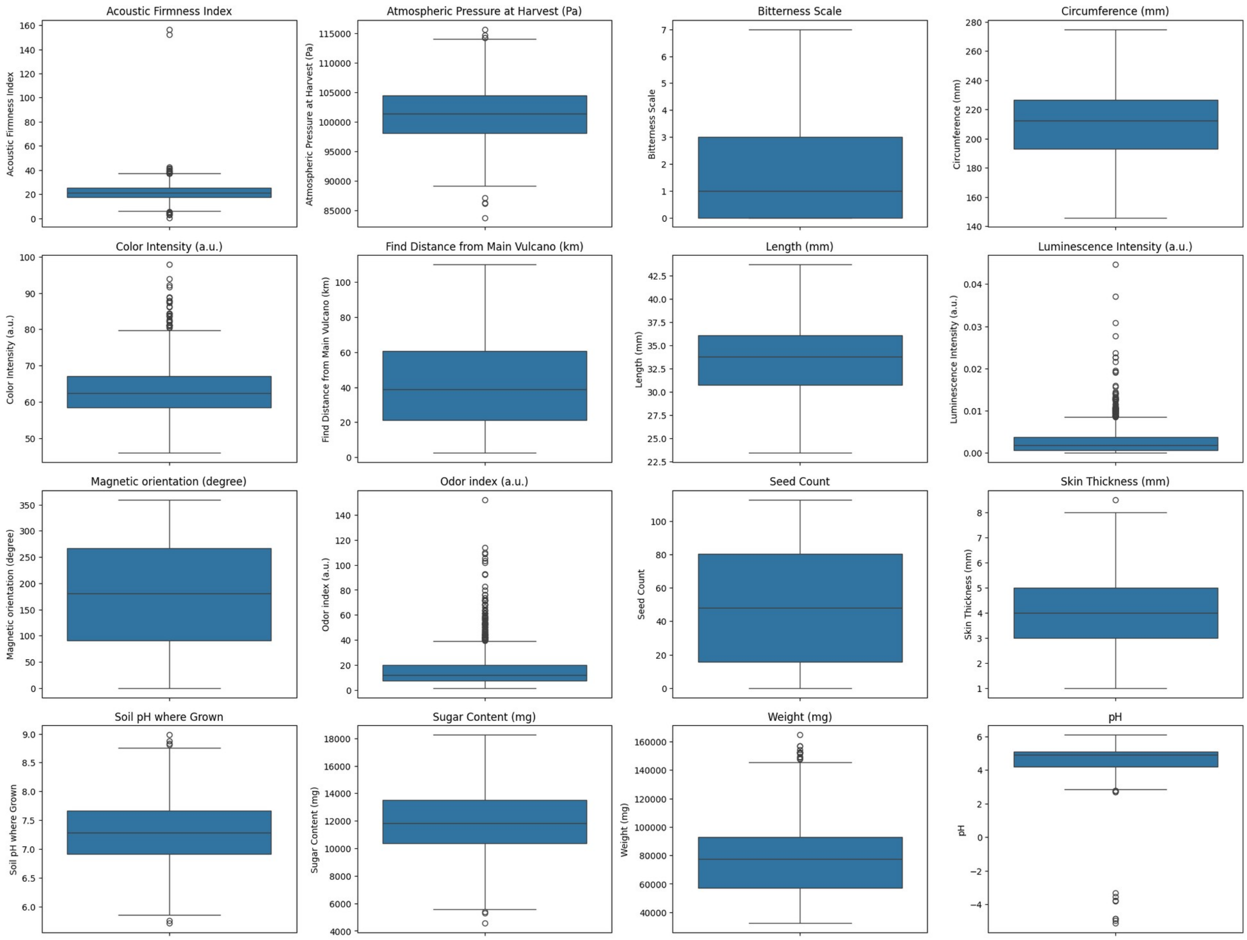
Histogram

```python
# Plotting histograms for all columns in the dataset
df_train.hist(bins=10, figsize=(26, 15))
plt.show()
```



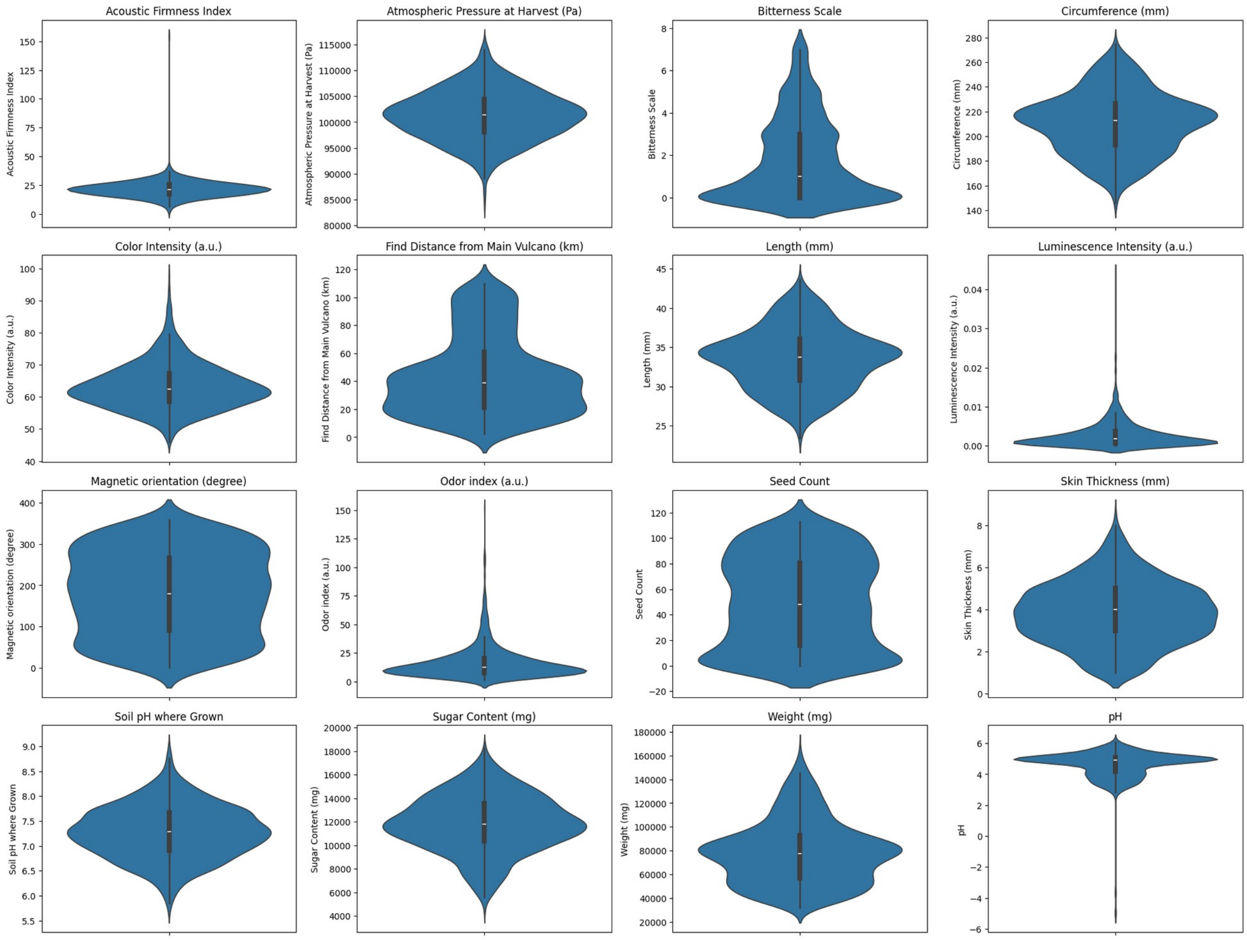

Box Plots

```python
# Removing the target variable
features = df_train.columns[:-1]

plt.figure(figsize=(20, 60))

for i, column in enumerate(features):
    plt.subplot(len(features), 4, i + 1)
    sns.boxplot(y=df_train[column])
    plt.title(column)

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



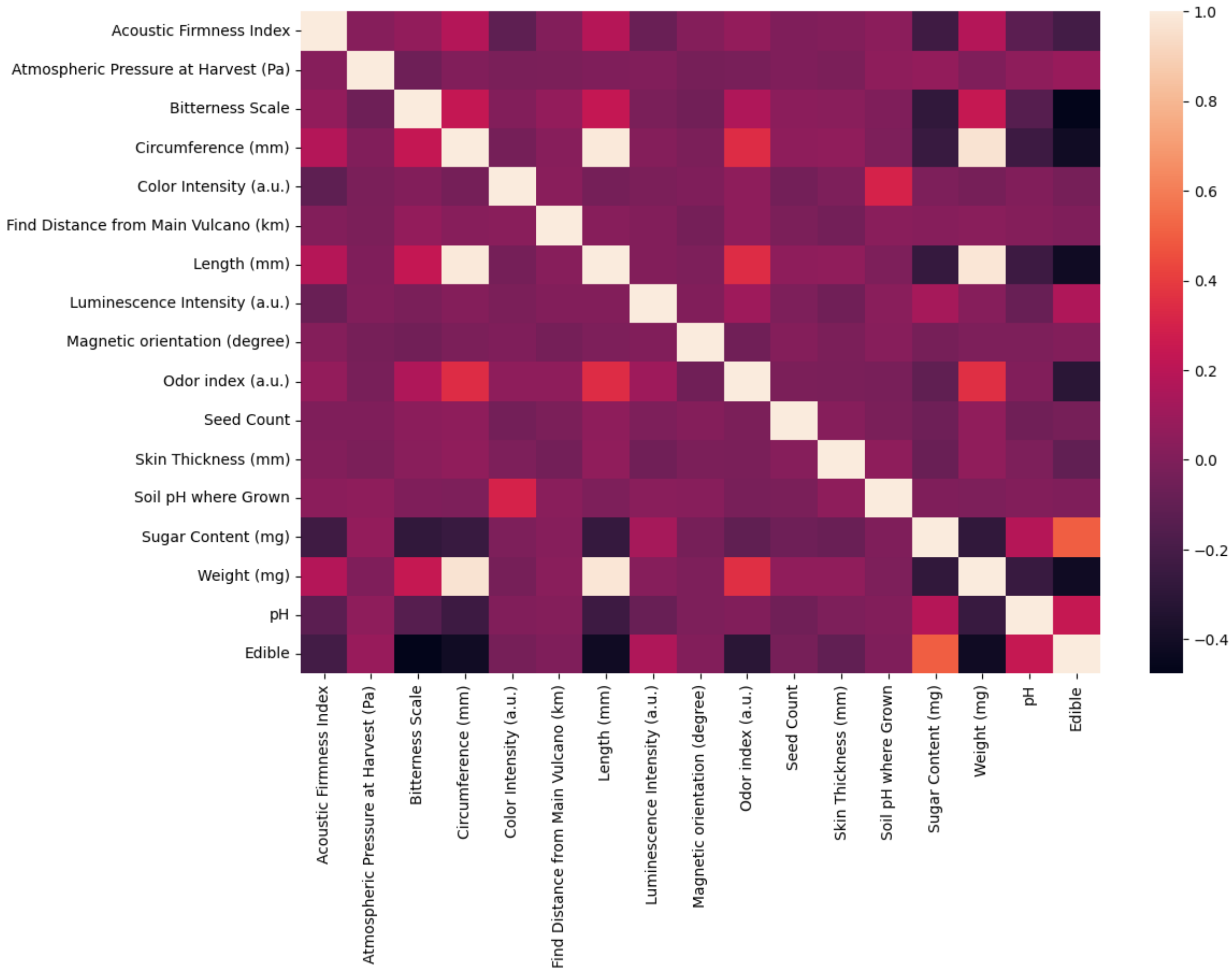

## Violin Plots

```python
# Removing the target variable
features = df_train.columns[:-1]

plt.figure(figsize=(20, 60))

for i, column in enumerate(features):
    plt.subplot(len(features), 4, i + 1)
    sns.violinplot(y=df_train[column])
    plt.title(column)

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



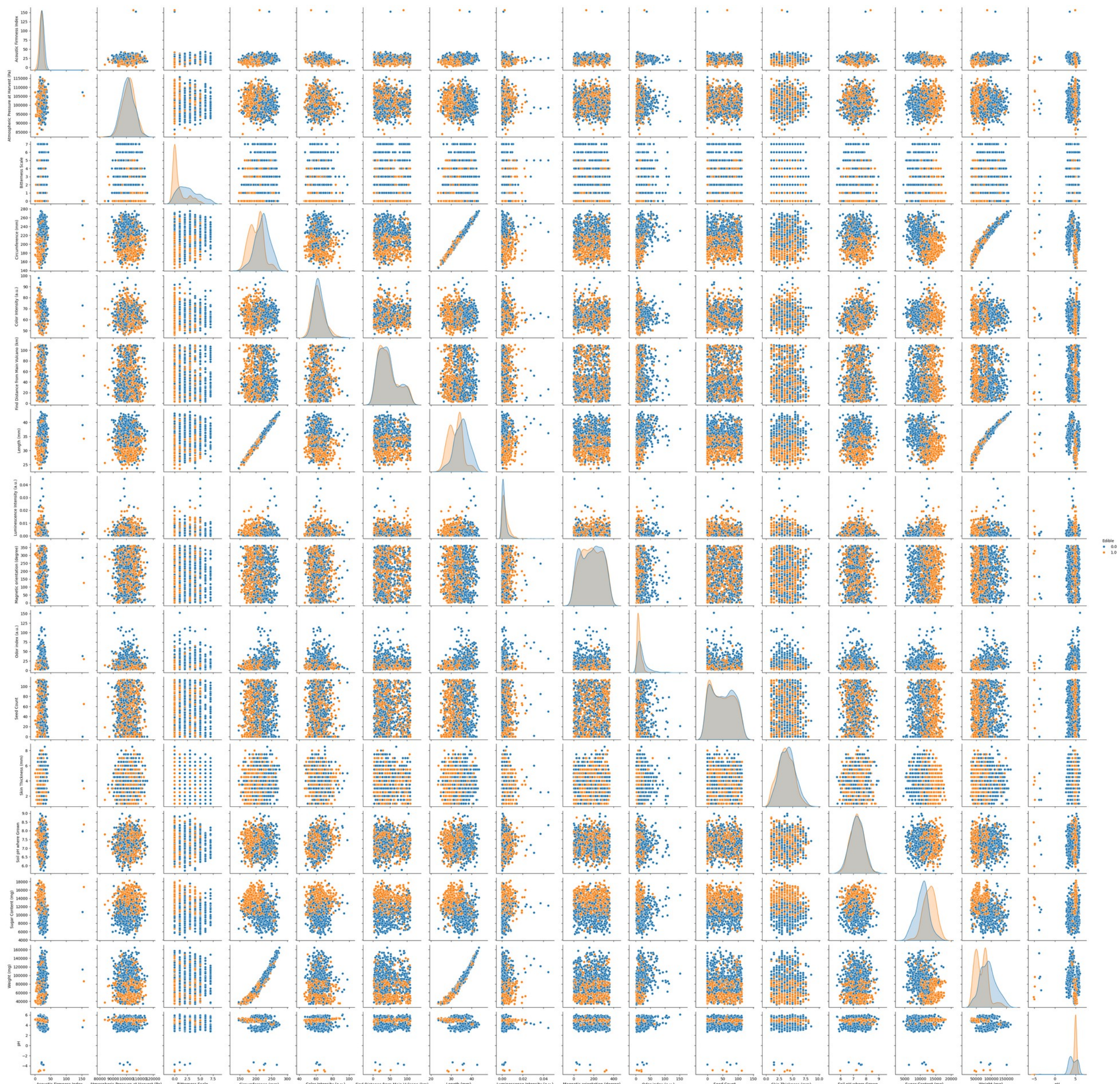

## Heatmap

```
corr_matrix = df_train.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, cbar=True)

plt.show()
```




## Scatter Plot

```
sns.pairplot(df_train, hue="Edible")
plt.show()
```



# Data cleaning

## Handling Missing Values

```
# Impute missing values using the column mean (Taken from Lecture)
imputer = SimpleImputer(missing_values=np.nan, strategy='mean') #
other popular choices: "median", "most_frequent"
imputer.fit(df_train.values)
imputed_data = imputer.transform(df_train.values)

# show the dataset
# note that the output of the SimpleImputer is a NumPy array
# so we need to convert it back to a pandas DataFrame to use our
helper function
```

```python
df_train_imp = pd.DataFrame(imputed_data, columns=df_train.columns)
df_train_imp.index = df_train.index

df_train_imp.isnull().sum()
```

```
Acoustic Firmness Index                   0
Atmospheric Pressure at Harvest (Pa)      0
Bitterness Scale                          0
Circumference (mm)                        0
Color Intensity (a.u.)                    0
Find Distance from Main Vulcano (km)      0
Length (mm)                               0
Luminescence Intensity (a.u.)             0
Magnetic orientation (degree)             0
Odor index (a.u.)                         0
Seed Count                                0
Skin Thickness (mm)                       0
Soil pH where Grown                       0
Sugar Content (mg)                        0
Weight (mg)                               0
pH                                        0
Edible                                    0
dtype: int64
```

Detecting the Outliers

```python
# Detect the outliers using the z-score
outliers_count = {}

# Iterating through each column in df_train_dna
for column in df_train_imp.columns:
    samples = df_train_imp[column].values
    z_scores = (samples - np.mean(samples)) / np.std(samples)
    outliers = np.abs(z_scores) > 3
    outliers_count[column] = np.sum(outliers)

for feature, count in outliers_count.items():
    print(f"Number of outliers in {feature}: {count}")
```

```
Number of outliers in Acoustic Firmness Index: 2
Number of outliers in Atmospheric Pressure at Harvest (Pa): 3
Number of outliers in Bitterness Scale: 0
Number of outliers in Circumference (mm): 0
Number of outliers in Color Intensity (a.u.): 12
Number of outliers in Find Distance from Main Vulcano (km): 0
Number of outliers in Length (mm): 0
Number of outliers in Luminescence Intensity (a.u.): 18
Number of outliers in Magnetic orientation (degree): 0
Number of outliers in Odor index (a.u.): 28
Number of outliers in Seed Count: 0
```

```
Number of outliers in Skin Thickness (mm): 1
Number of outliers in Soil pH where Grown: 2
Number of outliers in Sugar Content (mg): 1
Number of outliers in Weight (mg): 1
Number of outliers in pH: 8
Number of outliers in Edible: 0
```

For this assignment outliers have been ignored.

## Data preprocessing and visualisation

### Splitting the Dataset

```
#-----------------------------------------
# Spliting the dataset into test and train
#-----------------------------------------
X_imp = df_train_imp.iloc[:, :-1].values
y_imp = df_train_imp.iloc[:, -1].values
X_train_imp, X_test_imp, y_train_imp, y_test_imp =
train_test_split(X_imp, y_imp, test_size=0.20, stratify=y_imp,
random_state=42)
```

Scaling the Dataset

```
#
======================================================================
=================================
# Standardising unsing the StandardScaler (Taken from the lecture also
this is the common way of scaling)
#
======================================================================
=================================
# Initialise standard scaler and compute mean and stddev from training
data
sc = StandardScaler()
sc.fit(X_train_imp)

# Transform (standardise) both X_train_imp and X_test_imp with mean
and stddev from
# training data
X_train_imp_sc = sc.transform(X_train_imp)
X_test_imp_sc = sc.transform(X_test_imp)
```

### Exploring training data after cleaning and scaling

```
# Converting numpy array to dataframe
X_train_imp_sc_df = pd.DataFrame(X_train_imp_sc)
X_test_imp_sc_df = pd.DataFrame(X_test_imp_sc)

X_train_imp_sc_df.info()
```

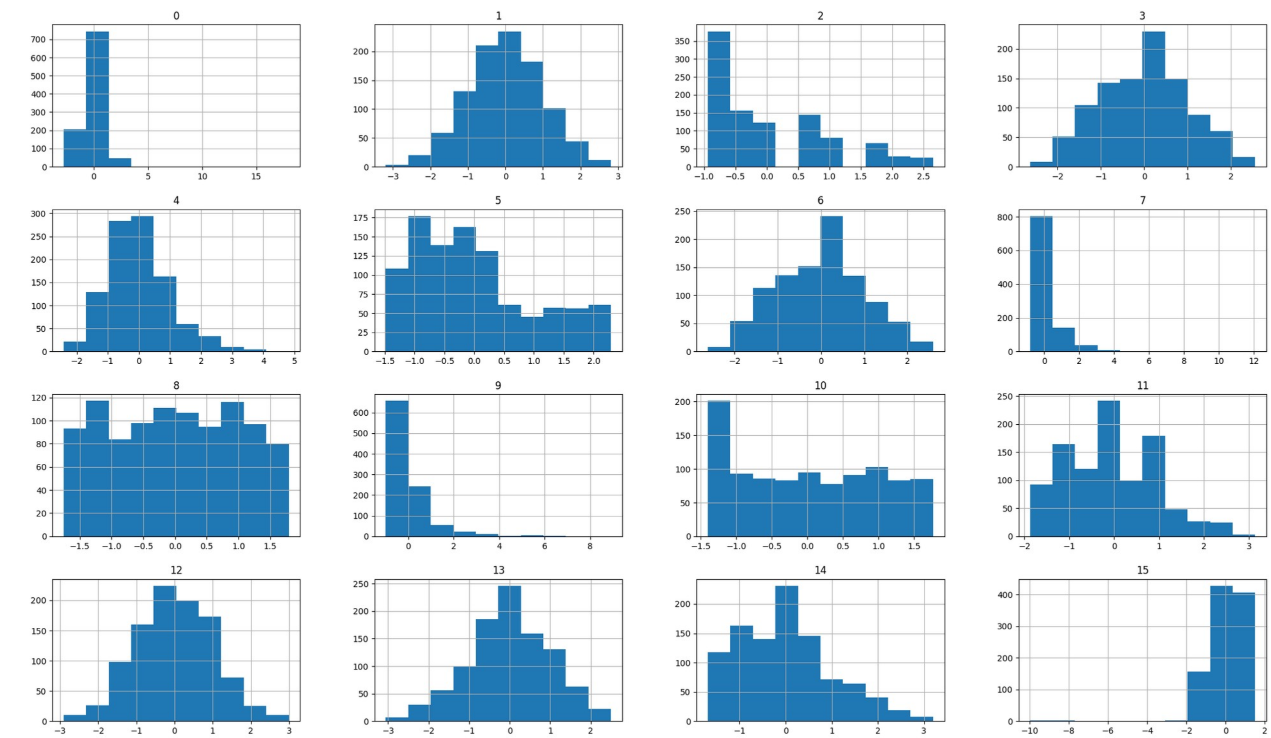
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 998 entries, 0 to 997
Data columns (total 16 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       998 non-null    float64
 1   1       998 non-null    float64
 2   2       998 non-null    float64
 3   3       998 non-null    float64
 4   4       998 non-null    float64
 5   5       998 non-null    float64
 6   6       998 non-null    float64
 7   7       998 non-null    float64
 8   8       998 non-null    float64
 9   9       998 non-null    float64
 10  10      998 non-null    float64
 11  11      998 non-null    float64
 12  12      998 non-null    float64
 13  13      998 non-null    float64
 14  14      998 non-null    float64
 15  15      998 non-null    float64
dtypes: float64(16)
memory usage: 124.9 KB
```

```
X_train_imp_sc_df.describe()
```

```
                 0             1             2             3
4  \
count  9.980000e+02  9.980000e+02  9.980000e+02  9.980000e+02
9.980000e+02
mean   1.203224e-15  7.591345e-16 -1.690921e-17 -5.385138e-15
7.671441e-16
std    1.000501e+00  1.000501e+00  1.000501e+00  1.000501e+00
1.000501e+00
min   -2.790267e+00 -3.192178e+00 -9.400674e-01 -2.637676e+00 -
2.421179e+00
25%   -5.767442e-01 -6.614693e-01 -9.400674e-01 -7.379985e-01 -
6.535684e-01
50%   -1.002903e-02  5.589991e-03 -4.263936e-01  5.209417e-02 -
1.180030e-01
75%    5.033483e-01  6.355494e-01  6.009541e-01  6.287116e-01
5.392977e-01
max    1.800094e+01  2.812833e+00  2.655650e+00  2.558980e+00
4.819973e+00

                 5             6             7             8
9  \
count  9.980000e+02  9.980000e+02  9.980000e+02  9.980000e+02
9.980000e+02
mean  -3.150453e-16 -2.669875e-16 -9.433558e-17  2.036225e-15
```

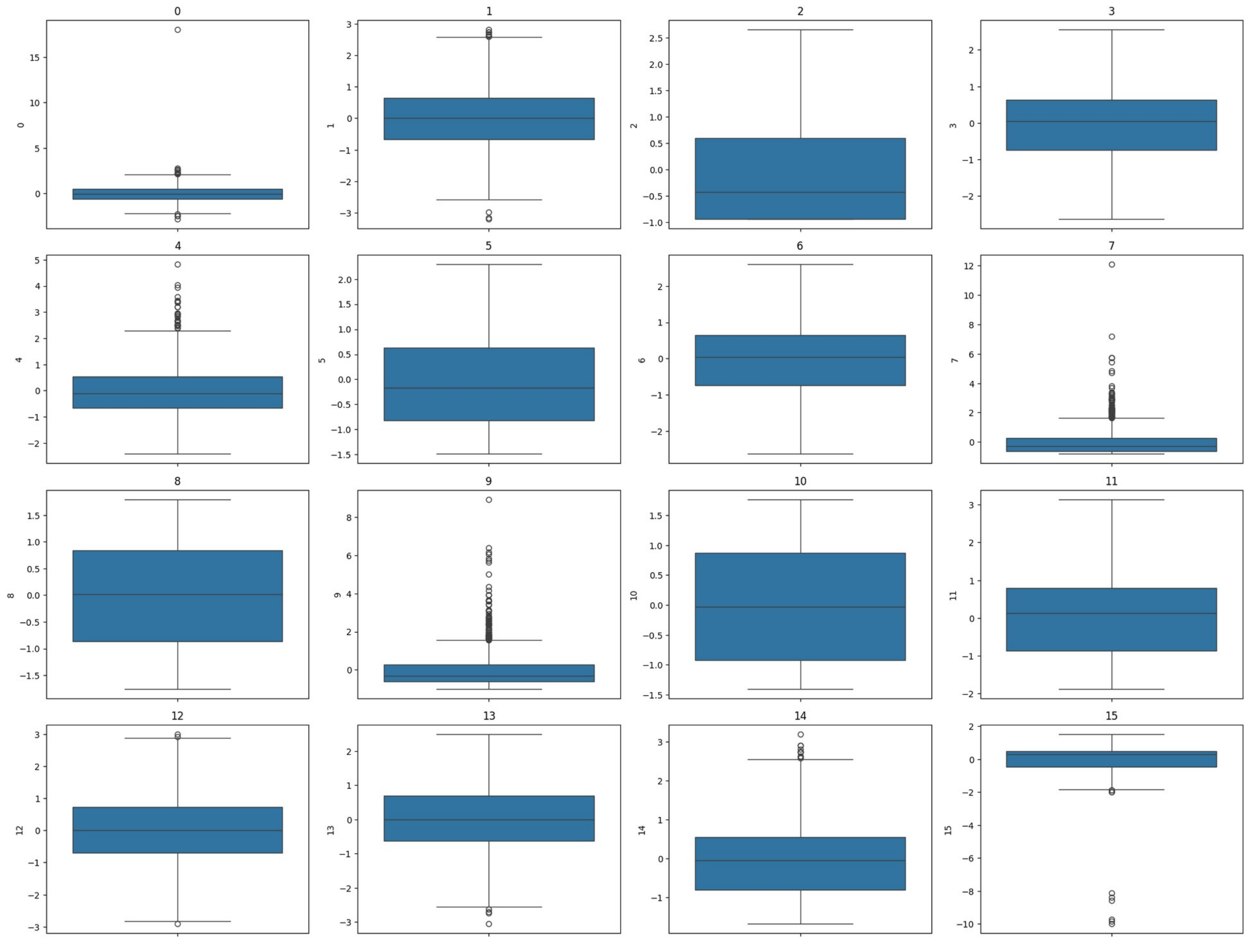
```
1.459532e-15
std    1.000501e+00  1.000501e+00  1.000501e+00  1.000501e+00
1.000501e+00
min   -1.485719e+00 -2.620729e+00 -8.202004e-01 -1.753441e+00 -
9.915981e-01
25%   -8.184595e-01 -7.314885e-01 -6.379509e-01 -8.690324e-01 -
6.032569e-01
50%   -1.719907e-01  4.262328e-02 -3.115349e-01  1.105358e-02 -
3.013487e-01
75%    6.343581e-01  6.444112e-01  2.732684e-01  8.434427e-01
2.636343e-01
max    2.290280e+00  2.591265e+00  1.208737e+01  1.793447e+00
8.919630e+00

                 10            11            12            13
14  \
count  9.980000e+02  9.980000e+02  9.980000e+02  9.980000e+02
9.980000e+02
mean   9.682747e-16  1.779917e-17 -1.940109e-15 -7.600244e-16 -
3.287150e-14
std    1.000501e+00  1.000501e+00  1.000501e+00  1.000501e+00
1.000501e+00
min   -1.400326e+00 -1.877736e+00 -2.908752e+00 -3.057209e+00 -
1.686056e+00
25%   -9.239207e-01 -8.737602e-01 -7.038083e-01 -6.294217e-01 -
8.081063e-01
50%   -3.176661e-02  1.302153e-01  6.258341e-03 -5.000689e-03 -
4.853229e-02
75%    8.728676e-01  7.995323e-01  7.350109e-01  6.914323e-01
5.476844e-01
max    1.766415e+00  3.142142e+00  2.996013e+00  2.497759e+00
3.197890e+00

                 15
count  9.980000e+02
mean   7.977587e-15
std    1.000501e+00
min   -9.988594e+00
25%   -4.590113e-01
50%    2.962997e-01
75%    4.707939e-01
max    1.509464e+00
```

```
# Plotting histograms for all columns in the dataset
X_train_imp_sc_df.hist(bins=10, figsize=(26, 15))
plt.show()
```



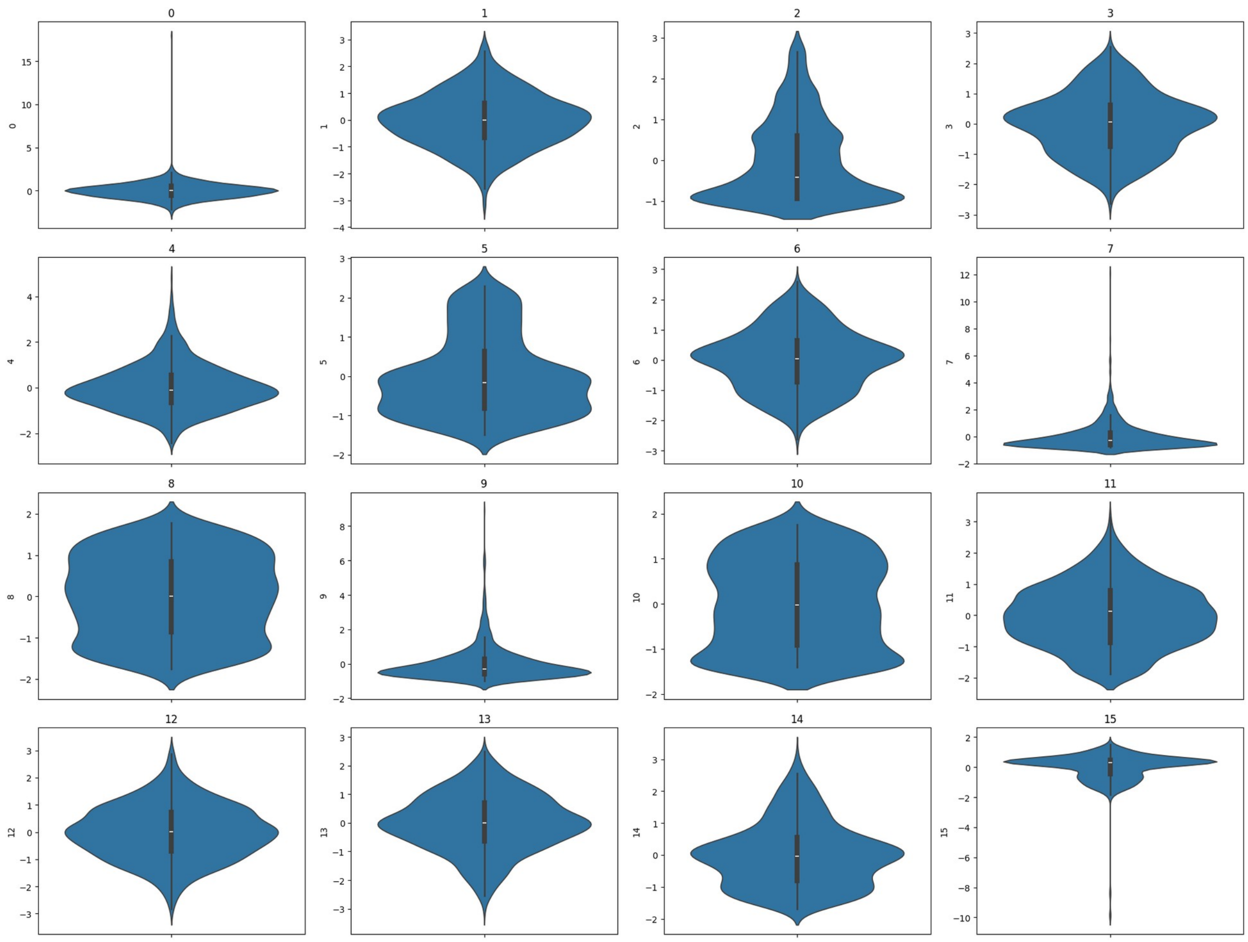

## Box Plots

```
features = X_train_imp_sc_df.columns

plt.figure(figsize=(20, 60))

for i, column in enumerate(features):
    plt.subplot(len(features), 4, i + 1)
    sns.boxplot(y=X_train_imp_sc_df[column])
    plt.title(column)

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



Violin Plots

```
features = X_train_imp_sc_df.columns

plt.figure(figsize=(20, 60))

for i, column in enumerate(features):
    plt.subplot(len(features), 4, i + 1)
    sns.violinplot(y=X_train_imp_sc_df[column])
    plt.title(column)

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




# Modelling

Random Forest

```
#-------------------------------------------------------------------------------------
# RANDOM FOREST()
# Parameters tuned for this model
# 'n_estimators' : Number of Trees(High->Robustness but time consuming)
# 'max_depth' : Max depth of Trees(High->Accurate model but overfitting)
# 'max_features' : The number of features to consider when looking for the best split
#-------------------------------------------------------------------------------------

# Parameters to test
param_grid = {'n_estimators': [50, 100, 200], 'max_depth': [None, 5, 10, 25], 'max_features': [*np.arange(0.1, 1.1, 0.1)]}

# Store the best parameter combination and its accuracy
```

```
best_params_rf = None
best_accuracy_rf = 0

for n_estimators in param_grid['n_estimators']:
    for max_depth in param_grid['max_depth']:
        for max_feature in param_grid['max_features']:
            accuracies = []
            for random_state in range(40, 50):
                # Splitting Dataset
                X_train, X_val, y_train, y_val = 
train_test_split(X_train_imp, y_train_imp, test_size=0.25, 
random_state=random_state)
                # Standardize the data
                scaler = StandardScaler()
                X_train_scaled = scaler.fit_transform(X_train)
                X_val_scaled = scaler.transform(X_val)

                #  Defining the model
                rfc = 
RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth, 
max_features=max_feature, random_state=42)
                # Fitting the model
                rfc.fit(X_train_scaled, y_train)
                # Evaluating on the test dataset
                y_pred = rfc.predict(X_val_scaled)
                accuracy = accuracy_score(y_val, y_pred)
                accuracies.append(accuracy)

            # Measuring the average accuracy for different splits of 
dataset
            accuracy = np.mean(accuracies)

        if accuracy > best_accuracy_rf:
            best_accuracy_rf = accuracy
            best_params_rf= {'n_estimators': n_estimators, 
'max_depth': max_depth, 'max_features': max_feature}

print("Best Parameters:", best_params_rf)
print("Best Accuracy:", best_accuracy_rf)
```

```
Best Parameters: {'n_estimators': 100, 'max_depth': 10, 
'max_features': 1.0}
Best Accuracy: 0.8976000000000001
```

Testing for X_train and X_test of Train_df

```
rfc = 
RandomForestClassifier(n_estimators=best_params_rf['n_estimators'], 
max_depth=best_params_rf['max_depth'], 
max_features=best_params_rf['max_features'], random_state=42)
```

```
rfc.fit(X_train_imp_sc, y_train_imp)

y_pred_rfc = rfc.predict(X_test_imp_sc)
accuracy_rfc = accuracy_score(y_pred_rfc, y_test_imp)
print(f'For Random Forest with Best Parameters: {best_params_rf} and
Accuracy: {accuracy_rfc}')
```

```
For Random Forest with Best Parameters: {'n_estimators': 100,
'max_depth': 10, 'max_features': 1.0} and Accuracy: 0.904
```

Random Forest

For Random Forest we can see it has the best accuracy

## Final evaluation

```
#-------------------------------------------------
# Train the best model on the entire training set
#-------------------------------------------------
scaler = StandardScaler()
scaler.fit(X_imp)
X_train_scaled = scaler.transform(X_imp)
rfc.fit(X_train_scaled, y_imp)

#--------------------------------------------------------
# Use the test set to evaluate the best k on unseen data
#--------------------------------------------------------
X_test_scaled = scaler.transform(df_test)
y_pred_rf = rfc.predict(X_test_scaled)
```

## Kaggle submission

```
#-----------------------------------------
# Creating csv file for Kaggle submission
#-----------------------------------------
DF = pd.DataFrame(y_pred_rf)
headers = ["Edible"]
DF.columns = headers
DF.to_csv('predictions.csv', index_label='index', index=True)
```