🫐 Harvesting Insights: Machine Learning Models for Blueberry Yield Prediction

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📖 INTRODUCTION

Welcome to my notebook for the Kaggle competition! In this notebook, I will be tackling the challenge of predicting crop yield using various machine learning techniques. The dataset provided contains valuable features such as fruit set, seeds, and weather-related variables, which are known to influence crop productivity.

I will begin by performing exploratory data analysis to gain insights into the data and understand the relationships between different variables. Next, I will preprocess the data, including scaling certain features for optimal modeling performance.

To approach the prediction task, I will experiment with three different regression models: Random Forest, Linear Regression, and XGBoost. Each model will be trained and evaluated using a 100-fold cross-validation strategy to ensure robustness and accuracy. I will assess the performance of each model based on mean absolute error (MAE) and compare the results.

Finally, I will use the best-performing model to make predictions on the test dataset and generate a submission file for the competition.

Join me on this exciting journey as we leverage machine learning techniques to forecast crop yield and contribute to the field of agriculture. Let's dive in and uncover valuable insights for optimizing agricultural productivity!"

Feel free to customize and expand upon this introduction based on the specifics of your notebook and the Kaggle competition you are participating in.

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🦴 BODY

🛠️ Import important libraries, Read the data

In [ ]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from xgboost import XGBRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
```

In [ ]:

```
train = pd.read_csv("train.csv",index_col = "id")
test = pd.read_csv("test.csv",index_col = "id")
```

In [ ]:

```
# Decide to run the model_selection part or not
model_selection = False

# Random State
RS = 13
```

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👁️ Overview

In [ ]:
```
train.shape
```

Out[ ]:
```
(15289, 17)
```

In [ ]:
```
train.head()
```

Out[ ]:

id	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUpperTRange	Averaş
0	25.0	0.50	0.25	0.75	0.50	69.7	42.1	
1	25.0	0.50	0.25	0.50	0.50	69.7	42.1	
2	12.5	0.25	0.25	0.63	0.63	86.0	52.0	
3	12.5	0.25	0.25	0.63	0.50	77.4	46.8	
4	25.0	0.50	0.25	0.63	0.63	77.4	46.8	

In [ ]:
```
train.tail()
```

Out[ ]:

id	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange	MinOfUpperTRange	Av
15284	12.5	0.25	0.25	0.38	0.50	77.4	46.8	
15285	12.5	0.25	0.25	0.25	0.50	86.0	52.0	
15286	25.0	0.50	0.25	0.38	0.75	77.4	46.8	
15287	25.0	0.50	0.25	0.63	0.63	69.7	42.1	
15288	25.0	0.50	0.25	0.63	0.50	77.4	46.8	

In [ ]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15289 entries, 0 to 15288
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   clonesize             15289 non-null  float64
 1   honeybee              15289 non-null  float64
 2   bumbles               15289 non-null  float64
 3   andrena               15289 non-null  float64
 4   osmia                 15289 non-null  float64
 5   MaxOfUpperTRange      15289 non-null  float64
 6   MinOfUpperTRange      15289 non-null  float64
 7   AverageOfUpperTRange  15289 non-null  float64
 8   MaxOfLowerTRange      15289 non-null  float64
 9   MinOfLowerTRange      15289 non-null  float64
 10  AverageOfLowerTRange  15289 non-null  float64
 11  RainingDays           15289 non-null  float64
 12  AverageRainingDays    15289 non-null  float64
 13  fruitset              15289 non-null  float64
 14  fruitmass             15289 non-null  float64
 15  seeds                 15289 non-null  float64
 16  yield                 15289 non-null  float64
dtypes: float64(17)
memory usage: 2.1 MB
```

In [ ]:
```
train.describe()
```

Out[ ]:

	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange
count	15289.000000	15289.000000	15289.000000	15289.000000	15289.000000	15289.000000
mean	19.704690	0.389314	0.286768	0.492675	0.592355	82.169887
std	6.595211	0.361643	0.059917	0.148115	0.139489	9.146703
min	10.000000	0.000000	0.000000	0.000000	0.000000	69.700000
25%	12.500000	0.250000	0.250000	0.380000	0.500000	77.400000
50%	25.000000	0.500000	0.250000	0.500000	0.630000	86.000000
75%	25.000000	0.500000	0.380000	0.630000	0.750000	86.000000
max	40.000000	18.430000	0.585000	0.750000	0.750000	94.600000

In [ ]:
```
train.dtypes
```

```
Out[ ]: clonesize               float64
        honeybee                float64
        bumbles                 float64
        andrena                 float64
        osmia                   float64
        MaxOfUpperTRange        float64
        MinOfUpperTRange        float64
        AverageOfUpperTRange    float64
        MaxOfLowerTRange        float64
        MinOfLowerTRange        float64
        AverageOfLowerTRange    float64
        RainingDays             float64
        AverageRainingDays      float64
        fruitset                float64
        fruitmass               float64
        seeds                   float64
        yield                   float64
        dtype: object
```

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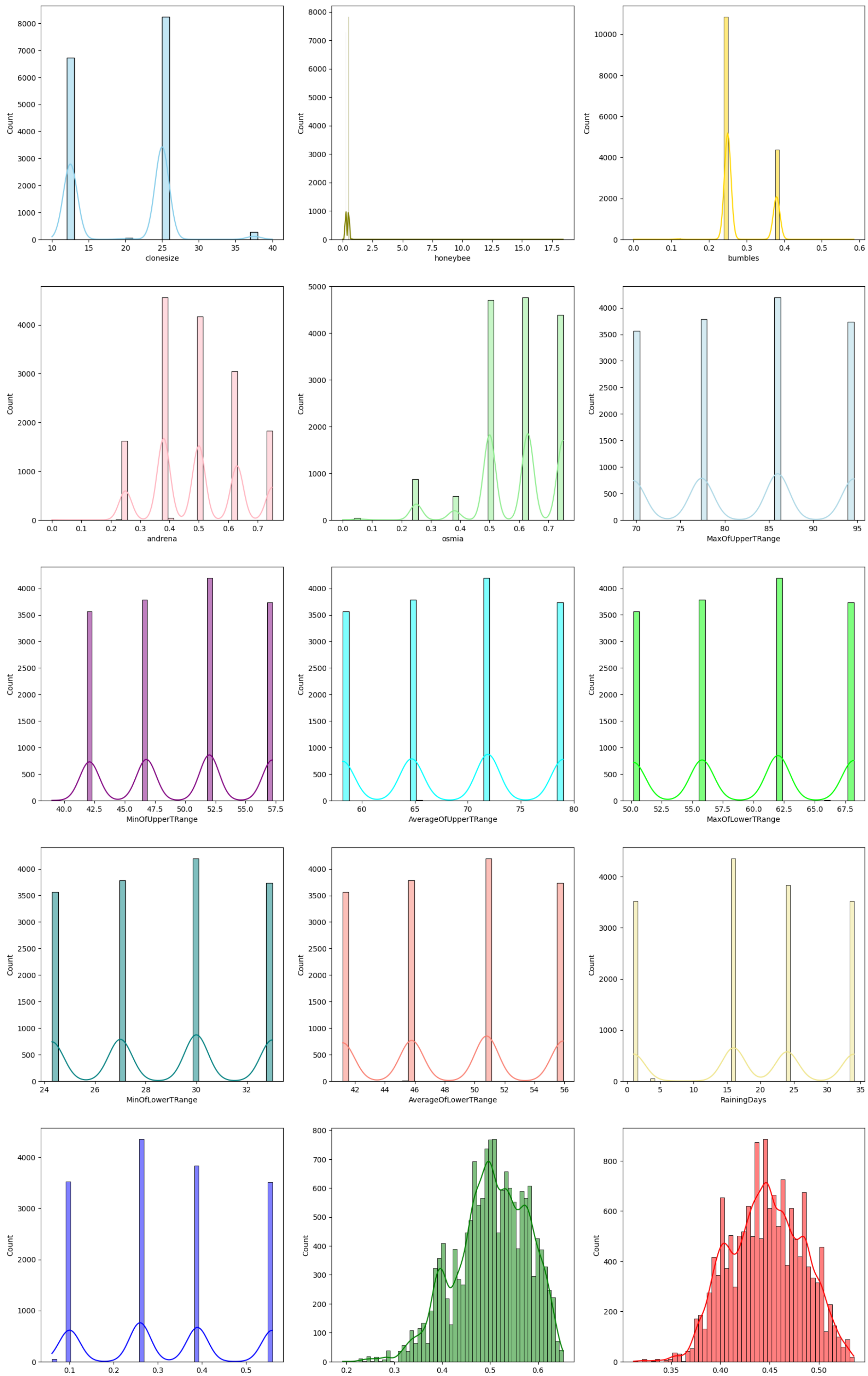
🔎 EDA

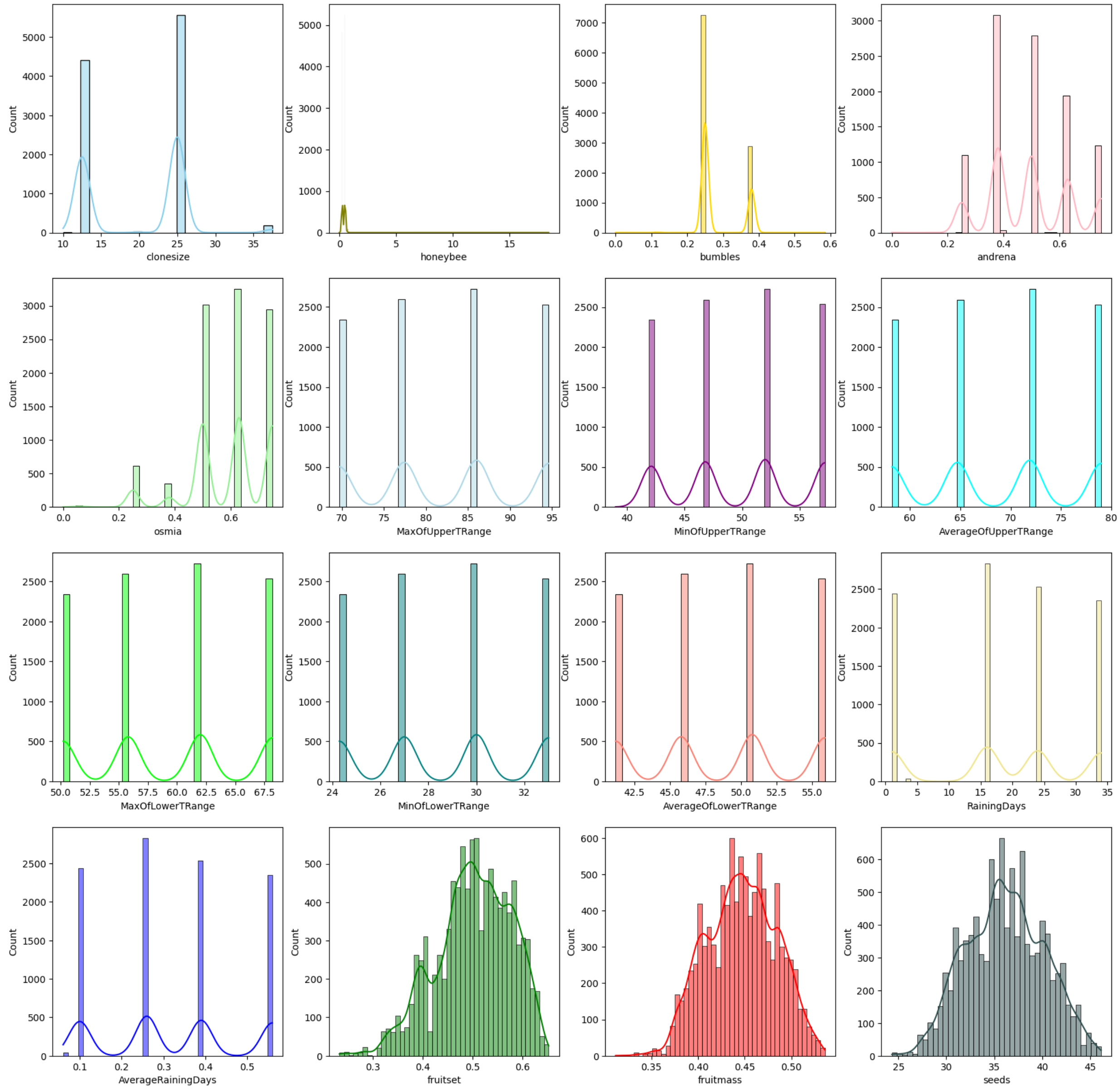
🔎 Univariate Analysis

```
In [ ]: fig, axs = plt.subplots(6, 3, figsize=(20, 40))

sns.histplot(data = train, x = train.columns[0], kde=True, color="skyblue", ax
sns.histplot(data = train, x = train.columns[1], kde=True, color="olive", ax=a
sns.histplot(data = train, x = train.columns[2], kde=True, color="gold", ax=ax
sns.histplot(data = train, x = train.columns[3], kde=True, color="lightpink", 
sns.histplot(data = train, x = train.columns[4], kde=True, color="lightgreen",
sns.histplot(data = train, x = train.columns[5], kde=True, color="lightblue", 
sns.histplot(data = train, x = train.columns[6], kde=True, color="purple", ax=
sns.histplot(data = train, x = train.columns[7], kde=True, color="aqua", ax=ax
sns.histplot(data = train, x = train.columns[8], kde=True, color="lime", ax=ax
sns.histplot(data = train, x = train.columns[9], kde=True, color="teal", ax=ax
sns.histplot(data = train, x = train.columns[10], kde=True, color="salmon", ax
sns.histplot(data = train, x = train.columns[11], kde=True, color="khaki", ax=
sns.histplot(data = train, x = train.columns[12], kde=True, color="blue", ax=a
sns.histplot(data = train, x = train.columns[13], kde=True, color="green", ax=
sns.histplot(data = train, x = train.columns[14], kde=True, color="red", ax=ax
sns.histplot(data = train, x = train.columns[15], kde=True, color="DarkSlateGr
sns.histplot(data = train, x = train.columns[16], kde=True, color="indigo", ax
plt.show()
```


Count
clonesize
honeybee
bumbles
andrena
osmia
MaxOfUpperTRange
MinOfUpperTRange
AverageOfUpperTRange
MaxOfLowerTRange
MinOfLowerTRange
AverageOfLowerTRange
RainingDays
AverageRainingDays
fruitset
fruitmass

In [ ]:

```
fig, axs = plt.subplots(4, 4, figsize=(20, 20))

sns.histplot(data = test, x = test.columns[0], kde=True, color="skyblue", ax=a
sns.histplot(data = test, x = test.columns[1], kde=True, color="olive", ax=axs
sns.histplot(data = test, x = test.columns[2], kde=True, color="gold", ax=axs[
sns.histplot(data = test, x = test.columns[3], kde=True, color="lightpink", ax
sns.histplot(data = test, x = test.columns[4], kde=True, color="lightgreen", a
sns.histplot(data = test, x = test.columns[5], kde=True, color="lightblue", ax
sns.histplot(data = test, x = test.columns[6], kde=True, color="purple", ax=ax
sns.histplot(data = test, x = test.columns[7], kde=True, color="aqua", ax=axs[
sns.histplot(data = test, x = test.columns[8], kde=True, color="lime", ax=axs[
sns.histplot(data = test, x = test.columns[9], kde=True, color="teal", ax=axs[
sns.histplot(data = test, x = test.columns[10], kde=True, color="salmon", ax=a
sns.histplot(data = test, x = test.columns[11], kde=True, color="khaki", ax=ax
sns.histplot(data = test, x = test.columns[12], kde=True, color="blue", ax=axs
sns.histplot(data = test, x = test.columns[13], kde=True, color="green", ax=ax
sns.histplot(data = test, x = test.columns[14], kde=True, color="red", ax=axs[
sns.histplot(data = test, x = test.columns[15], kde=True, color="DarkSlateGray
plt.show()
```



🔎 Correlation Analysis

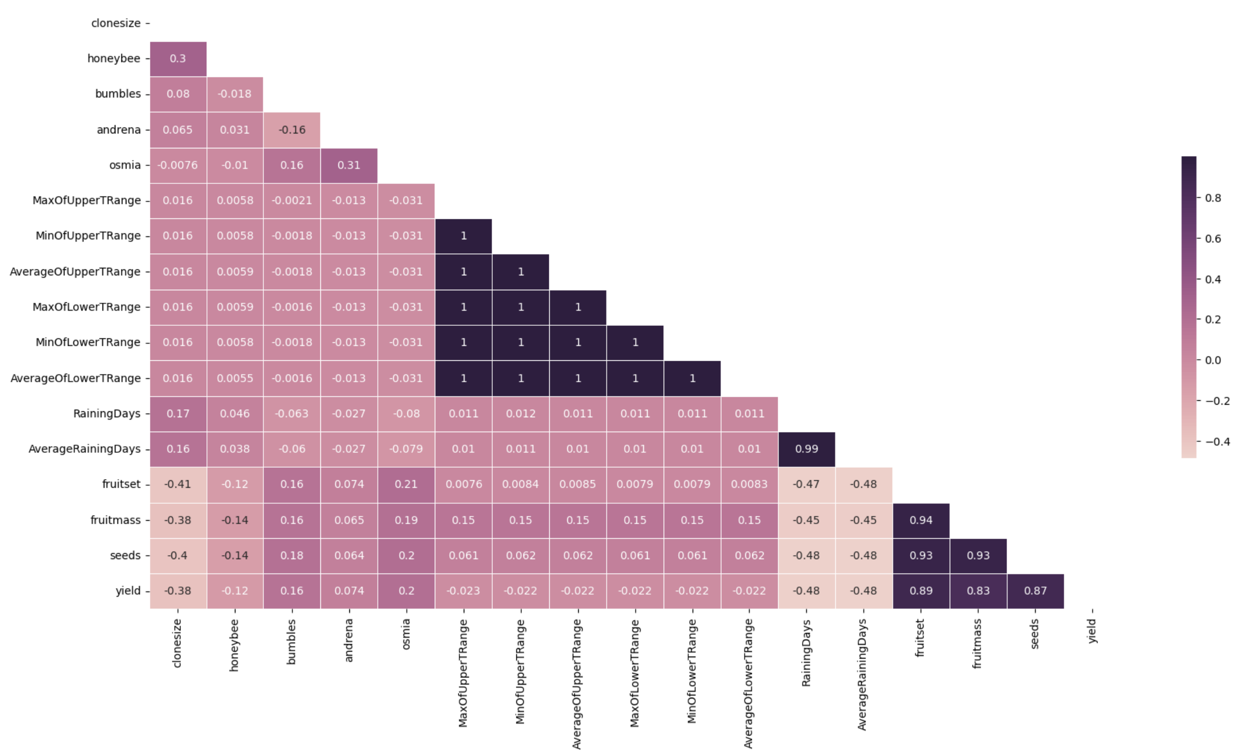
In [ ]:
```
train.corr()
```

Out[ ]:

	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange
clonesize	1.000000	0.304130	0.080433	0.065131	-0.007607	0.016159
honeybee	0.304130	1.000000	-0.017937	0.030671	-0.010394	0.005840
bumbles	0.080433	-0.017937	1.000000	-0.164962	0.158001	-0.002104
andrena	0.065131	0.030671	-0.164962	1.000000	0.309556	-0.013061
osmia	-0.007607	-0.010394	0.158001	0.309556	1.000000	-0.031391
MaxOfUpperTRange	0.016159	0.005840	-0.002104	-0.013061	-0.031391	1.000000
MinOfUpperTRange	0.015838	0.005755	-0.001813	-0.012928	-0.030819	0.998599
AverageOfUpperTRange	0.016057	0.005892	-0.001769	-0.012993	-0.031415	0.999806
MaxOfLowerTRange	0.016343	0.005942	-0.001613	-0.012924	-0.031398	0.999503
MinOfLowerTRange	0.016026	0.005809	-0.001804	-0.013035	-0.031486	0.999829
AverageOfLowerTRange	0.015987	0.005485	-0.001644	-0.013071	-0.031337	0.999772
RainingDays	0.165770	0.046494	-0.063294	-0.026572	-0.079874	0.011322
AverageRainingDays	0.164823	0.037532	-0.060232	-0.027193	-0.078720	0.010352
fruitset	-0.406793	-0.120492	0.160447	0.073669	0.209495	0.007580
fruitmass	-0.377688	-0.135310	0.163987	0.064722	0.192210	0.146237
seeds	-0.396898	-0.139261	0.177022	0.063504	0.200597	0.060963
yield	-0.382619	-0.118001	0.161145	0.073969	0.198264	-0.022517

In [ ]:

```
fig, axes = plt.subplots(figsize=(20, 10))
sns.heatmap(train.corr() , cmap = sns.cubehelix_palette(as_cmap=True), mask=np
plt.show()
```



In [ ]:
```
train.corr()["yield"].sort_values(ascending = False)
```

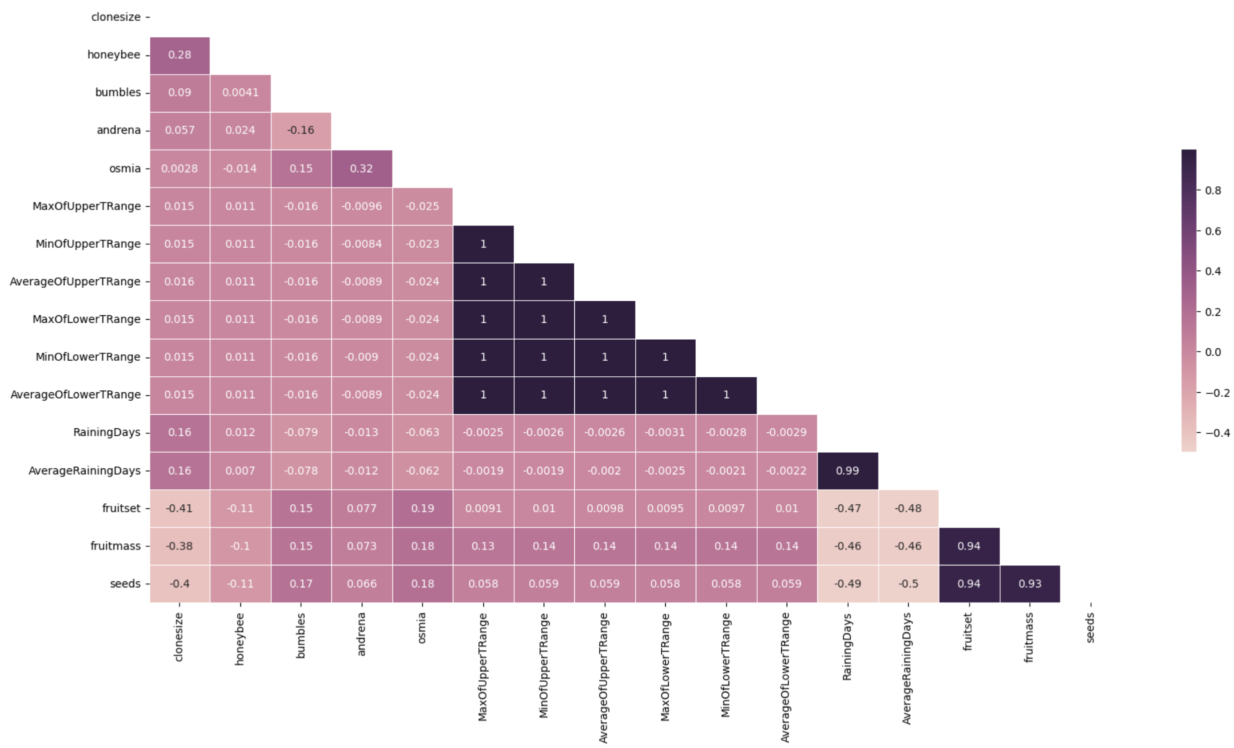
Out[ ]:
```
yield                   1.000000
fruitset                0.885967
seeds                   0.868853
fruitmass               0.826481
osmia                   0.198264
bumbles                 0.161145
andrena                 0.073969
MinOfUpperTRange       -0.021929
AverageOfUpperTRange   -0.021940
AverageOfLowerTRange   -0.022081
MaxOfLowerTRange       -0.022197
MinOfLowerTRange       -0.022319
MaxOfUpperTRange       -0.022517
honeybee               -0.118001
clonesize              -0.382619
RainingDays            -0.477191
AverageRainingDays     -0.483870
Name: yield, dtype: float64
```

In [ ]:
```
test.corr()
```

Out[ ]:

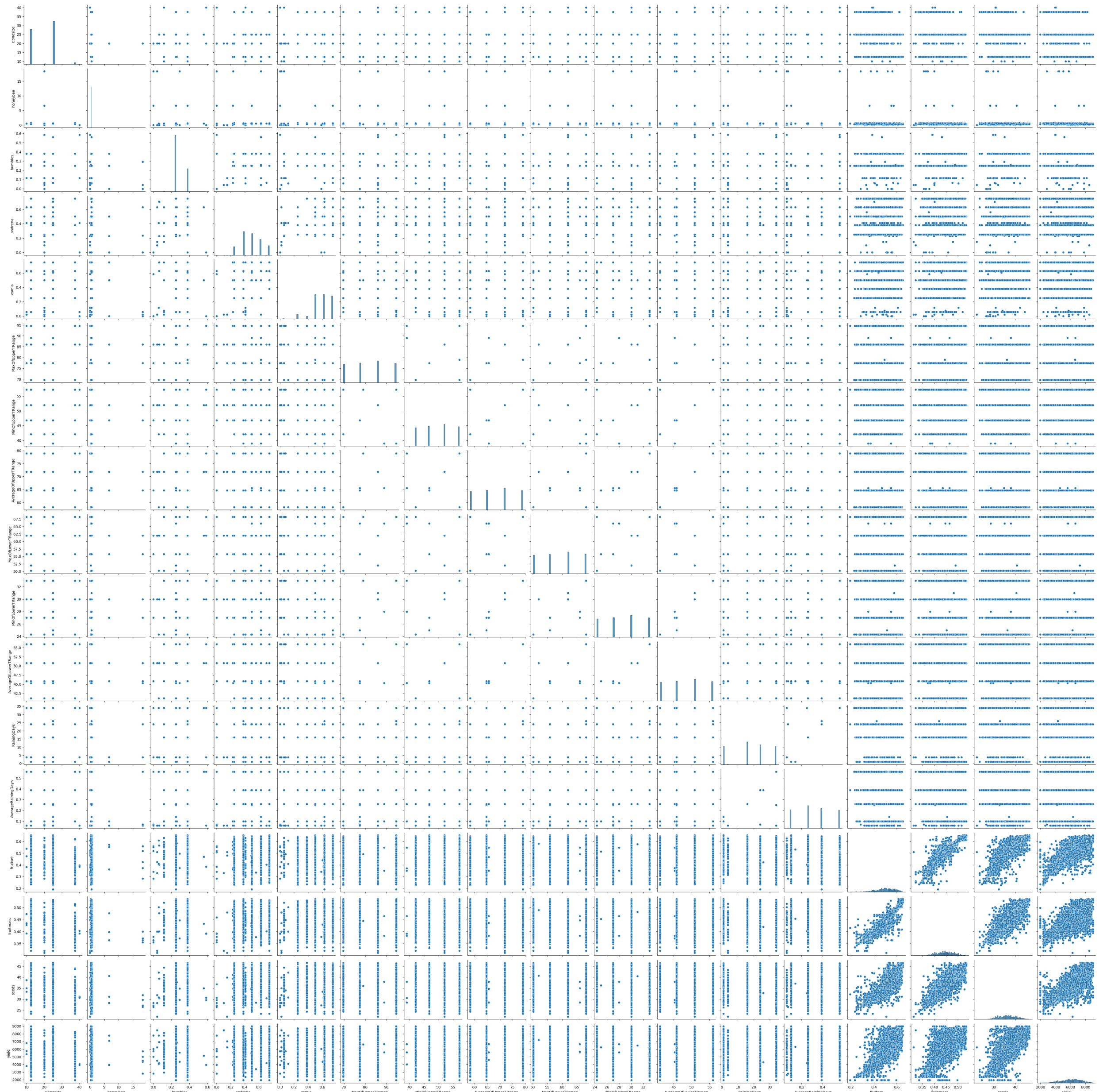
	clonesize	honeybee	bumbles	andrena	osmia	MaxOfUpperTRange
clonesize	1.000000	0.284055	0.090499	0.057267	0.002827	0.014973
honeybee	0.284055	1.000000	0.004051	0.024337	-0.013691	0.010622
bumbles	0.090499	0.004051	1.000000	-0.157961	0.153796	-0.016493
andrena	0.057267	0.024337	-0.157961	1.000000	0.315916	-0.009636
osmia	0.002827	-0.013691	0.153796	0.315916	1.000000	-0.024727
MaxOfUpperTRange	0.014973	0.010622	-0.016493	-0.009636	-0.024727	1.000000
MinOfUpperTRange	0.014969	0.010711	-0.015601	-0.008430	-0.023090	0.998390
AverageOfUpperTRange	0.015609	0.010987	-0.016291	-0.008932	-0.023975	0.998911
MaxOfLowerTRange	0.015201	0.010858	-0.016361	-0.008916	-0.024229	0.998996
MinOfLowerTRange	0.015311	0.010775	-0.016118	-0.008983	-0.023729	0.999125
AverageOfLowerTRange	0.015165	0.010629	-0.015886	-0.008880	-0.023553	0.999027
RainingDays	0.157616	0.012349	-0.079251	-0.013161	-0.062996	-0.002474
AverageRainingDays	0.157116	0.007012	-0.077672	-0.012142	-0.062202	-0.001876
fruitset	-0.407436	-0.106718	0.150247	0.077315	0.192000	0.009062
fruitmass	-0.377495	-0.102644	0.148575	0.073045	0.177814	0.134520
seeds	-0.399425	-0.107096	0.166412	0.065656	0.182509	0.057824

In [ ]:
```
fig, axes = plt.subplots(figsize=(20, 10))
sns.heatmap(test.corr() , cmap = sns.cubehelix_palette(as_cmap=True), mask=np.
plt.show()
```

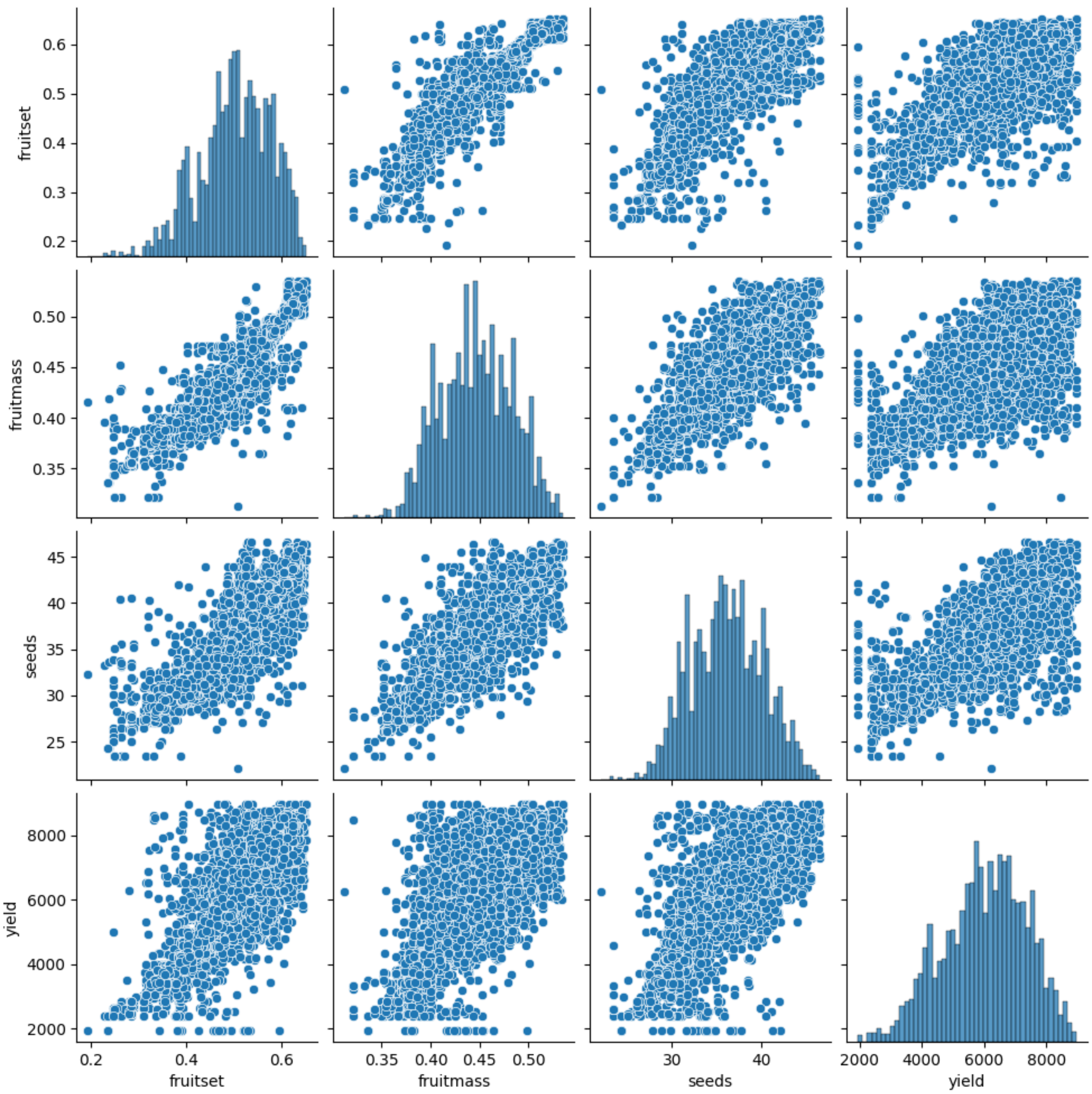


🔎 Feature Interactions

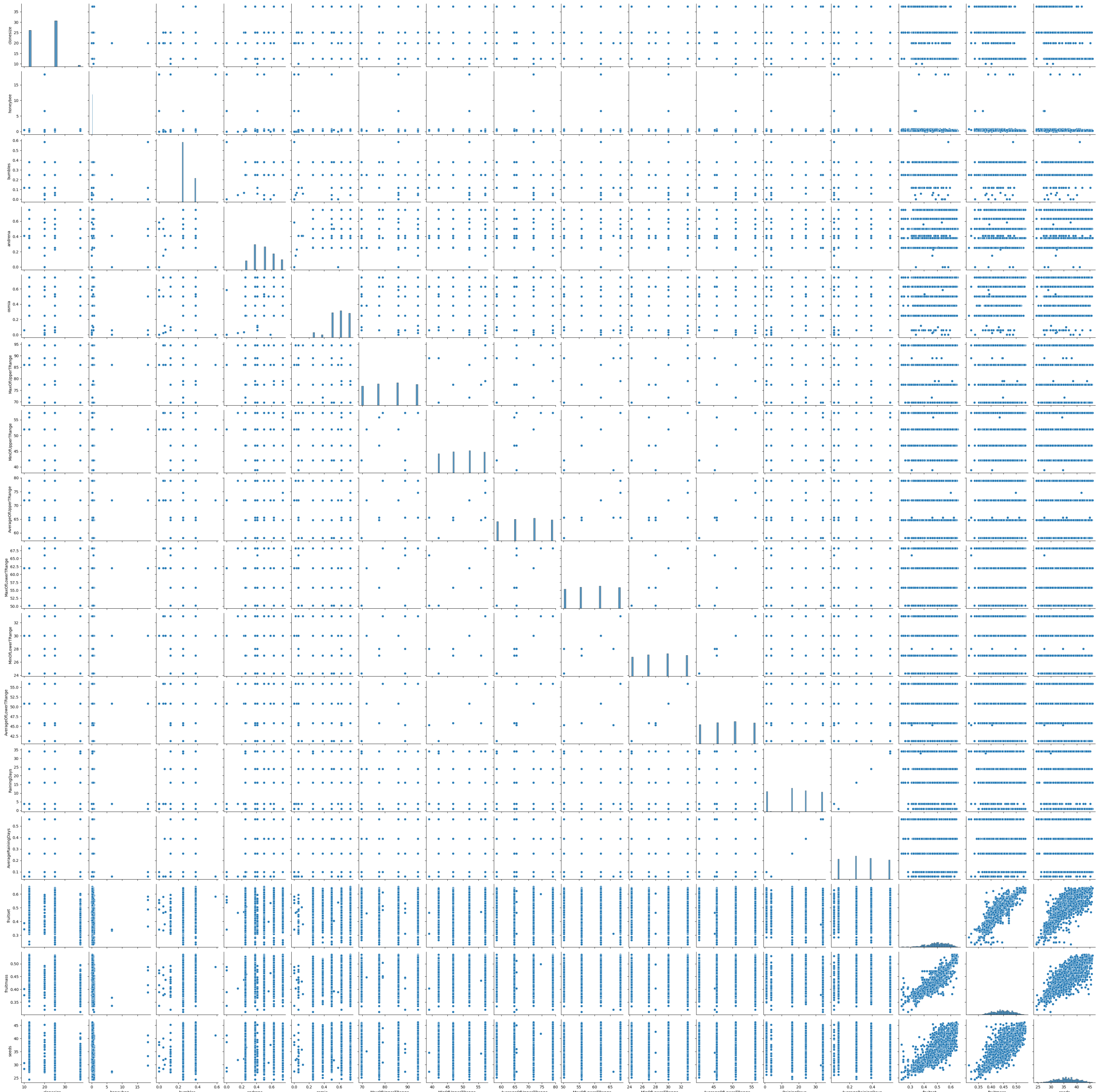
In [ ]:
```
sns.pairplot(train)
plt.show()
```



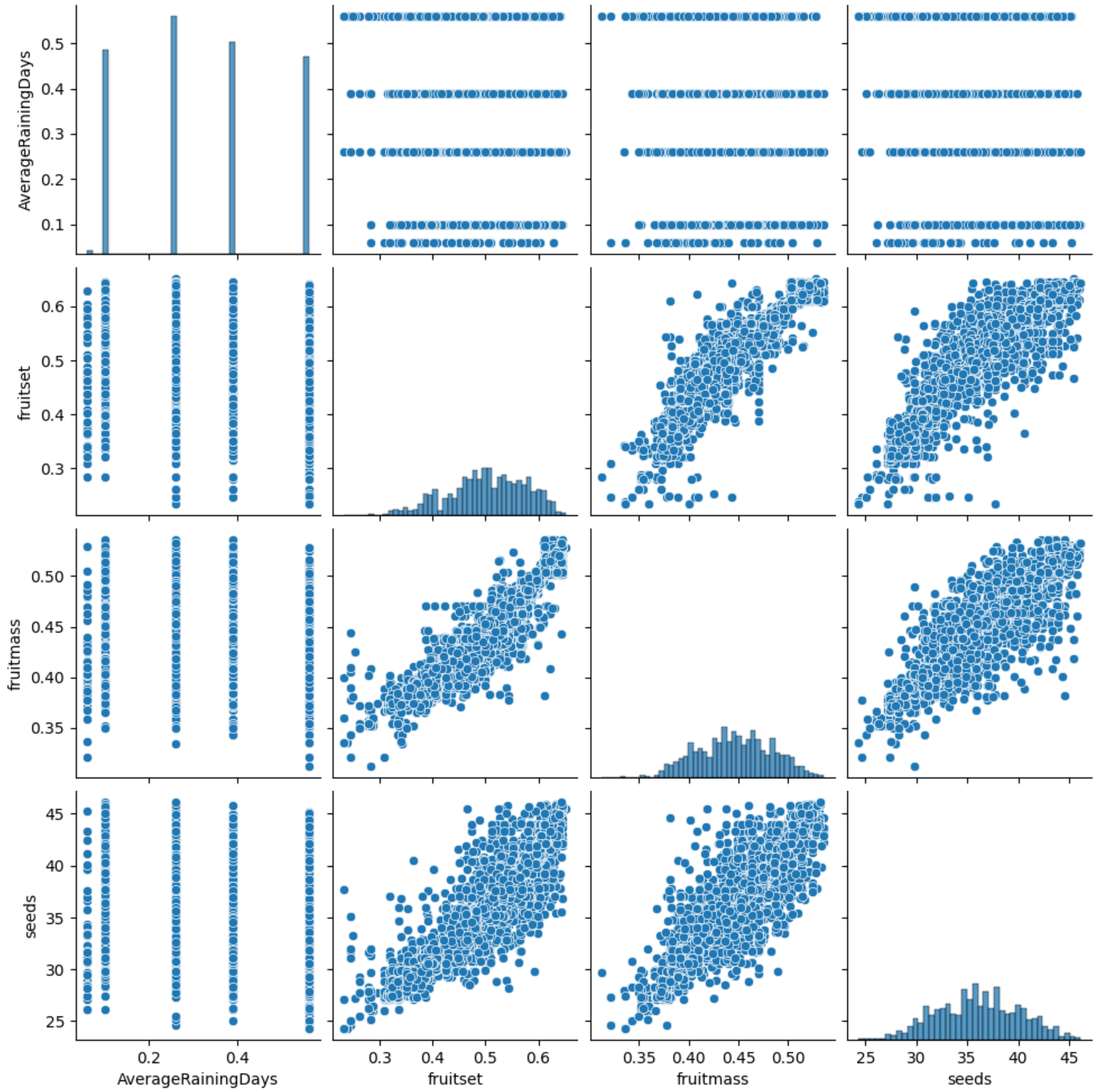
In [ ]:
```
sns.pairplot(train.iloc[:,-4:])
plt.show()
```



In [ ]:
```
sns.pairplot(test)
plt.show()
```



In [ ]:
```
sns.pairplot(test.iloc[:,-4:])
plt.show()
```



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⚙️ Feature Engineering

⚙️ Dimensionality Reduction

In [ ]:
```
train.corr()["MaxOfUpperTRange"].sort_values(ascending = False)
```

Out[ ]:

```
MaxOfUpperTRange        1.000000
MinOfLowerTRange        0.999829
AverageOfUpperTRange    0.999806
AverageOfLowerTRange    0.999772
MaxOfLowerTRange        0.999503
MinOfUpperTRange        0.998599
fruitmass               0.146237
seeds                   0.060963
clonesize               0.016159
RainingDays             0.011322
AverageRainingDays      0.010352
fruitset                0.007580
honeybee                0.005840
bumbles                -0.002104
andrena                -0.013061
yield                  -0.022517
osmia                  -0.031391
Name: MaxOfUpperTRange, dtype: float64
```

It seems that the columns related to temperature **`(MaxOfUpperTRange, MinOfLowerTRange, AverageOfUpperTRange, AverageOfLowerTRange, MaxOfLowerTRange, MinOfUpperTRange)`** are highly correlated with each other, with correlation coefficients close to 1.0. In this case, keeping only one representative column, such as **`MaxOfUpperTRange`**, can be a reasonable approach to reduce redundancy and multicollinearity in the dataset.

In [ ]:

```
train.drop(["MinOfUpperTRange", "AverageOfUpperTRange", "AverageOfLowerTRange"
test.drop(["MinOfUpperTRange", "AverageOfUpperTRange", "AverageOfLowerTRange",
```

In [ ]:

```
train.corr()["RainingDays"].sort_values(ascending = False)
```

Out[ ]:

```
RainingDays           1.000000
AverageRainingDays    0.990864
clonesize             0.165770
honeybee              0.046494
MaxOfUpperTRange      0.011322
andrena              -0.026572
bumbles              -0.063294
osmia                -0.079874
fruitmass            -0.447033
fruitset             -0.468066
yield                -0.477191
seeds                -0.478818
Name: RainingDays, dtype: float64
```

In [ ]:

```
train.corr()["yield"].sort_values(ascending = False)
```

Out[ ]:
```
yield                   1.000000
fruitset                0.885967
seeds                   0.868853
fruitmass               0.826481
osmia                   0.198264
bumbles                 0.161145
andrena                 0.073969
MaxOfUpperTRange       -0.022517
honeybee               -0.118001
clonesize              -0.382619
RainingDays            -0.477191
AverageRainingDays     -0.483870
Name: yield, dtype: float64
```

Since the target column `(yield)` has a higher correlation with `AverageRainingDays` (-0.483870) compared to `RainingDays` (-0.477191), it would be a reasonable choice to keep `AverageRainingDays` and drop RainingDays. By doing so, retained the information related to average raining days while removing a highly correlated column that provides similar information.

In [ ]:
```
train.drop(["RainingDays"], axis = 1, inplace = True)
test.drop(["RainingDays"], axis = 1, inplace = True)
```

In [ ]:
```
train.corr()["fruitset"].sort_values(ascending = False)
```

Out[ ]:
```
fruitset                1.000000
fruitmass               0.936988
seeds                   0.929654
yield                   0.885967
osmia                   0.209495
bumbles                 0.160447
andrena                 0.073669
MaxOfUpperTRange        0.007580
honeybee               -0.120492
clonesize              -0.406793
AverageRainingDays     -0.475876
Name: fruitset, dtype: float64
```

In [ ]:
```
train.corr()["yield"].sort_values(ascending = False)
```

Out[ ]:
```
yield                   1.000000
fruitset                0.885967
seeds                   0.868853
fruitmass               0.826481
osmia                   0.198264
bumbles                 0.161145
andrena                 0.073969
MaxOfUpperTRange       -0.022517
honeybee               -0.118001
clonesize              -0.382619
AverageRainingDays     -0.483870
Name: yield, dtype: float64
```

It appears that the columns `fruitmass`, `fruitset`, and `seeds` are highly correlated with each other, with correlation coefficients of approximately `0.93`. Among these three columns, `fruitset` has the highest correlation with the target column `(yield)` at 0.885967.

In [ ]:
```
train.drop(["fruitmass","seeds"], axis = 1, inplace = True)
test.drop(["fruitmass","seeds"], axis = 1, inplace = True)
```

⚙️ Standardization

In [ ]:
```
def scaling(feature):
    global X_train, X_test
    scaler = MinMaxScaler()
    scaler.fit
    scaler.fit(X_train[feature].to_numpy().reshape(-1,1))
    X_train[feature] = scaler.transform(X_train[feature].to_numpy().reshape(-1
    X_test[feature] = scaler.transform(X_test[feature].to_numpy().reshape(-1,1
```

In [ ]:
```
# scale_needed_features = [
# "MaxOfUpperTRange",
# "MinOfUpperTRange",
# "AverageOfUpperTRange",
# "MaxOfLowerTRange",
# "MinOfLowerTRange",
# "AverageOfLowerTRange",
# "RainingDays",
# "seeds" ]

scale_needed_features = [
"MaxOfUpperTRange"]
```

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🧑‍🔬 Model Selection

In [ ]:
```
if model_selection == True:
    X = train.drop(["yield"], axis = 1)
    y = train[["yield"]]
    list_mae_rfr = []
    list_mae_lr = []
    list_mae_xgb = []


    for i in range(1,100):
        X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0

        for feature in scale_needed_features:
```

```
            scaling(feature)

        # Random Forest
        rfr = RandomForestRegressor(random_state = RS)
        rfr.fit(X_train,y_train.values.ravel())
        rfr_prediction = rfr.predict(X_test)
        mae_rfr = mean_absolute_error(y_test,rfr_prediction)
        list_mae_rfr.append(mae_rfr)

        # Linear Regression
        lr = LinearRegression()
        lr.fit(X_train,y_train)
        lr_prediction = lr.predict(X_test)
        mae_lr = mean_absolute_error(y_test,lr_prediction)
        list_mae_lr.append(mae_lr)

        # XGBoost
        xgb = XGBRegressor(random_state = RS, max_depth = 3, n_estimators= 100
        xgb.fit(X_train,y_train)
        xgb_prediction = xgb.predict(X_test)
        mae_xgb = mean_absolute_error(y_test,xgb_prediction)
        list_mae_xgb.append(mae_xgb)



    print(f"Mean RFR 100-FOLD: {np.mean(list_mae_rfr)}")
    print(f"Median RFR 100-FOLD: {np.median(list_mae_rfr)}")

    print(f"Mean LR 100-FOLD: {np.mean(list_mae_lr)}")
    print(f"Median LR 100-FOLD: {np.median(list_mae_lr)}")

    print(f"Mean XGB 100-FOLD: {np.mean(list_mae_xgb)}")
    print(f"Median XGB 100-FOLD: {np.median(list_mae_xgb)}")
```

XGBoost was chosen over Random Forest Regressor and Linear Regression based on the mean and median of the 100-fold mean absolute error (MAE) of these models. The evaluation of the models revealed that XGBoost had the lowest MAE, indicating better predictive performance compared to the other two models.

Additionally, the performance of XGBoost was observed to be fast, which is advantageous when working with larger datasets or requiring quicker model iterations. This efficiency in training and prediction times further contributed to the decision of selecting XGBoost as the preferred model.

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Final Evaluation

In [ ]:
```
X_train = train.drop(["yield"], axis = 1)
y_train = train[["yield"]]
```

```
X_test = test.copy()

for feature in scale_needed_features:
    scaling(feature)

xgb_final = XGBRegressor(random_state = RS, max_depth = 3, n_estimators= 100,e
xgb_final.fit(X_train,y_train)
xgb_final_prediction = xgb_final.predict(X_test)
```

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📋 Result

In [ ]:

```
result = pd.DataFrame({
    "yield" : xgb_final_prediction
}).set_index(X_test.index)
```

In [ ]:

```
result
```

Out[ ]:

id	yield
15289	4202.810059
15290	6048.218262
15291	7223.557129
15292	4689.556152
15293	3796.140869
...	...
25478	5376.573242
25479	5651.451660
25480	6809.795898
25481	4381.233398
25482	7201.355957

10194 rows × 1 columns

In [ ]:

```
result.to_csv("output.csv")
```

In [ ]:

```
# Author: amyrmahdy
# Date: 12 May 2023
```

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📕 CONCLUSION

In conclusion, this notebook explored the task of predicting crop yield using machine learning techniques. The dataset provided valuable features related to fruit set, seeds, and weather conditions, which were crucial in understanding and predicting crop productivity.

Through extensive data analysis and preprocessing, we gained insights into the relationships between variables and prepared the data for modeling. Three regression models, namely Random Forest, Linear Regression, and XGBoost, were trained and evaluated using a 100-fold cross-validation strategy.

After evaluating the models based on mean absolute error (MAE), XGBoost emerged as the top-performing model, exhibiting the lowest MAE among the three. This superior performance, coupled with its fast execution time, led to the selection of XGBoost as the final model for predicting crop yield.

The chosen model, XGBoost, offers high predictive accuracy, robustness to overfitting, and the ability to handle complex relationships within the data. The feature importance analysis provided valuable insights into the key factors influencing crop productivity.

By leveraging XGBoost, we can make reliable predictions on the test dataset and contribute to the field of agriculture by optimizing crop yield. The results of this notebook demonstrate the effectiveness of machine learning in agricultural applications and open avenues for further research and exploration in this domain.

Overall, this notebook serves as a valuable resource for understanding and implementing machine learning techniques in predicting crop yield, showcasing the importance of feature engineering, model selection, and evaluation in agricultural analytics.

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