Prerequisites

- Python
- Machine learning libraries such as Scikit-learn and XGBoost, along with their packages
- NumPy (Numerical Python), Pandas
- Data visualization libraries such as Seaborn and Matplotlib

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import numpy as np
import pandas as pd
```

In [3]:
```
df = pd.read_csv("q3_data_for_assignment.csv")
```

In [4]:
```
df.head(10) # Starting 10 rows of dataset in pandas dataframe format
```

Out[4]:

	Tree species	TreeHeight_foot	TreeCrown_foot	TreeDBH_cm
0	Lemon	6	4.5	6.687898
1	Lemon	6	4.0	7.002817
2	Lemon	5	4.0	6.366198
3	Lemon	7	5.0	7.002817
4	Lemon	5	4.0	8.594367
5	Lemon	5	4.0	7.002817
6	Lemon	6	4.0	10.504226
7	Lemon	5	3.0	5.729578
8	Lemon	7	5.0	10.185916
9	Lemon	5	4.0	5.729578

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Tree species     200 non-null    object 
 1   TreeHeight_foot  200 non-null    int64  
 2   TreeCrown_foot   200 non-null    float64
 3   TreeDBH_cm       200 non-null    float64
dtypes: float64(2), int64(1), object(1)
memory usage: 6.4+ KB
```

There are 200 row and 4 columns with no null values

- Hense n need of gap filling
- Tree species column contain text data hense need to covert it into numeric format by using
- label encoder or OneHotEncoder (commonly used)

In [6]:
```
df.describe() # statestical information about the dataset
# Import to understand the data and its numeric features
```

Out[6]:

	TreeHeight_foot	TreeCrown_foot	TreeDBH_cm
count	200.000000	200.000000	200.000000
mean	9.095000	5.940000	10.534365
std	6.832966	2.126384	4.489946
min	3.000000	1.000000	2.547771
25%	7.000000	4.375000	7.002817
50%	9.000000	6.000000	10.191083
75%	10.000000	7.000000	13.136943
max	99.000000	18.500000	31.847134

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Tree species       0
TreeHeight_foot    0
TreeCrown_foot     0
TreeDBH_cm         0
dtype: int64
```

In [8]:
```
df['Tree species'].unique()
```

Out[8]:
```
array(['Lemon', 'Mango', 'Custard apple', 'Orange'], dtype=object)
```

In [9]:
```
df['Tree species'].value_counts()
# by lokking at the data there is good balance in data so no need to balancing the data
```

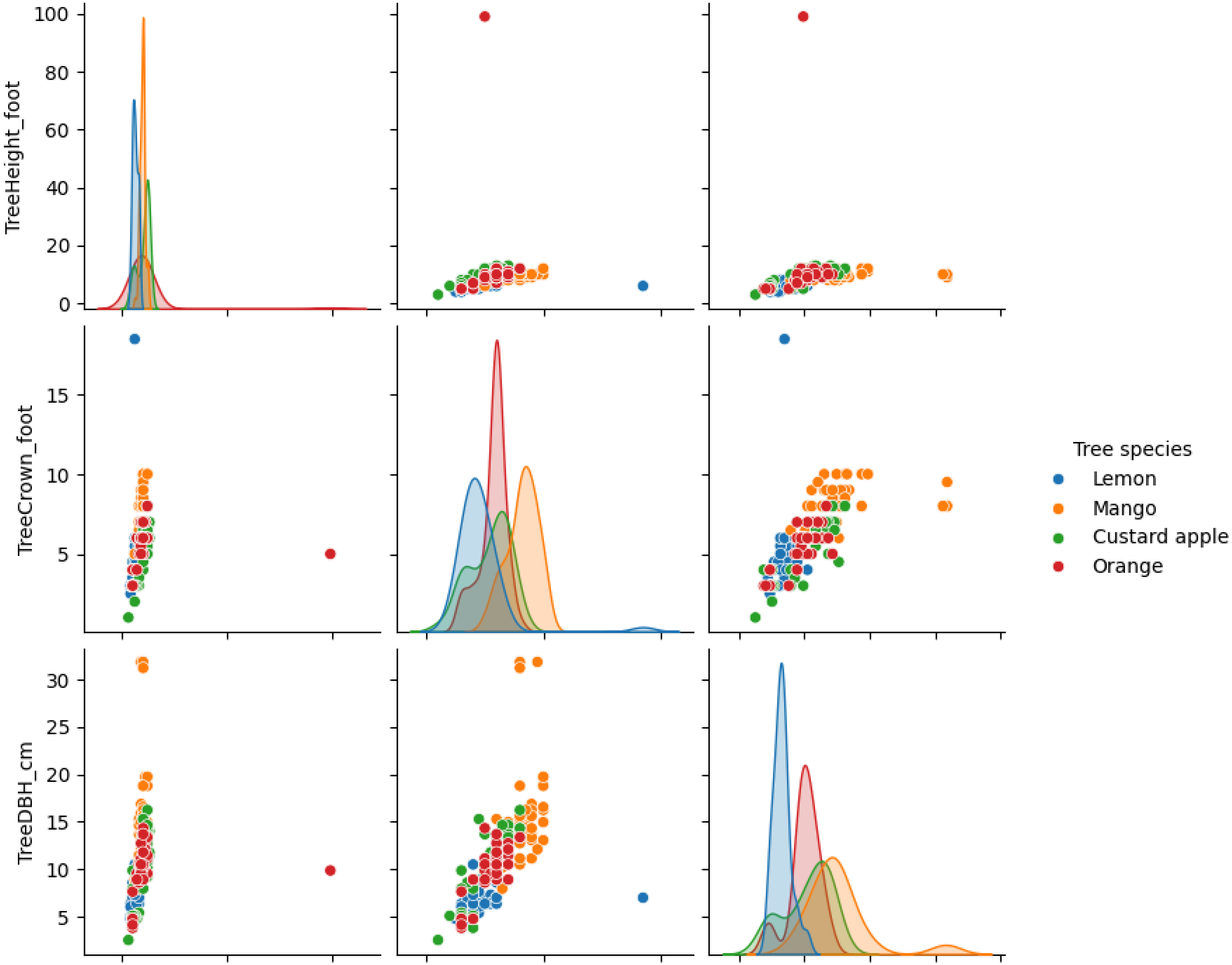
Out[9]:
```
Tree species
Orange           53
Lemon            50
Mango            50
Custard apple    47
Name: count, dtype: int64
```

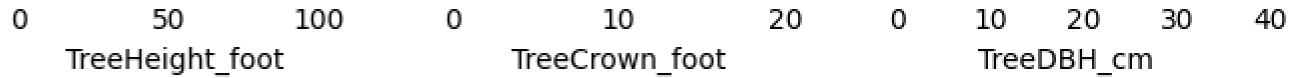
There are 4 species of tree in dataset

- Balanced dataset (no need to balance it)
- After the label encoding:
- 0- Custard apple
- 1- Lemon
- 2- Mango
- 3- Orange

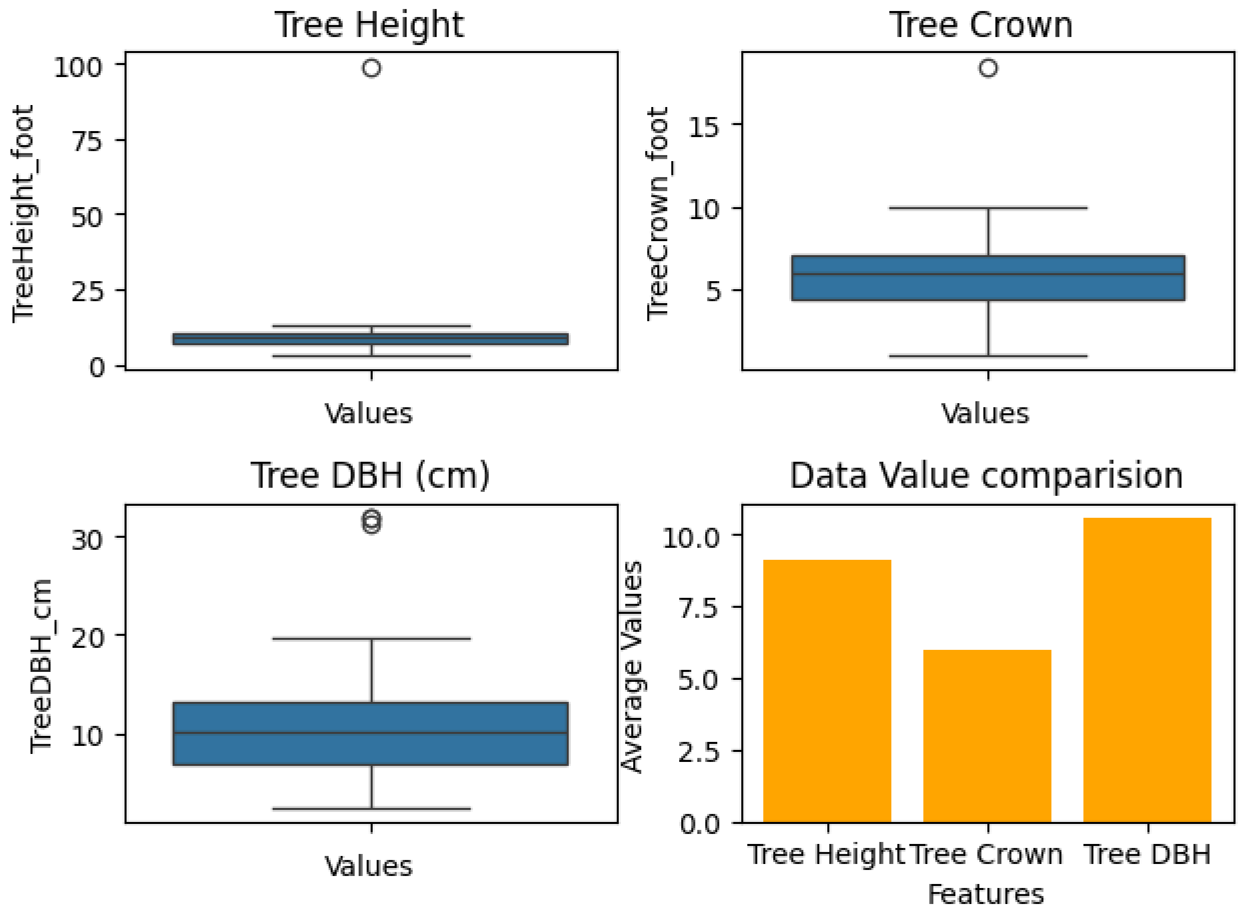
In [10]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [11]:
```
sns.pairplot(df, hue='Tree species')
plt.show()
```


TreeHeight_foot
TreeCrown_foot
TreeDBH_cm
100
80
60
40
20
0
15
10
5
30
25
20
15
10
5
Tree species
Lemon
Mango
Custard apple
Orange



In [12]:
```python
plt.subplot(2, 2, 1)  # (rows, columns, panel number)
sns.boxplot(data=df['TreeHeight_foot'])
plt.title('Tree Height')
plt.xlabel('Values')

plt.subplot(2, 2, 2)
sns.boxplot(data=df['TreeCrown_foot'])
plt.title('Tree Crown ')
plt.xlabel('Values')

plt.subplot(2, 2, 3)
sns.boxplot(data=df['TreeDBH_cm'])
plt.title('Tree DBH (cm)')
plt.xlabel('Values')

plt.subplot(2, 2, 4)
categories = ['Tree Height', 'Tree Crown', 'Tree DBH']
values = [df['TreeHeight_foot'].mean(), df['TreeCrown_foot'].mean(), df['TreeDBH_cm'].mean()]
plt.bar(categories, values, color='orange')
plt.title('Data Value comparision')
plt.xlabel('Features')
plt.ylabel('Average Values')

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



Data visualization

- Scatter plot - Show the average positive correlation
- Data having little posive skewness
- Box plot - Data contains few outliers
- Bar graph show the Numeric Value difference (Hense needed scaling for few models like SVR)

In [13]:
```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
```

```
df["Tree species"] = lb.fit_transform(df["Tree species"])
df.head()
```

Out[13]:

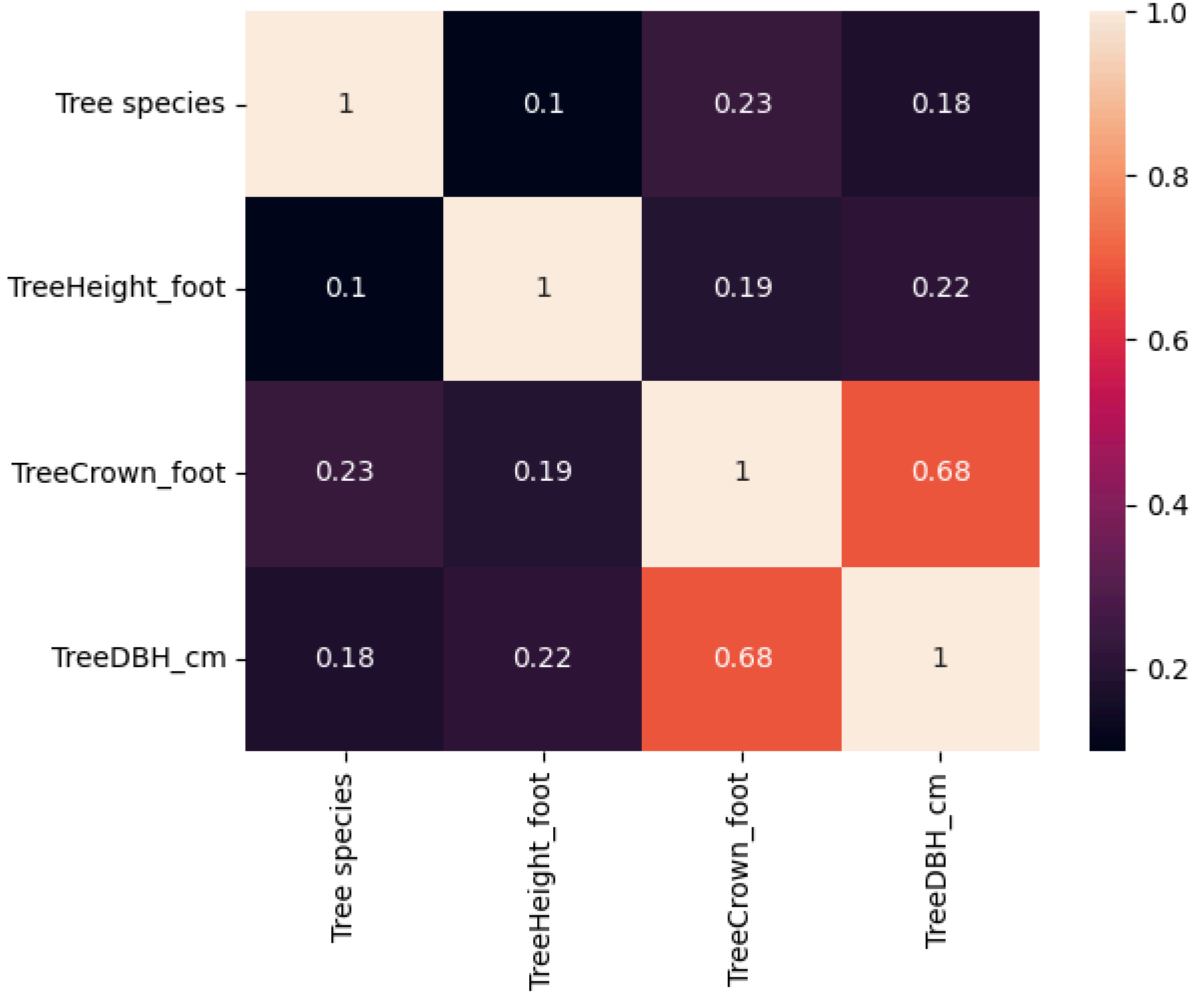
	Tree species	TreeHeight_foot	TreeCrown_foot	TreeDBH_cm
0	1	6	4.5	6.687898
1	1	6	4.0	7.002817
2	1	5	4.0	6.366198
3	1	7	5.0	7.002817
4	1	5	4.0	8.594367

In [14]:
```
for index, class_name in enumerate(lb.classes_):
    print(f"{class_name}: {index}")
```

```
Custard apple: 0
Lemon: 1
Mango: 2
Orange: 3
```

In [15]:
```
sns.heatmap(df.corr(), annot=True)
## By looking at correlation the TreeCrown_foot feature is more important and Tree species are less important
# but the dataset is very small hense we are hense we are taking all features.
```

Out[15]:
```
<Axes: >
```



- From Above correlation it seem like TreeCrown_foot is more important feature
- Tree species are less important

In [16]:
```
df1 =pd.read_csv("q3_data_for_assignment.csv")
X = pd.get_dummies(df1[['Tree species']])
X = X.astype(int)
```

```
df1 = pd.concat([df1, X], axis=1)
df1.head()
```

Out[16]:

	Tree species	TreeHeight_foot	TreeCrown_foot	TreeDBH_cm	Tree species_Custard apple	Tree species_Lemon	Tree species_Mango	Tree species_Orange
0	Lemon	6	4.5	6.687898	0	1	0	0
1	Lemon	6	4.0	7.002817	0	1	0	0
2	Lemon	5	4.0	6.366198	0	1	0	0
3	Lemon	7	5.0	7.002817	0	1	0	0
4	Lemon	5	4.0	8.594367	0	1	0	0

Import models basic

In [17]:

```
# Model Building (The below models are simple and not tree based)
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge, Lasso, ElasticNet
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor

lr = LinearRegression()
ridge = Ridge(alpha=1.0)
lasso = Lasso(alpha=0.1)
enet = ElasticNet(alpha=0.1, l1_ratio=0.5)
svr = SVR(kernel='rbf', C=12, epsilon=0.2)
knn = KNeighborsRegressor(metric='manhattan', n_neighbors = 13, p= 1, weights= 'uniform')

model_r = [lr, ridge, lasso, enet, svr, knn]
```

Tree based models

In [18]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
```

```
from sklearn.ensemble import GradientBoostingRegressor
from xgboost import XGBRegressor

dt = DecisionTreeRegressor(max_depth = 4, min_samples_leaf= 1, min_samples_split= 2)
rm = RandomForestRegressor(max_features ='sqrt', min_samples_leaf= 4, min_samples_split= 10, n_estimators= 100, ran
gb = GradientBoostingRegressor(learning_rate = 0.02, max_depth= 3, n_estimators=300, subsample=1.0)
xgb = XGBRegressor(n_estimators=90, learning_rate = 0.03, max_depth = 2, subsample = 1.0, gamma = 1)

model_tree = [dt, rm, gb, xgb]
```

model building and model Evaluation Function

In [19]:

```
# Model Evaluation
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
def model_evaluation(x_train, x_test, y_train, y_test, model_list):
    model_evaluation1 = {
        "model_name" :[],
        "Mean_absolute_error" : [],
        "Mean_squared_error" : [],
        "Root_mean_squared_error" : [],
        "r2_score" :[]
    }
    for model in model_list:
        model.fit(x_train, y_train)
        y_pred = model.predict(x_test)
        MAE = mean_absolute_error(y_test, y_pred)
        MSE = mean_squared_error(y_test, y_pred)
        RMSE = np.sqrt(MSE)
        R2 = r2_score(y_test, y_pred)
        model_evaluation1["model_name"].append(model.__class__.__name__)
        model_evaluation1["Mean_absolute_error"].append(MAE)
        model_evaluation1["Mean_squared_error"].append(MSE)
        model_evaluation1["Root_mean_squared_error"].append(RMSE)
        model_evaluation1["r2_score"].append(R2)

    model_evaluation1_df = pd.DataFrame(model_evaluation1)
    return model_evaluation1_df
```

Data with scaling

- Data is scaled using standard scalar

In [20]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
x = df1.drop(['Tree species', 'TreeDBH_cm'], axis=1)
y = df1['TreeDBH_cm']
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [21]:
```
m1 = model_evaluation(X_train_scaled, X_test_scaled, y_train, y_test, model_r)
m1
```

Out[21]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	LinearRegression	2.033676	9.762773	3.124544	0.482862
1	Ridge	2.031959	9.752511	3.122901	0.483406
2	Lasso	2.039969	9.755135	3.123321	0.483267
3	ElasticNet	2.028110	9.695961	3.113834	0.486401
4	SVR	1.725532	8.611702	2.934570	0.543835
5	KNeighborsRegressor	2.287647	11.181164	3.343825	0.407730

In [22]:
```
m2 = model_evaluation(X_train_scaled, X_test_scaled, y_train, y_test, model_tree)
m2
```

Out[22]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	DecisionTreeRegressor	2.246457	16.104056	4.012986	0.146962
1	RandomForestRegressor	1.803837	8.306380	2.882079	0.560008
2	GradientBoostingRegressor	2.166368	14.982778	3.870759	0.206357
3	XGBRegressor	1.839425	8.638268	2.939093	0.542428

Data without scaling

In [23]:
```
X1_train, X1_test, y1_train, y1_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

In [24]:
```
m3 = model_evaluation(X1_train, X1_test, y1_train, y1_test, model_r)
m3
```

Out[24]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	LinearRegression	2.033676	9.762773	3.124544	0.482862
1	Ridge	2.002516	9.599309	3.098275	0.491521
2	Lasso	1.972246	9.319270	3.052748	0.506355
3	ElasticNet	1.902087	8.988738	2.998122	0.523863
4	SVR	1.726433	8.337440	2.887463	0.558363
5	KNeighborsRegressor	1.872465	8.302786	2.881456	0.560198

In [25]:
```
m4 = model_evaluation(X1_train, X1_test, y1_train, y1_test, model_tree)
m4
```

Out[25]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	DecisionTreeRegressor	2.246457	16.104056	4.012986	0.146962
1	RandomForestRegressor	1.823836	8.535340	2.921530	0.547880
2	GradientBoostingRegressor	2.178045	15.116016	3.887932	0.199299
3	XGBRegressor	1.839425	8.638268	2.939093	0.542428

Data without [Tree spacies] feature

- The tree species are having less correlation hense dropped

In [26]:
```
# x and y taken from df not df1
x2 = df.drop(['Tree species', 'TreeDBH_cm'], axis=1)
y2 = df['TreeDBH_cm']
X2_train, X2_test, y2_train, y2_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

In [27]:
```
m5 = model_evaluation(X2_train, X2_test, y2_train, y2_test, model_r)
m5
```

Out[27]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	LinearRegression	2.033676	9.762773	3.124544	0.482862
1	Ridge	2.002516	9.599309	3.098275	0.491521
2	Lasso	1.972246	9.319270	3.052748	0.506355
3	ElasticNet	1.902087	8.988738	2.998122	0.523863
4	SVR	1.726433	8.337440	2.887463	0.558363
5	KNeighborsRegressor	1.872465	8.302786	2.881456	0.560198

with label encoded data

In [28]:
```
x3 = df.drop('TreeDBH_cm', axis = 1)
y3 = df['TreeDBH_cm']
x3_train, x3_test, y3_train, y3_test = train_test_split(x3, y3, test_size= 0.3, random_state= 12345)
```

In [29]:
```
m6 = model_evaluation(x3_train, x3_test, y3_train, y3_test, model_tree)
m6
```

Out[29]:

	model_name	Mean_absolute_error	Mean_squared_error	Root_mean_squared_error	r2_score
0	DecisionTreeRegressor	1.890187	12.934324	3.596432	0.538365
1	RandomForestRegressor	1.919730	12.776883	3.574477	0.543984
2	GradientBoostingRegressor	1.861708	13.341554	3.652609	0.523831
3	XGBRegressor	1.973025	13.110993	3.620910	0.532059

With polynomial regression also get maximum r2 score is 0.50

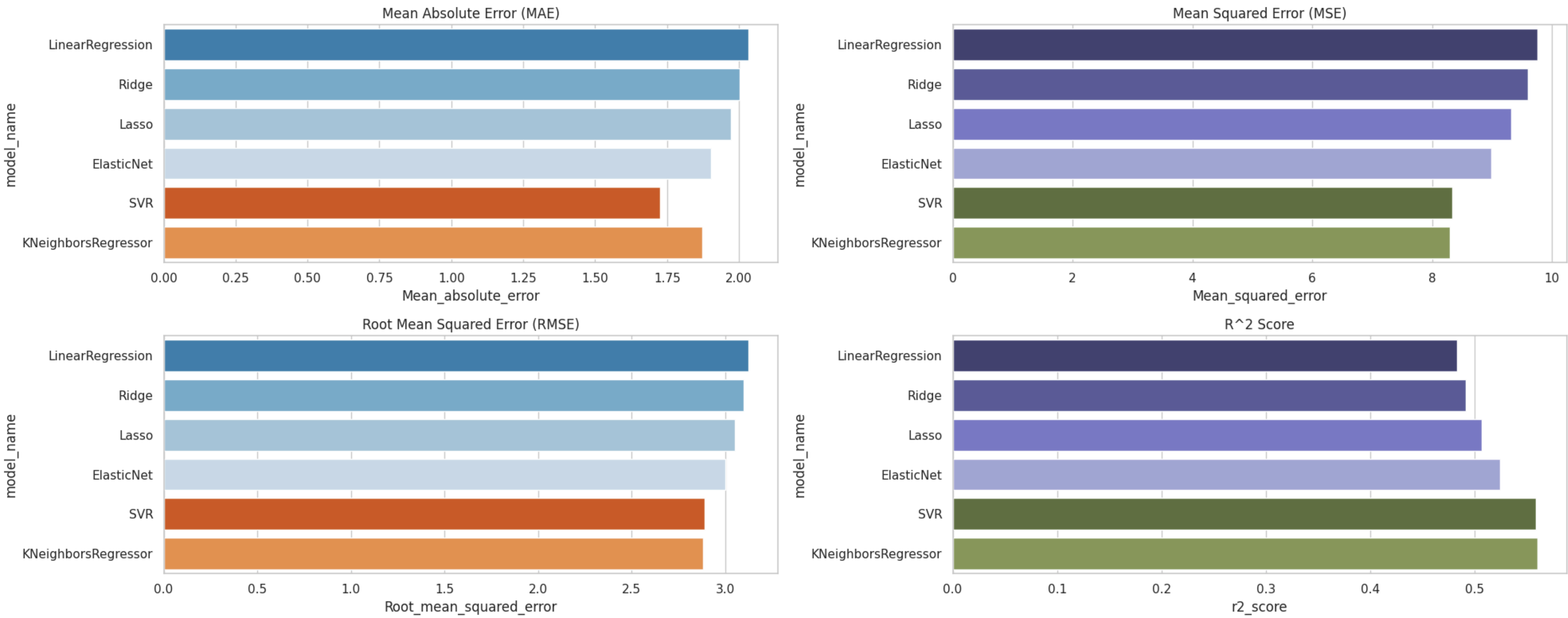
- degree = 2
- poly = PolynomialFeatures(degree=degree)
- x_train_poly = poly.fit_transform(x_train)
- x_test_poly = poly.transform(x_test)
- Polynomial Regression (Degree 2) Results:
- MAE = 1.9591254284592368
- MSE = 9.295227360598423
- RMSE = 3.048807530920642
- R2 = 0.5076283956833628

Result Discussion

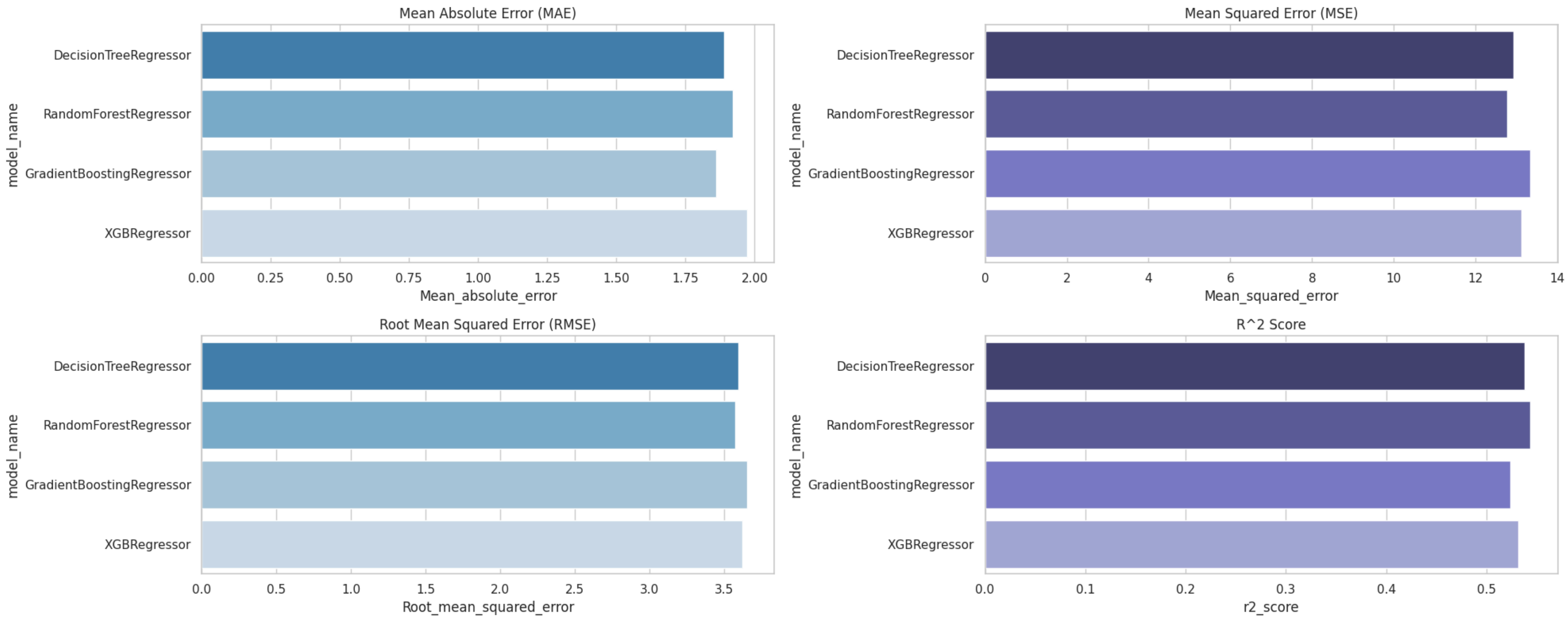
- All algorithms are used with thier Best Hyperparameters
- Hyperparameter tuning is done seperately using the Grid search cv for better output
- By comapring all Models it seems that - The r2 score is between 45 - 55 % - Hense we cannot use it for prediction

- The reason behind this output might be - Less amount of data - Requires more feature (This features are not enough to predict output)

In [30]:
```
sns.set(style="whitegrid")

def visualize_model_evaluation(evaluation_df):
    plt.figure(figsize=(20, 8))

    plt.subplot(2, 2, 1)
    sns.barplot(x='Mean_absolute_error', y='model_name', data=evaluation_df, palette='tab20c')
    plt.title('Mean Absolute Error (MAE)')

    plt.subplot(2, 2, 2)
    sns.barplot(x='Mean_squared_error', y='model_name', data=evaluation_df, palette='tab20b')
    plt.title('Mean Squared Error (MSE)')

    plt.subplot(2, 2, 3)
    sns.barplot(x='Root_mean_squared_error', y='model_name', data=evaluation_df, palette='tab20c')
    plt.title('Root Mean Squared Error (RMSE)')

    plt.subplot(2, 2, 4)
    sns.barplot(x='r2_score', y='model_name', data=evaluation_df, palette='tab20b')
    plt.title('R^2 Score')

    plt.tight_layout()

    plt.show()

visualize_model_evaluation(m5)
```



In [31]:
```
visualize_model_evaluation(m6)
```



We can show Result in different types for different Models

E.g.

- Linear_regression : - Scatter Plot With Best Fit Line
- Support Vector Regressor : - Scatter plot with best fit Hyper Plane
- KNN : - with clustering
- Decision Tree : - Tree map
- But with this result I think there is no use of this result visualization

In [32]:
```
# To save the trained model using pickle
''' with open('decision_tree_model.pkl', 'wb') as file:
    pickle.dump(dt, file)'''

# To load the model later use
```

```
'''
with open('decision_tree_model.pkl', 'rb') as file:
    loaded_model = pickle.load(file)
    '''
```

Out[32]:
```
"\nwith open('decision_tree_model.pkl', 'rb') as file:\n    loaded_model = pickle.load(file)\n    "
```

In [ ]: