Comparison of Individual, Bagging and Boostir Algorithms

Diamond Dataset Features

In this section, we outline the features of the diamond dataset used for analysis.

Selected Features

The features included in the dataset are:

- **carat**: Weight of the diamond (measured in carats)
- **cut**: Quality of the cut (e.g., Fair, Good, Very Good, Ideal, Premium) *(Target Variable)*
- **color**: Diamond color, from J (worst) to D (best)
- **clarity**: A measurement of how clear the diamond is (e.g., IF, VVS1, VVS2, VS1, VS2, SI1, S
- **depth**: Total depth percentage, calculated as (\frac{z}{\text{mean}(x, y)})
- **table**: Width of the top of the diamond relative to the widest point
- **price**: Price of the diamond (in US dollars)
- **x**: Length of the diamond (in mm)
- **y**: Width of the diamond (in mm)
- **z**: Depth of the diamond (in mm)

Target Variable

The target variable for prediction is:

- **cut**: This is the target variable we aim to predict using the selected features.

In [1]:
```
# !pip install xgboost -q
```

In [2]:
```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

In [3]:
```
# import the data
df = sns.load_dataset('diamonds')
```

In [4]:
```
df.head()
```

Out[4]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

In [5]:
```
df.shape
```

Out[5]:
```
(53940, 10)
```

In [6]:
```
# split the data into X and y
X = df.drop('cut', axis=1)
y = df['cut']

# encode the input variables
le = LabelEncoder()
X['color'] = le.fit_transform(X['color'])
X['clarity'] = le.fit_transform(X['clarity'])

# encode the target variable
y = le.fit_transform(y)

# split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

DecisionTreeClassifier

Accuracy score: 0.70

In [7]:
```
# %%time
# train the decision tree model
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

# predict the test data
y_pred = dt.predict(X_test)

print('Accuracy score: ', accuracy_score(y_test, y_pred))
print('Precision score: ', precision_score(y_test, y_pred, average='micro
print('Recall score: ', recall_score(y_test, y_pred, average='micro'))
print('F1 score: ', f1_score(y_test, y_pred, average='micro'))
```

```
Accuracy score:  0.71449758991472
Precision score:  0.71449758991472
Recall score:  0.71449758991472
F1 score:  0.71449758991472
```

RandomForestClassifier

Accuracy score: 0.78

In [8]:
```
# %%time
# train the random forest model
```

```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)

# predict the test data
y_pred = rf.predict(X_test)

print('Accuracy score: ', accuracy_score(y_test, y_pred))
print('Precision score: ', precision_score(y_test, y_pred, average='micro
print('Recall score: ', recall_score(y_test, y_pred, average='micro'))
print('F1 score: ', f1_score(y_test, y_pred, average='micro'))
```

```
Accuracy score:  0.7886540600667408
Precision score:  0.7886540600667408
Recall score:  0.7886540600667408
F1 score:  0.7886540600667408
```

XGBClassifier

Accuracy score: 0.79

In [9]:

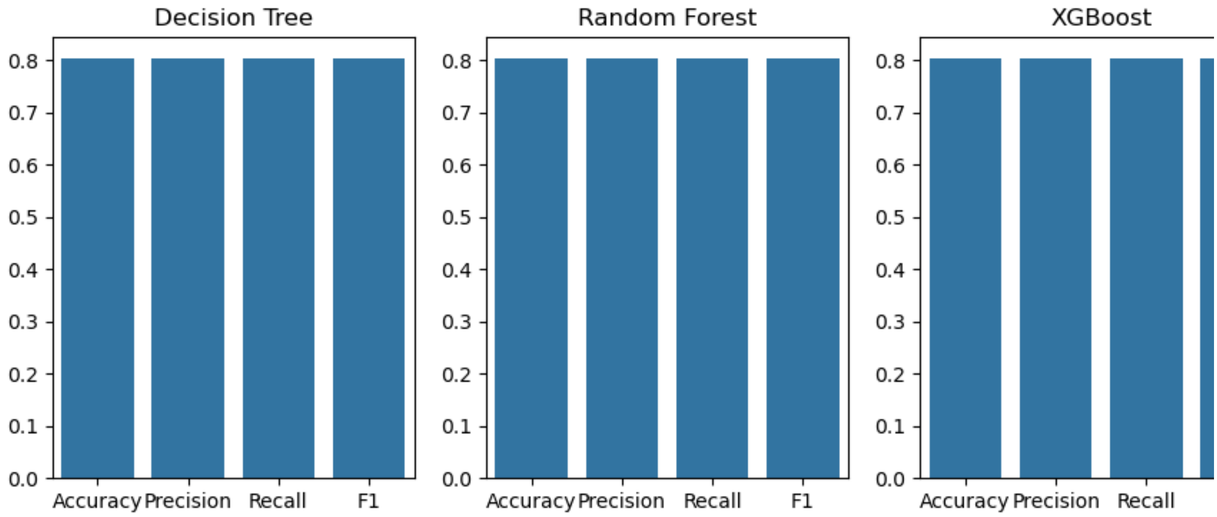
```
# %%time
# train the xgboost model
xgb = XGBClassifier()
xgb.fit(X_train, y_train)

# predict the test data
y_pred = xgb.predict(X_test)

print('Accuracy score: ', accuracy_score(y_test, y_pred))
print('Precision score: ', precision_score(y_test, y_pred, average='micro
print('Recall score: ', recall_score(y_test, y_pred, average='micro'))
print('F1 score: ', f1_score(y_test, y_pred, average='micro'))
```

```
Accuracy score:  0.803578049684835
Precision score:  0.803578049684835
Recall score:  0.803578049684835
F1 score:  0.803578049684835
```

Comparison

In [10]:

```
# make a bar plot showing each of the matrix with respect to the model
plt.figure(figsize=(15, 4))
plt.subplot(1, 4, 1)
sns.barplot(x=['Accuracy', 'Precision', 'Recall', 'F1'], y=[accuracy_scor
plt.title('Decision Tree')
plt.subplot(1, 4, 2)
sns.barplot(x=['Accuracy', 'Precision', 'Recall', 'F1'], y=[accuracy_scor
plt.title('Random Forest')
plt.subplot(1, 4, 3)
sns.barplot(x=['Accuracy', 'Precision', 'Recall', 'F1'], y=[accuracy_scor
plt.title('XGBoost')
# plt.tight_layout()
plt.show()
```



In [11]:
```
from sklearn.ensemble import BaggingClassifier

# Create a Bagging classifier
bagging = BaggingClassifier(estimator=DecisionTreeClassifier(), n_estimat

# Train the Bagging classifier
bagging.fit(X_train, y_train)

# Predict the test data
y_pred_bagging = bagging.predict(X_test)

# Print the evaluation metrics
print('Accuracy score: ', accuracy_score(y_test, y_pred_bagging))
print('Precision score: ', precision_score(y_test, y_pred_bagging, averag
print('Recall score: ', recall_score(y_test, y_pred_bagging, average='mic
print('F1 score: ', f1_score(y_test, y_pred_bagging, average='micro'))
```

```
Accuracy score:  0.7923618835743419
Precision score:  0.7923618835743419
Recall score:  0.7923618835743419
F1 score:  0.7923618835743419
```

In [ ]:
```
```