## In [130]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

## In [131]:

df = pd.read\_csv('/kaggle/input/gender-classification/Transformed Data Set - Sheet
1.csv')

### In [132]:

df

## Out[132]:

	Favorite Color	Favorite Music Genre	Favorite Beverage	Favorite Soft Drink	Gender
0	Cool	Rock	Vodka	7UP/Sprite	F
1	Neutral	Hip hop	Vodka	Coca Cola/Pepsi	F
2	Warm	Rock	Wine	Coca Cola/Pepsi	F
3	Warm	Folk/Traditional	Whiskey	Fanta	F
4	Cool	Rock	Vodka	Coca Cola/Pepsi	F
61	Cool	Rock	Vodka	Coca Cola/Pepsi	М
62	Cool	Hip hop	Beer	Coca Cola/Pepsi	М
63	Neutral	Hip hop	Doesn't drink	Fanta	М
64	Cool	Rock	Wine	Coca Cola/Pepsi	М
65	Cool	Electronic	Beer	Coca Cola/Pepsi	М

66 rows × 5 columns

```
gender-classification-lr-dt-rf-svm-and-knn
In [133]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 66 entries, 0 to 65
Data columns (total 5 columns):
     Column
                            Non-Null Count Dtype
 #
    Favorite Color
 0
                            66 non-null
                                             object
 1
    Favorite Music Genre 66 non-null
                                             object
 2
   Favorite Beverage
                            66 non-null
                                             object
    Favorite Soft Drink
                            66 non-null
                                             object
 4
     Gender
                            66 non-null
                                             object
dtypes: object(5)
memory usage: 2.7+ KB
In [134]:
df.isna().sum()
Out[134]:
Favorite Color
Favorite Music Genre
                         0
Favorite Beverage
                         0
Favorite Soft Drink
                         0
Gender
                         0
dtype: int64
In [135]:
# Check for Duplicates
df.duplicated().sum()
Out[135]:
4
In [136]:
# Drop the Duplicates
df.drop_duplicates(inplace=True)
In [137]:
df.shape
```

#### Out[137]:

(62, 5)

#### **Encoding the Categorical Data:**

```
In [138]:
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
In [139]:
df['Favorite Color'].unique()
Out[139]:
array(['Cool', 'Neutral', 'Warm'], dtype=object)
In [140]:
df['Favorite Color'] = encoder.fit_transform(df['Favorite Color'])
In [141]:
df['Favorite Music Genre'].unique()
Out[141]:
array(['Rock', 'Hip hop', 'Folk/Traditional', 'Jazz/Blues', 'Pop',
       'Electronic', 'R&B and soul'], dtype=object)
In [142]:
df['Favorite Music Genre'] = encoder.fit_transform(df['Favorite Music Genre'])
In [143]:
df['Favorite Beverage'].unique()
Out[143]:
array(['Vodka', 'Wine', 'Whiskey', "Doesn't drink", 'Beer', 'Other'],
      dtype=object)
In [144]:
df['Favorite Beverage'] = encoder.fit transform(df['Favorite Beverage'])
In [145]:
df['Favorite Soft Drink'].unique()
Out[145]:
array(['7UP/Sprite', 'Coca Cola/Pepsi', 'Fanta', 'Other'], dtype=objec
t)
In [146]:
```

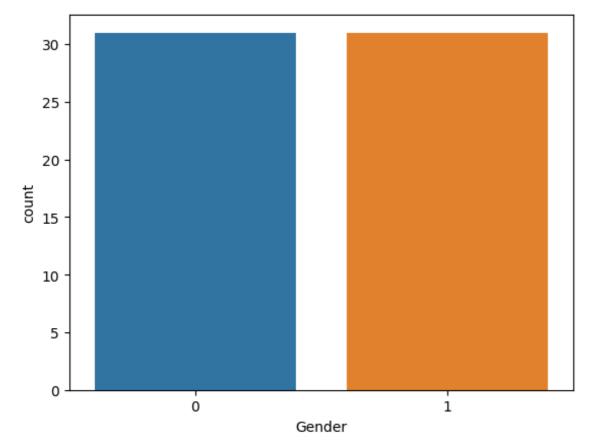
df['Favorite Soft Drink'] = encoder.fit\_transform(df['Favorite Soft Drink'])

```
In [147]:
df['Gender'].unique()
Out[147]:
array(['F', 'M'], dtype=object)
In [148]:
df['Gender'] = encoder.fit_transform(df['Gender'])
In [149]:
df.info()
<class 'pandas.core.frame.DataFrame'>
Index: 62 entries, 0 to 65
Data columns (total 5 columns):
#
    Column
                          Non-Null Count Dtype
                                         ----
                          62 non-null
                                          int64
0
   Favorite Color
    Favorite Music Genre 62 non-null
1
                                          int64
   Favorite Beverage 62 non-null
                                          int64
 3
   Favorite Soft Drink 62 non-null
                                          int64
4
    Gender
                          62 non-null
                                          int64
dtypes: int64(5)
memory usage: 2.9 KB
```

Visualize the Data:

## In [150]:

```
sns.countplot(x=df['Gender'])
plt.show()
```



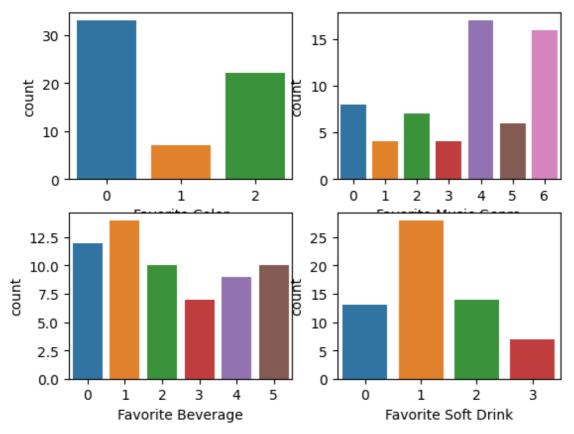
#### In [151]:

```
fig, ax =plt.subplots(2,2)

plt.figure(figsize=(10,12))

sns.countplot(x=df['Favorite Color'], ax=ax[0,0])
sns.countplot(x=df['Favorite Music Genre'], ax=ax[0,1])
sns.countplot(x=df['Favorite Beverage'], ax=ax[1,0])
sns.countplot(x=df['Favorite Soft Drink'], ax=ax[1,1])

plt.show()
```



<Figure size 1000x1200 with 0 Axes>

#### In [152]:

```
X = df.drop('Gender', axis=1)
Y = df['Gender']
```

#### In [153]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.20, random_state=42)
```

## **Logistic Regression Model**

#### **Create and Train the Model:**

## In [154]:

```
from sklearn.linear_model import LogisticRegression
```

## In [155]:

```
log_regressor = LogisticRegression()
log_regressor.fit(x_train, y_train)
```

#### Out[155]:

```
▼ LogisticRegression
LogisticRegression()
```

#### **Predict Test Set Results:**

#### In [156]:

```
log_regr_y_pred = log_regressor.predict(x_test)
```

```
In [157]:
```

```
pd.DataFrame({'Actual':y_test, 'Predicted':log_regr_y_pred})
```

#### Out[157]:

	Actual	Predicted
52	1	1
58	1	0
0	0	0
59	1	1
5	0	0
50	1	1
16	0	1
12	0	0
27	0	1
63	1	1
32	0	1
9	0	0
49	1	0

## **Evaluate Performance of the Model:**

#### In [158]:

from sklearn.metrics import accuracy\_score, confusion\_matrix, classification\_report

#### In [159]:

```
log_regr_score = accuracy_score(y_test, log_regr_y_pred)
log_regr_score
```

#### Out[159]:

## 0.6153846153846154

## In [160]:

```
log_regr_mat = confusion_matrix(y_test, log_regr_y_pred)
log_regr_mat
```

## Out[160]:

```
array([[4, 3], [2, 4]])
```

#### In [161]:

```
log_regr_report = classification_report(y_test, log_regr_y_pred)
print(log_regr_report)
```

	precision	recall	f1-score	support
0	0.67	0.57	0.62	7
1	0.57	0.67	0.62	6
accuracy			0.62	13
macro avg	0.62	0.62	0.62	13
weighted avg	0.62	0.62	0.62	13

## **Decision Tree**

#### **Create and Train Model:**

#### In [162]:

from sklearn.tree import DecisionTreeClassifier

#### In [163]:

```
dt_clf = DecisionTreeClassifier(criterion='entropy')
dt_model = dt_clf.fit(x_train, y_train)
```

#### **Predict Test Set Results:**

#### In [164]:

```
dt_y_pred = dt_clf.predict(x_test)
```

```
In [165]:
```

```
pd.DataFrame({'Actual':y_test, 'Predicted':dt_y_pred})
```

#### Out[165]:

	Actual	Predicted
52	1	1
58	1	0
0	0	1
59	1	1
5	0	0
50	1	1
16	0	0
12	0	0
27	0	1
63	1	1
32	0	0
9	0	1
49	1	1

## **Evaluate Performance of the Model:**

## In [166]:

```
dt_score = accuracy_score(y_test, dt_y_pred)
dt_score
```

#### Out[166]:

#### 0.6923076923076923

#### In [167]:

```
dt_mat = confusion_matrix(y_test, dt_y_pred)
dt_mat
```

## Out[167]:

```
array([[4, 3], [1, 5]])
```

## In [168]:

dt\_report = classification\_report(y\_test, dt\_y\_pred) print(dt\_report)

	precision	recall	f1-score	support
0	0.80	0.57	0.67	7
1	0.62	0.83	0.71	6
accuracy			0.69	13
macro avg	0.71	0.70	0.69	13
weighted avg	0.72	0.69	0.69	13

Plot the Tree:

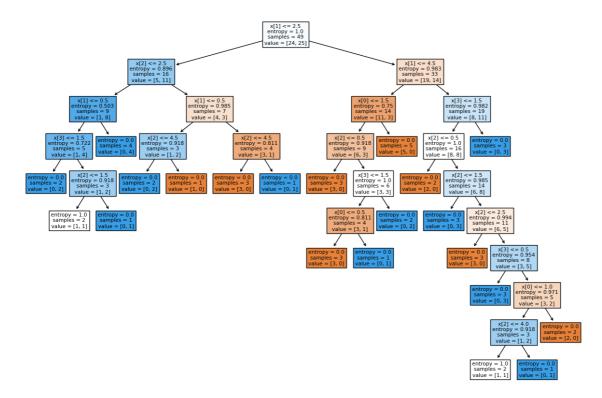
## In [169]:

```
from sklearn import tree
plt.figure(figsize=(15,10))
tree.plot_tree(dt_model, filled=True)
```

Out[169]:

```
[\text{Text}(0.46875, 0.95, 'x[1] <= 2.5 \setminus \text{nentropy} = 1.0 \setminus \text{nsamples} = 49 \setminus \text{nvalue}]
= [24, 25]'),
      s = 16 \setminus value = [5, 11]'),
      Text(0.125, 0.75, 'x[1] \le 0.5 \cdot entropy = 0.503 \cdot entropy = 9 \cdot entrop
[1, 8]'),
       s = 5 \mid value = [1, 4]'),
      Text(0.04166666666666664, 0.55, 'entropy = 0.0\nsamples = 2\nvalue =
[0, 2]'),
       Text(0.125, 0.55, x[2] <= 1.5 \le 0.918 \le 3 \le 3
[1, 2]'),
      [1, 1]'),
       [0, 1]'),
       [0, 4]'),
      = 7 \cdot (3)'
       Text(0.25, 0.65, 'x[2] \le 4.5 \neq 0.918 = 3 \le 2.5 
[1, 2]'),
       Text(0.20833333333333334, 0.55, 'entropy = 0.0\nsamples = 2\nvalue =
[0, 2]'),
      Text(0.291666666666667, 0.55, 'entropy = 0.0\nsamples = 1\nvalue =
[1, 0]'),
      Text(0.416666666666667, 0.65, 'x[2] \le 4.5 \cdot entropy = 0.811 \cdot en
= 4 \cdot nvalue = [3, 1]'),
      Text(0.375, 0.55, 'entropy = 0.0 \times = 3 \times = [3, 0]'),
      Text(0.458333333333333, 0.55, 'entropy = 0.0\nsamples = 1\nvalue =
[0, 1]'),
      Text(0.708333333333334, 0.85, x[1] \le 4.5 \neq 0.983 
= 33\nvalue = [19, 14]'),
      Text(0.625, 0.75, 'x[0] <= 1.5 \neq 0.75 = 0.75 = 14 = 1.5 = 14
[11, 3]'),
       Text(0.583333333333333334, 0.65, 'x[2] <= 0.5\nentropy = 0.918\nsamples
= 9 \text{ nvalue} = [6, 3]'),
      [3, 0]'),
      Text(0.625, 0.55, 'x[3] <= 1.5 \setminus = 1.0 \setminus = 6 \setminus
[3, 3]'),
      = 4 \ln = [3, 1]'
      Text(0.541666666666666, 0.35, 'entropy = 0.0\nsamples = 3\nvalue =
[3, 0]'),
      Text(0.625, 0.35, 'entropy = 0.0 \nsamples = 1 \nvalue = [0, 1]'),
       Text(0.666666666666666, 0.45, 'entropy = 0.0\nsamples = 2\nvalue =
[0, 2]'),
      Text(0.666666666666666, 0.65, 'entropy = 0.0\nsamples = 5\nvalue =
[5, 0]'),
      = 19\nvalue = [8, 11]'),
       Text(0.75, 0.65, 'x[2] \leftarrow 0.5 \neq 1.0 \Rightarrow 1.0
[8, 8]'),
      Text(0.708333333333334, 0.55, 'entropy = 0.0 \nsamples = 2 \nvalue =
[2, 0]'),
       Text(0.7916666666666666, 0.55, 'x[2] <= 1.5\nentropy = 0.985\nsamples
= 14 \setminus value = [6, 8]'),
```

```
Text(0.75, 0.45, 'entropy = 0.0 \nsamples = 3 \nvalue = [0, 3]'),
     Text(0.833333333333334, 0.45, |x[2]| \le 2.5 \le 0.994 \le
= 11 \setminus value = [6, 5]'),
     [3, 0]'),
     Text(0.875, 0.35, 'x[3] \leftarrow 0.5 \neq 0.954 = 8 = 8 = 8
[3, 5]'),
     Text(0.833333333333334, 0.25, 'entropy = 0.0 \nsamples = 3 \nvalue =
[0, 3]'),
     = 5 \cdot \text{nvalue} = [3, 2]'),
     Text(0.875, 0.15, 'x[2] \leftarrow 4.0 \neq 0.918 = 3 = 3 = 0.918 = 0.918 = 3 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 0.918 = 
[1, 2]'),
     Text(0.833333333333334, 0.05, 'entropy = 1.0 \nsamples = 2 \nvalue =
[1, 1]'),
     [0, 1]'),
     Text(0.9583333333333334, 0.15, 'entropy = 0.0\nsamples = 2\nvalue =
[2, 0]'),
     Text(0.833333333333334, 0.65, 'entropy = 0.0\nsamples = 3\nvalue =
[0, 3]')]
```



## **Random Forest Model**

#### **Create and Train the Model:**

#### In [170]:

from sklearn.ensemble import RandomForestClassifier

```
In [171]:
```

```
rf_clf = RandomForestClassifier(n_estimators=10, criterion='entropy')
rf_clf.fit(x_train, y_train)
```

## Out[171]:

```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

#### **Predict Test Set Results:**

```
In [172]:
```

```
rf_y_pred = rf_clf.predict(x_test)
```

#### In [173]:

```
pd.DataFrame({'Actual':y_test, 'Predicted':rf_y_pred})
```

#### Out[173]:

	Actual	Predicted
52	1	1
58	1	0
0	0	1
59	1	1
5	0	1
50	1	1
16	0	0
12	0	0
27	0	1
63	1	1
32	0	0
9	0	0
49	1	1

#### **Evaluate Performance of the Model:**

#### In [174]:

```
rf_clf_score = accuracy_score(y_test, rf_y_pred)
rf_clf_score
```

#### Out[174]:

#### 0.6923076923076923

## In [175]:

```
rf_clf_mat = confusion_matrix(y_test, rf_y_pred)
rf_clf_mat
```

## Out[175]:

```
array([[4, 3], [1, 5]])
```

#### In [176]:

```
rf_clf_report = classification_report(y_test, rf_y_pred)
print(rf_clf_report)
```

	precision	recall	f1-score	support
0	0.80	0.57	0.67	7
1	0.62	0.83	0.71	6
accuracy			0.69	13
macro avg	0.71	0.70	0.69	13
weighted avg	0.72	0.69	0.69	13

## **SVM Classifier**

#### **Create and Train the Model:**

#### In [177]:

```
from sklearn.svm import SVC
```

### In [180]:

```
svm_clf = SVC(kernel='poly', degree=5, random_state=42)
svm_clf.fit(x_train, y_train)
```

#### Out[180]:

```
SVC
SVC(degree=5, kernel='poly', random_state=42)
```

#### **Predict Test Set Results:**

## In [198]:

```
svm_clf_y_pred = svm_clf.predict(x_test)
```

#### In [182]:

```
pd.DataFrame({'Actual':y_test, 'Predicted':svm_clf_y_pred})
```

## Out[182]:

	Actual	Predicted
52	1	1
58	1	0
0	0	0
59	1	1
5	0	1
50	1	1
16	0	1
12	0	0
27	0	1
63	1	1
32	0	0
9	0	1
49	1	1

#### **Evaluate Performance of the Model:**

#### In [199]:

```
svm_clf_score = accuracy_score(y_test, svm_clf_y_pred)
svm_clf_score
```

#### Out[199]:

#### 0.6153846153846154

#### In [200]:

```
svm_clf_mat = confusion_matrix(y_test, svm_clf_y_pred)
svm_clf_mat
```

#### Out[200]:

```
array([[3, 4], [1, 5]])
```

#### In [201]:

```
svm_clf_report = classification_report(y_test, svm_clf_y_pred)
print(svm_clf_report)
```

support	f1-score	recall	precision	
7	0.55	0.43	0.75	0
6	0.67	0.83	0.56	1
13	0.62			accuracy
13	0.61	0.63	0.65	macro avg
13	0.60	0.62	0.66	weighted avg

## **KNN Classification Model**

#### **Create and Train the Model:**

#### In [187]:

from sklearn.neighbors import KNeighborsClassifier

#### In [188]:

```
knn_clf = KNeighborsClassifier(n_neighbors=5, p=2, metric='minkowski')
knn_clf.fit(x_train,y_train)
```

#### Out[188]:

```
* KNeighborsClassifier
KNeighborsClassifier()
```

#### **Predict Test Set Results:**

```
In [190]:
```

```
knn_clf_y_pred = knn_clf.predict(x_test)
```

## In [191]:

```
pd.DataFrame({'Actual':y_test, 'Predicted':knn_clf_y_pred})
```

#### Out[191]:

	Actual	Predicted
52	1	1
58	1	0
0	0	1
59	1	1
5	0	0
50	1	0
16	0	1
12	0	0
27	0	0
63	1	1
32	0	0
9	0	0
49	1	1

#### **Evaluate Performance of the Model:**

#### In [195]:

```
knn_clf_score = accuracy_score(y_test, knn_clf_y_pred)
knn_clf_score
```

#### Out[195]:

#### 0.6923076923076923

#### In [196]:

```
knn_clf_mat = confusion_matrix(y_test, knn_clf_y_pred)
knn_clf_mat
```

## Out[196]:

```
array([[5, 2],
       [2, 4]])
```

#### In [197]:

```
knn_clf_report = classification_report(y_test, knn_clf_y_pred)
print(knn_clf_report)
```

	precision	recall	f1-score	support
0	0.71	0.71	0.71	7
1	0.67	0.67	0.67	6
accuracy			0.69	13
macro avg	0.69	0.69	0.69	13
weighted avg	0.69	0.69	0.69	13

# **Compare Performances of all the Models**

#### In [211]:

```
data = [log_regr_score, dt_score, rf_clf_score, svm_clf_score, knn_clf_score]
categories = ['Logistic Regression', 'Decision Tree', 'Random Forest', 'SVM', 'KN
N']

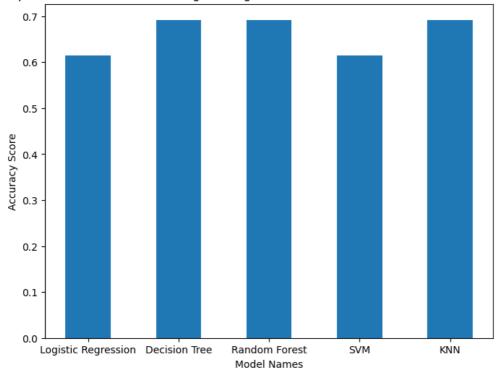
plt.figure(figsize=(8,6))

plt.bar(categories, data, width=0.50)

plt.xlabel('Model Names')
plt.ylabel('Accuracy Score')
plt.title('Compare Evaluation Metrics of Logistic Regression, Decision Tree, Random Forest, SVM, KNN')

# Show the plot
plt.show()
```





(Decision\_Tree == Random\_Forest == KNN) > (Logistic\_Regression == SVM)

#### In [ ]: