

```
#Code to upload files from storage to Google Colab
```

```
from google.colab import files  
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving mushroom_data.csv to mushroom_data.csv
```

```
# Importing the libraries for data processing, model training,  
evaluation, and plotting
```

```
import pandas as pd  
from sklearn.model_selection import train_test_split  
from sklearn.preprocessing import LabelEncoder, StandardScaler  
from sklearn.tree import DecisionTreeClassifier  
from sklearn.neighbors import KNeighborsClassifier  
from sklearn.metrics import accuracy_score, precision_score,  
recall_score, f1_score, confusion_matrix  
import matplotlib.pyplot as plt
```

```
# 1. Loading the Dataset
```

```
# Load the mushroom dataset
```

```
df = pd.read_csv("mushroom_data.csv")
```

```
# Display first rows to confirm dataset structure
```

```
print(df.head())
```

	class	cap-diameter	cap-shape	cap-surface	cap-color	does-bruise-or-bleed
0	p	15.26	x	g	o	
1	p	16.60	x	g	o	
2	p	14.07	x	g	o	
3	p	14.17	f	h	e	
4	p	14.64	x	h	o	

	gill-attachment	gill-spacing	gill-color	stem-height	...	stem-root
0	e	NaN	w	16.95	...	s
1	e	NaN	w	17.99	...	s
2	e	NaN	w	17.80	...	s
3	e	NaN	w	15.77	...	s
4	e	NaN	w	16.53	...	s

	stem-surface	stem-color	veil-type	veil-color	has-ring	ring-type	\
0	y	w	u	w	t	g	
1	y	w	u	w	t	g	
2	y	w	u	w	t	g	
3	y	w	u	w	t	p	
4	y	w	u	w	t	p	

	spore-print-color	habitat	season
0	NaN	d	w
1	NaN	d	u
2	NaN	d	w
3	NaN	d	w
4	NaN	d	w

[5 rows x 21 columns]

2. Checking any Missing Values

*# This code will check the whole dataset to
#confirm whether there are missing values or not.*

```
print("Missing values per column:")
print(df.isnull().sum())
```

Handling the missing values for DT

```
for col in df.columns:
    if df[col].isnull().sum() > 0:
        df[col].fillna(df[col].mode()[0], inplace=True)
```

Missing values per column:

class	0
cap-diameter	0
cap-shape	0
cap-surface	0
cap-color	0
does-bruise-or-bleed	0
gill-attachment	0
gill-spacing	0
gill-color	0
stem-height	0
stem-width	0
stem-root	0
stem-surface	0
stem-color	0
veil-type	0
veil-color	0
has-ring	0
ring-type	0
spore-print-color	0
habitat	0

```

season                0
dtype: int64

# 3. Outlier Handling by using the IQR method
# We will identify numeric columns in this dataset
num_cols = df.select_dtypes(include=['int64', 'float64']).columns

# Then we will loop through each numeric column and apply IQR
filtering
for col in num_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1

    lower_limit = Q1 - 1.5 * IQR
    upper_limit = Q3 + 1.5 * IQR

    # This will remove values outside acceptable range
    df = df[(df[col] >= lower_limit) & (df[col] <= upper_limit)]

print("Shape after removing outliers:", df.shape)

Shape after removing outliers: (53900, 21)

# 4. Encoding All Categorical Columns
# Machine learning models require numerical inputs,
#so Label Encoding converts text categories to numbers.
encoder = LabelEncoder()
for col in df.columns:
    df[col] = encoder.fit_transform(df[col])

# 5. Train-Test Split + Scaling
# Feature matrix (X) and target variable (y)
X = df.drop("class", axis=1)
y = df["class"]

# Standardization improves distance-based algorithms like KNN
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Splitting the dataset into 80% train and 20% test
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# 6. Decision Tree (DT) Implementation
# Creating the model where entropy is used for information gain)
dt = DecisionTreeClassifier(criterion="entropy", random_state=42)

# Training the model
dt.fit(X_train, y_train)

```

```

# Prediction on test data
dt_pred = dt.predict(X_test)

# Compute the performance metrics
dt_accuracy = accuracy_score(y_test, dt_pred)
dt_precision = precision_score(y_test, dt_pred)
dt_recall = recall_score(y_test, dt_pred)
dt_f1 = f1_score(y_test, dt_pred)

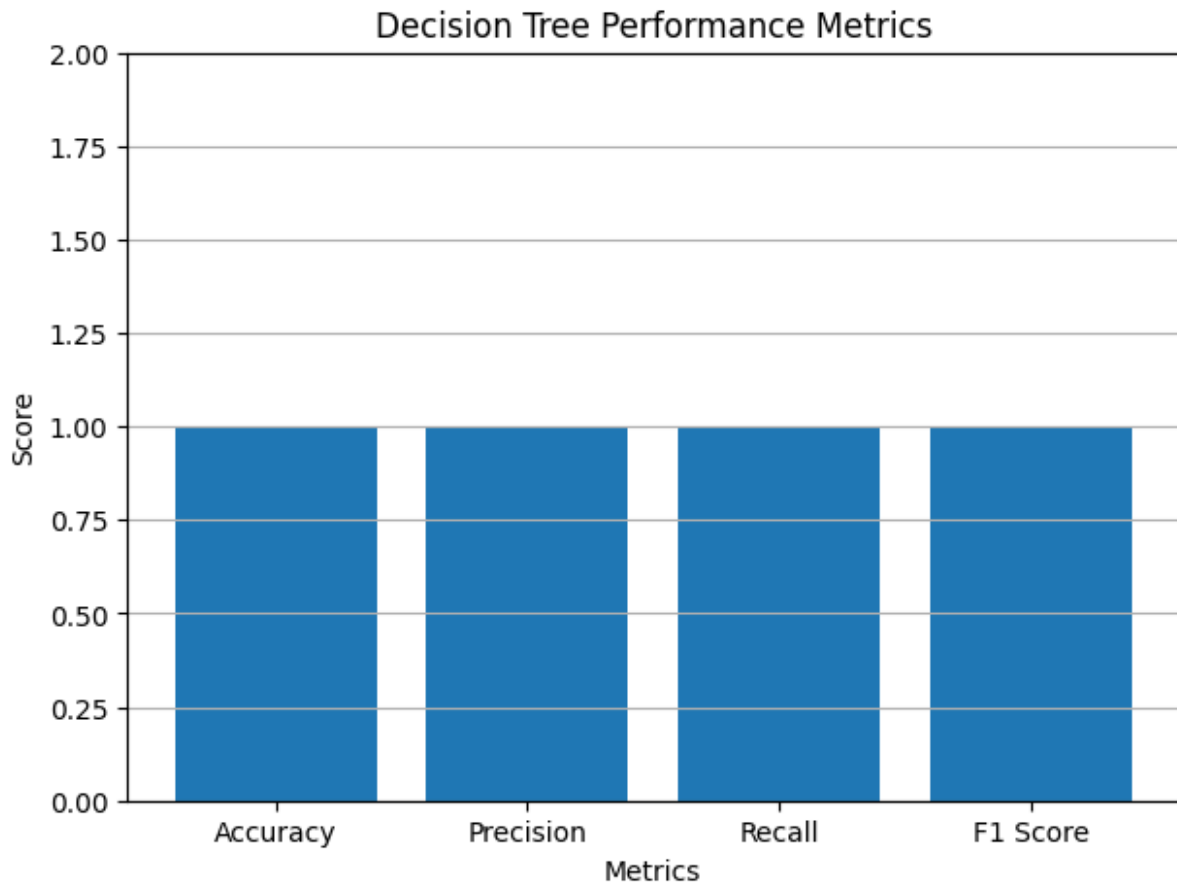
# Print all results
print("\n=== Decision Tree Results ===")
print("Accuracy :", dt_accuracy)
print("Precision:", dt_precision)
print("Recall    :", dt_recall)
print("F1 Score  :", dt_f1)
print("Confusion Matrix:\n", confusion_matrix(y_test, dt_pred))

=== Decision Tree Results ===
Accuracy : 0.9978664192949908
Precision: 0.9979767324228629
Recall    : 0.9981450252951096
F1 Score  : 0.9980608717646067
Confusion Matrix:
[[4838  12]
 [ 11 5919]]

#Bar graph for Decision Tree (DT)
dt_scores = [dt_accuracy, dt_precision, dt_recall, dt_f1]
metrics = ["Accuracy", "Precision", "Recall", "F1 Score"]

plt.figure(figsize=(7,5))
plt.bar(metrics, dt_scores)
plt.title("Decision Tree Performance Metrics")
plt.xlabel("Metrics")
plt.ylabel("Score")
plt.ylim(0, 2)
plt.grid(axis='y')
plt.show()

```



```
# 7. KNN Implementation
# k = 5 (We will use K = 5)
knn = KNeighborsClassifier(n_neighbors=5)

# Train the KNN model
knn.fit(X_train, y_train)

# Prediction on test data
knn_pred = knn.predict(X_test)

# Compute performance metrics
knn_accuracy = accuracy_score(y_test, knn_pred)
knn_precision = precision_score(y_test, knn_pred)
knn_recall = recall_score(y_test, knn_pred)
knn_f1 = f1_score(y_test, knn_pred)

# Print all results
print("\n=== KNN Results ===")
print("Accuracy :", knn_accuracy)
print("Precision:", knn_precision)
print("Recall   :", knn_recall)
```

```
print("F1 Score :", knn_f1)
print("Confusion Matrix:\n", confusion_matrix(y_test, knn_pred))
```

```
=== KNN Results ===
```

```
Accuracy : 0.9993506493506493
```

```
Precision: 0.999831223628692
```

```
Recall    : 0.9989881956155143
```

```
F1 Score : 0.9994095318431042
```

```
Confusion Matrix:
```

```
[[4849    1]
```

```
 [    6 5924]]
```

```
#Line Graph for KNN (K-Nearest Neighbor)
```

```
knn_scores = [knn_accuracy, knn_precision, knn_recall, knn_f1]
```

```
plt.figure(figsize=(7,5))
```

```
plt.plot(metrics, knn_scores, marker='o', linewidth=2)
```

```
plt.title("KNN Performance Metrics")
```

```
plt.xlabel("Metrics")
```

```
plt.ylabel("Score")
```

```
plt.ylim(0, 2)
```

```
plt.grid(True)
```

```
plt.show()
```

