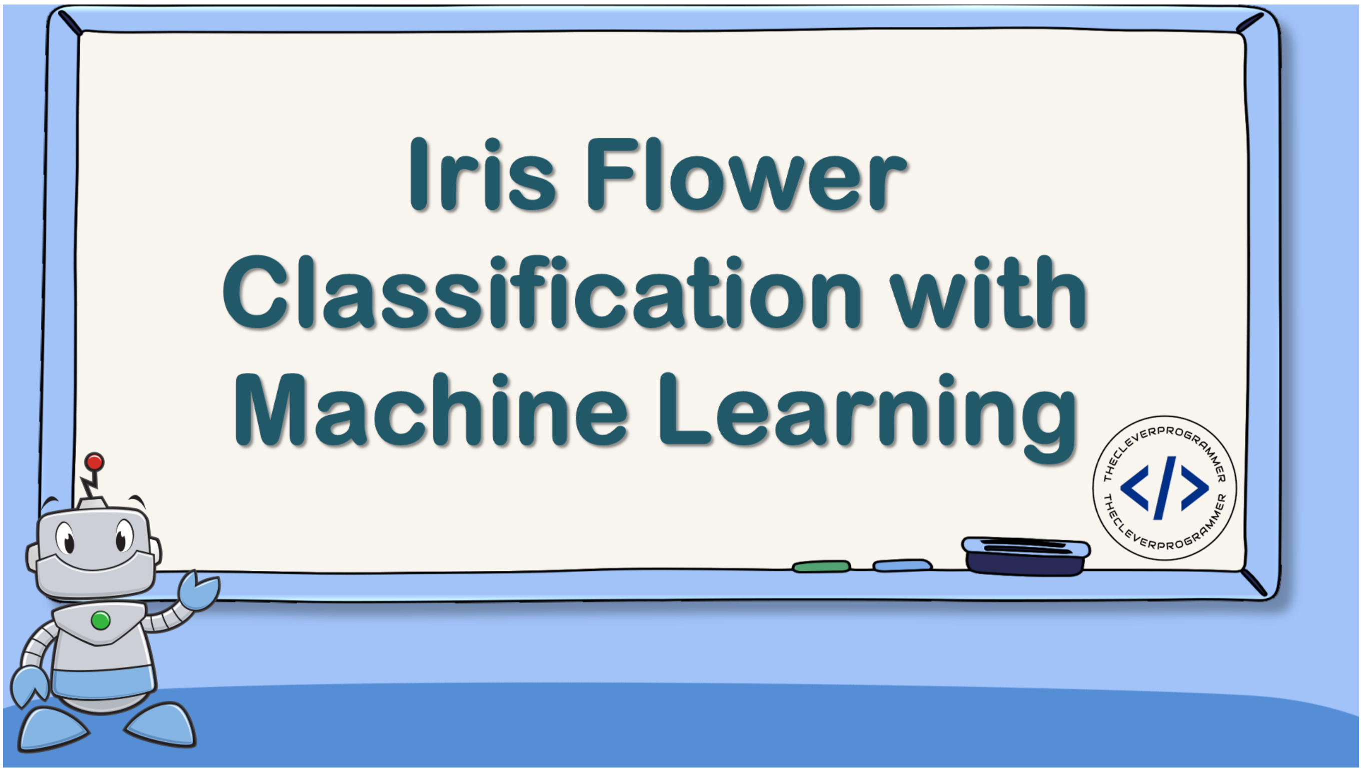


APPROACH

1. Import all the libraries
2. Load and Audit the data
3. Data preparation and Data Transformation
    1. Missing values: impute all missing values using Mean,Median and Mode
    2. Inconistent values: Replace all inconsistence with consistent values
    3. Outliers: Transform or let algorithm deal
4. Data Visualization
5. Data Analysis
    1. Uni-Variant Analysis
    2. Bi-Varient Analysis
    3. Multi-Varient Analysis
        1. Classification Problem
        2. Apply Machine Learing Models
        3. Compare and bring out the best Model

IMPORTING ALL THE LIBRARIES

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

```
df = pd.read_csv("/content/Iris.csv")
```

```
df.head(7).style.background_gradient(cmap='Reds')
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.100000	3.500000	1.400000	0.200000	Iris-setosa
1	2	4.900000	3.000000	1.400000	0.200000	Iris-setosa
2	3	4.700000	3.200000	1.300000	0.200000	Iris-setosa
3	4	4.600000	3.100000	1.500000	0.200000	Iris-setosa
4	5	5.000000	3.600000	1.400000	0.200000	Iris-setosa
5	6	5.400000	3.900000	1.700000	0.400000	Iris-setosa
6	7	4.600000	3.400000	1.400000	0.300000	Iris-setosa

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

There is only 1 column in object datatype.

```
print('No of Columns:',df.shape[1])
print('No of Rows:',df.shape[0])
```

```
No of Columns: 6
No of Rows: 150
```

```
# Univarient Analysis
```

```
df.describe().style.background_gradient(cmap='Oranges')
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

```
#Checking the missing value
```

```
df.isnull().sum()
```

```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

There is no missing value, Data is clean.

```
# Checking the skewness of the data

df.skew()
```

```
<ipython-input-20-9e0b1e29546f>:1: FutureWarning: The default value of numeric_only in DataFrame.skew is deprecated. In a
  df.skew()
Id               0.000000
SepalLengthCm    0.314911
SepalWidthCm     0.334053
PetalLengthCm   -0.274464
PetalWidthCm    -0.104997
dtype: float64
```

DATA MANIPULATION

```
# Drop the 'Id' column as it's not needed for the classification

df = df.drop(columns=["Id"])
```

```
#Displaying the modified data

df.info()
```

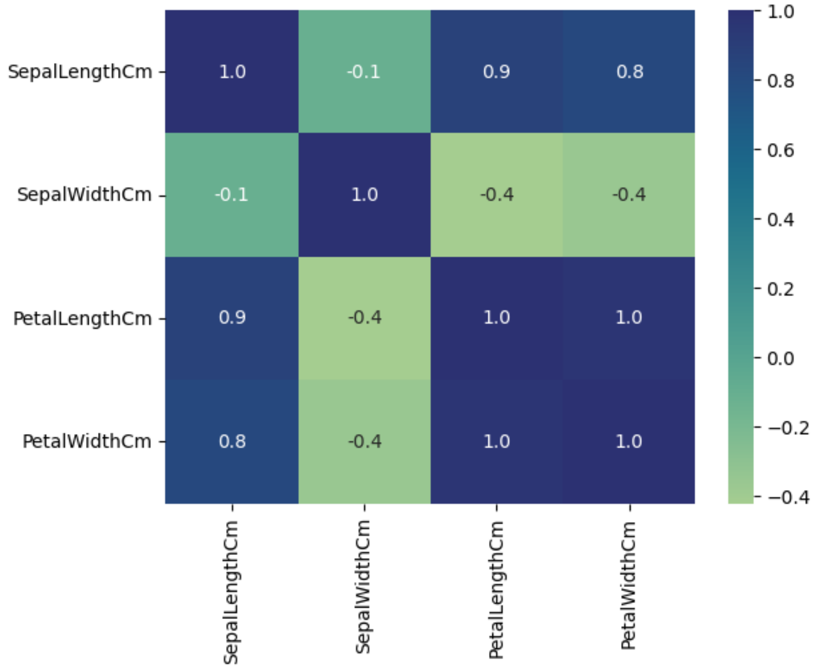
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

DATA VISUALISATION

```
# Visualising the correlation

sns.heatmap(df.corr(),annot=True,fmt='0.1f',cmap="crest")
```

```
<ipython-input-31-6be4e8974572>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a
  sns.heatmap(df.corr(),annot=True,fmt='0.1f',cmap="crest")
<Axes: >
```




```
# Count of the species
```

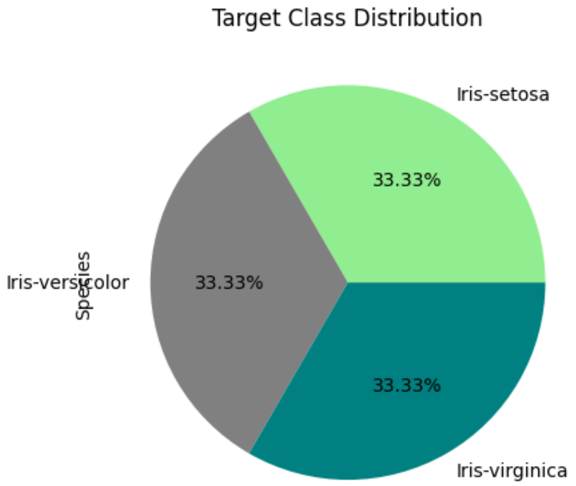
```
df['Species'].value_counts()
```

```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

```
# Distribution of Target variable

plt.title('Target Class Distribution')
df['Species'].value_counts().plot(kind='pie',autopct='%0.2f%%',colors=['lightgreen','grey','teal'])
```

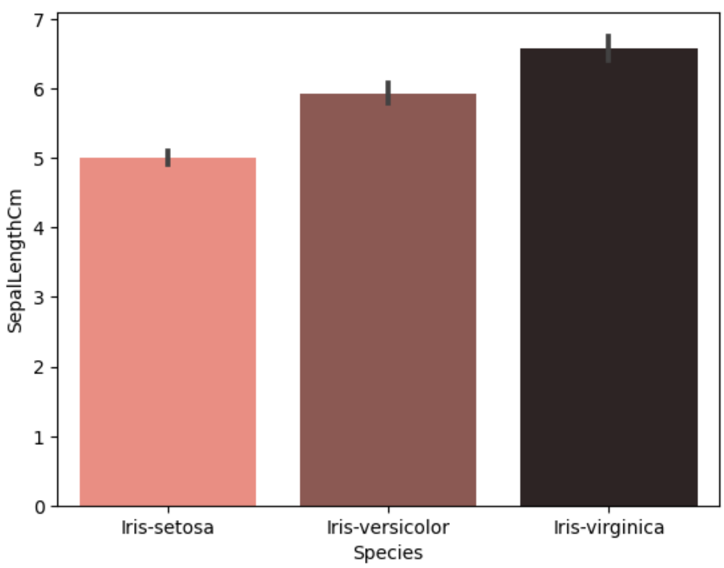
```
<Axes: title={'center': 'Target Class Distribution'}, ylabel='Species'>
```




```
# Visualize Species VS Sepal LengthCm

sns.barplot(data=df, x='Species', y='SepalLengthCm', palette='dark:salmon_r')
```

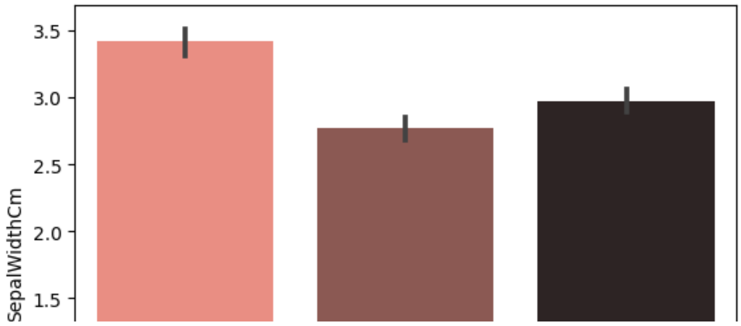
```
<Axes: xlabel='Species', ylabel='SepalLengthCm'>
```




```
# Visualize Species VS Sepal WidthCm

sns.barplot(data=df, x='Species', y='SepalWidthCm', palette='dark:salmon_r')
```

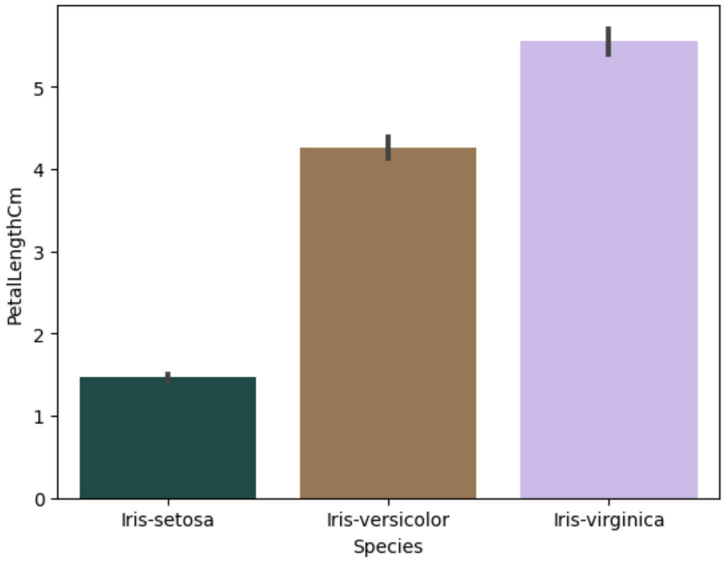
```
<Axes: xlabel='Species', ylabel='SepalWidthCm'>
```




```
# Visualize Species VS Petal LengthCm

sns.barplot(data=df, x='Species', y='PetalLengthCm', palette='cubehelix')
```

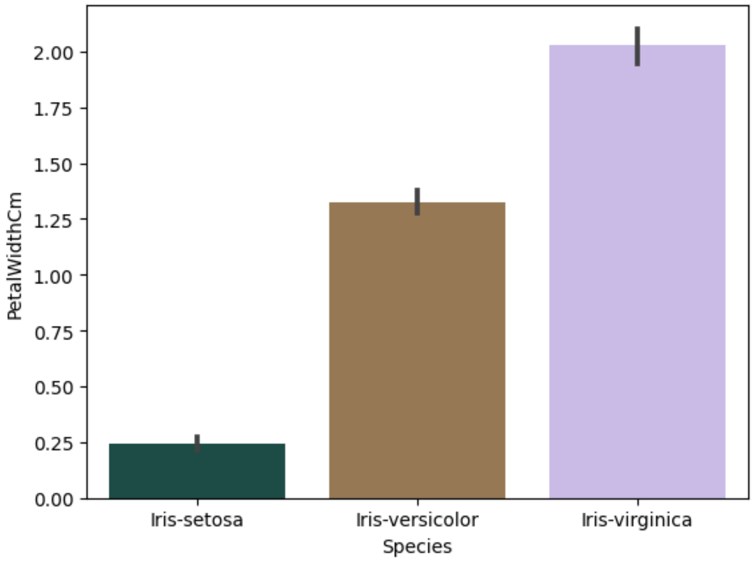
```
<Axes: xlabel='Species', ylabel='PetalLengthCm'>
```



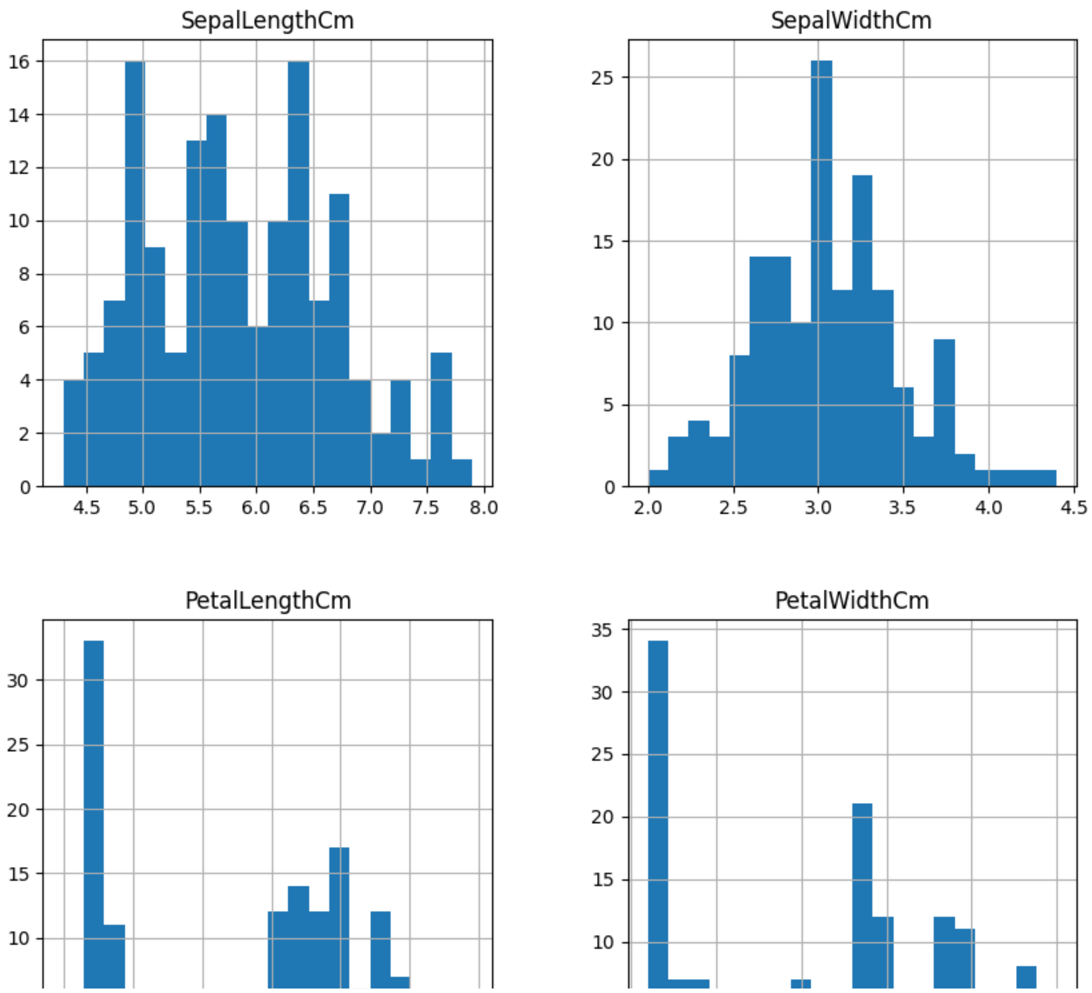

```
# Visualize Species VS Petal WidthCm

sns.barplot(data=df, x='Species', y='PetalWidthCm', palette='cubehelix')
```

```
<Axes: xlabel='Species', ylabel='PetalWidthCm'>
```




```
df.hist(bins=20, figsize=(10, 10))
plt.show()
```



SPLITTING TRAIN AND TEST DATA

```
# Feature Variable
x=df.drop(['Species'],axis=1)

#Target Variable
y=df['Species']


x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)


print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(120, 4)
(120,)
(30, 4)
(30,)
```

BUILDING MODEL

LOGISTIC REGRESSION

```
lr = LogisticRegression(max_iter=1000)

lr.fit(x_train, y_train)

lr_preds_train = lr.predict(x_train)
lr_preds_test = lr.predict(x_test)
```

```
print('Train accuracy score of the model is: ', round(accuracy_score(y_train, lr_preds_train),2))
print('Test accuracy score of the model is: ', round(accuracy_score(y_test, lr_preds_test),2))
```

```
Train accuracy score of the model is:  0.98
Test accuracy score of the model is:  1.0
```

DECISION TREE

```
dtree = DecisionTreeClassifier()

dtree.fit(x_train, y_train)

dtree_preds_train = dtree.predict(x_train)
dtree_preds_test = dtree.predict(x_test)

print('Train accuracy score of the model is: ', round(accuracy_score(y_train, dtree_preds_train),2))
print('Test accuracy score of the model is: ', round(accuracy_score(y_test, dtree_preds_test),2))
```

```
Train accuracy score of the model is:  1.0
Test accuracy score of the model is:  1.0
```

RANDOM FOREST

```
rf = RandomForestClassifier()

rf.fit(x_train, y_train)

rf_preds_train = rf.predict(x_train)
rf_preds_test = rf.predict(x_test)

print('Train accuracy score of the model is: ', round(accuracy_score(y_train, rf_preds_train),2))
print('Test accuracy score of the model is: ', round(accuracy_score(y_test, rf_preds_test),2))
```

```
Train accuracy score of the model is:  1.0
Test accuracy score of the model is:  1.0
```

KNN

```
knn=KNeighborsClassifier()

knn.fit(x_train, y_train)

knn_preds_train = knn.predict(x_train)
knn_preds_test = knn.predict(x_test)

print('Train accuracy score of the model is: ', round(accuracy_score(y_train, knn_preds_train),2))
print('Test accuracy score of the model is: ', round(accuracy_score(y_test,knn_preds_test),2))
```

```
Train accuracy score of the model is:  0.97
Test accuracy score of the model is:  1.0
```