Assignment-2:

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Problem-1

Import Libraries

In [ ]:
```
import pandas as pd  # Pandas for data manipulation
from sklearn.model_selection import train_test_split  # Train-test split for model evaluation
from sklearn.tree import DecisionTreeClassifier  # Decision tree classifier for modeling
from sklearn.metrics import accuracy_score  # Metric for evaluating model performance
from sklearn.compose import ColumnTransformer  # Used for transforming specific columns
from sklearn.preprocessing import OneHotEncoder  # One-hot encoding for categorical variables
import numpy as np  # NumPy for numerical operations
from sklearn.preprocessing import LabelEncoder  # Label encoding for categorical variables
import matplotlib.pyplot as plt  # Matplotlib for plotting
```

import Data from Dataset

In [ ]:
```
dataset = pd.read_csv('drug.csv') # Read the dataset from a CSV file named 'drug.csv' using Pandas
```

Data Preprocessing

Count Missing Values Occurs

In [ ]:
```
missing_values = dataset.isnull().sum() # Check for missing values in the dataset
print("Missing Values:\n", missing_values) # Print the count of missing values for each column
```

```
Missing Values:
 Age            0
Sex             0
BP              2
Cholesterol     2
Na_to_K         1
Drug            0
dtype: int64
```

Handling Missing Data Features

In [ ]:
```
# We Will Drop Records which have no BP and cholestrol Features
dataset.dropna(subset=['BP', 'Cholesterol'], inplace=True)

# Then We Will Fill Records has no Na_to_K Feature with Average of Na_to_K Values
dataset['Na_to_K'].fillna(dataset['Na_to_K'].mean(), inplace=True)
```

Double-Check Missing Features

In [ ]:
```
missing_values = dataset.isnull().sum() # Check for missing values in the dataset
print("Missing Values:\n", missing_values) # Print the count of missing values for each column
```

```
Missing Values:
 Age            0
Sex             0
BP              0
Cholesterol     0
```

```
Na_to_K        0
Drug           0
dtype: int64
```

Split Dataset Into Feature set and Target set

In [ ]:

```
# Extract the feature matrix (X) and target variable (Y) from the dataset
X = dataset.iloc[:, :-1].values  # Features (all columns except the last one)
Y = dataset.iloc[:, -1].values   # Target variable (last column)

# Display the feature matrix (X)
print("Feature Matrix (X):\n", X)
```

Out[ ]:

```
array([[23, 'F', 'HIGH', 'HIGH', 25.355],
       [47, 'M', 'LOW', 'HIGH', 13.093],
       [47, 'M', 'LOW', 'HIGH', 10.114],
       [28, 'F', 'NORMAL', 'HIGH', 16.08220512820512],
       [61, 'F', 'LOW', 'HIGH', 18.043],
       [22, 'F', 'NORMAL', 'HIGH', 8.607],
       [49, 'F', 'NORMAL', 'HIGH', 16.275],
       [41, 'M', 'LOW', 'HIGH', 11.037],
       [60, 'M', 'NORMAL', 'HIGH', 15.171],
       [47, 'F', 'LOW', 'HIGH', 11.767],
       [34, 'F', 'HIGH', 'NORMAL', 19.199],
       [43, 'M', 'LOW', 'HIGH', 15.376],
       [74, 'F', 'LOW', 'HIGH', 20.942],
       [50, 'F', 'NORMAL', 'HIGH', 12.703],
       [16, 'F', 'HIGH', 'NORMAL', 15.516],
       [69, 'M', 'LOW', 'NORMAL', 11.455],
       [43, 'M', 'HIGH', 'HIGH', 13.972],
       [23, 'M', 'LOW', 'HIGH', 7.298],
       [32, 'F', 'HIGH', 'NORMAL', 25.974],
       [57, 'M', 'LOW', 'NORMAL', 19.128],
       [63, 'M', 'NORMAL', 'HIGH', 25.917],
       [47, 'M', 'LOW', 'NORMAL', 30.568],
       [48, 'F', 'LOW', 'HIGH', 15.036],
       [33, 'F', 'LOW', 'HIGH', 33.486],
       [28, 'F', 'HIGH', 'NORMAL', 18.809],
       [31, 'M', 'HIGH', 'HIGH', 30.366],
       [49, 'F', 'NORMAL', 'NORMAL', 9.381],
       [39, 'F', 'LOW', 'NORMAL', 22.697],
       [45, 'M', 'LOW', 'HIGH', 17.951],
       [18, 'F', 'NORMAL', 'NORMAL', 8.75],
```

```
[74, 'M', 'HIGH', 'HIGH', 9.567],
[49, 'M', 'LOW', 'NORMAL', 11.014],
[65, 'F', 'HIGH', 'NORMAL', 31.876],
[53, 'M', 'NORMAL', 'HIGH', 14.133],
[46, 'M', 'NORMAL', 'NORMAL', 7.285],
[32, 'M', 'HIGH', 'NORMAL', 9.445],
[39, 'M', 'LOW', 'NORMAL', 13.938],
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[15, 'M', 'NORMAL', 'HIGH', 9.084],
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[50, 'M', 'NORMAL', 'NORMAL', 15.79],
[23, 'M', 'NORMAL', 'HIGH', 12.26],
[50, 'F', 'NORMAL', 'NORMAL', 12.295],
[66, 'F', 'NORMAL', 'NORMAL', 8.107],
[37, 'F', 'HIGH', 'HIGH', 13.091],
[68, 'M', 'LOW', 'HIGH', 10.291],
[23, 'M', 'NORMAL', 'HIGH', 31.686],
[28, 'F', 'LOW', 'HIGH', 19.796],
[58, 'F', 'HIGH', 'HIGH', 19.416],
[67, 'M', 'NORMAL', 'NORMAL', 10.898],
[62, 'M', 'LOW', 'NORMAL', 27.183],
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[68, 'F', 'HIGH', 'NORMAL', 10.189],
[26, 'F', 'LOW', 'HIGH', 14.16],
[65, 'M', 'HIGH', 'NORMAL', 11.34],
[40, 'M', 'HIGH', 'HIGH', 27.826],
[60, 'M', 'NORMAL', 'NORMAL', 10.091],
[34, 'M', 'HIGH', 'HIGH', 18.703],
[38, 'F', 'LOW', 'NORMAL', 29.875],
[24, 'M', 'HIGH', 'NORMAL', 9.475],
[67, 'M', 'LOW', 'NORMAL', 20.693],
[45, 'M', 'LOW', 'NORMAL', 8.37],
[60, 'F', 'HIGH', 'HIGH', 13.303],
[68, 'F', 'NORMAL', 'NORMAL', 27.05],
[29, 'M', 'HIGH', 'HIGH', 12.856],
[17, 'M', 'NORMAL', 'NORMAL', 10.832],
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[18, 'F', 'HIGH', 'NORMAL', 24.276],
[70, 'M', 'HIGH', 'HIGH', 13.967],
[28, 'F', 'NORMAL', 'HIGH', 19.675],
[24, 'F', 'NORMAL', 'HIGH', 10.605],
[41, 'F', 'NORMAL', 'NORMAL', 22.905],
[31, 'M', 'HIGH', 'NORMAL', 17.069],
```

```
[26, 'M', 'LOW', 'NORMAL', 20.909],
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[64, 'M', 'NORMAL', 'HIGH', 7.761],
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[28, 'F', 'LOW', 'HIGH', 13.127],
[56, 'M', 'NORMAL', 'HIGH', 8.966],
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[37, 'M', 'LOW', 'NORMAL', 8.968],
[22, 'M', 'NORMAL', 'HIGH', 11.953],
[42, 'M', 'LOW', 'HIGH', 20.013],
[72, 'M', 'HIGH', 'NORMAL', 9.677],
[23, 'M', 'NORMAL', 'HIGH', 16.85],
[50, 'M', 'HIGH', 'HIGH', 7.49],
[47, 'F', 'NORMAL', 'NORMAL', 6.683],
[35, 'M', 'LOW', 'NORMAL', 9.17],
[65, 'F', 'LOW', 'NORMAL', 13.769],
[20, 'F', 'NORMAL', 'NORMAL', 9.281],
[51, 'M', 'HIGH', 'HIGH', 18.295],
[67, 'M', 'NORMAL', 'NORMAL', 9.514],
[40, 'F', 'NORMAL', 'HIGH', 10.103],
[32, 'F', 'HIGH', 'NORMAL', 10.292],
```

```
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[28, 'M', 'NORMAL', 'HIGH', 27.064],
[15, 'M', 'HIGH', 'NORMAL', 17.206],
[36, 'F', 'NORMAL', 'HIGH', 16.753],
[53, 'F', 'HIGH', 'NORMAL', 12.495],
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[47, 'M', 'LOW', 'NORMAL', 33.542],
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[70, 'F', 'NORMAL', 'HIGH', 20.489],
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[24, 'M', 'NORMAL', 'HIGH', 25.786],
[42, 'F', 'HIGH', 'HIGH', 21.036],
[74, 'M', 'LOW', 'NORMAL', 11.939],
[55, 'F', 'HIGH', 'HIGH', 10.977],
[35, 'F', 'HIGH', 'HIGH', 12.894],
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[69, 'F', 'NORMAL', 'HIGH', 10.065],
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[61, 'M', 'NORMAL', 'HIGH', 9.443],
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[26, 'F', 'HIGH', 'NORMAL', 12.307],
[61, 'F', 'LOW', 'NORMAL', 7.34],
[22, 'M', 'LOW', 'HIGH', 8.151],
[49, 'M', 'HIGH', 'NORMAL', 8.7],
[68, 'M', 'HIGH', 'HIGH', 11.009],
[55, 'M', 'NORMAL', 'NORMAL', 7.261],
[72, 'F', 'LOW', 'NORMAL', 14.642],
[37, 'M', 'LOW', 'NORMAL', 16.724],
[49, 'M', 'LOW', 'HIGH', 10.537],
[31, 'M', 'HIGH', 'NORMAL', 11.227],
[53, 'M', 'LOW', 'HIGH', 22.963],
[59, 'F', 'LOW', 'HIGH', 10.444],
[34, 'F', 'LOW', 'NORMAL', 12.923],
[30, 'F', 'NORMAL', 'HIGH', 10.443],
[57, 'F', 'HIGH', 'NORMAL', 9.945],
[43, 'M', 'NORMAL', 'NORMAL', 12.859],
[21, 'F', 'HIGH', 'NORMAL', 28.632],
```

```
 [16, 'M', 'HIGH', 'NORMAL', 19.007],
 [38, 'M', 'LOW', 'HIGH', 18.295],
 [58, 'F', 'LOW', 'HIGH', 26.645],
 [57, 'F', 'NORMAL', 'HIGH', 14.216],
 [51, 'F', 'LOW', 'NORMAL', 23.003],
 [20, 'F', 'HIGH', 'HIGH', 11.262],
 [28, 'F', 'NORMAL', 'HIGH', 12.879],
 [45, 'M', 'LOW', 'NORMAL', 10.017],
 [41, 'F', 'LOW', 'NORMAL', 18.739],
 [42, 'M', 'HIGH', 'NORMAL', 12.766],
 [73, 'F', 'HIGH', 'HIGH', 18.348],
 [48, 'M', 'HIGH', 'NORMAL', 10.446],
 [25, 'M', 'NORMAL', 'HIGH', 19.011],
 [39, 'M', 'NORMAL', 'HIGH', 15.969],
 [67, 'F', 'NORMAL', 'HIGH', 15.891],
 [22, 'F', 'HIGH', 'NORMAL', 22.818],
 [59, 'F', 'NORMAL', 'HIGH', 13.884],
 [20, 'F', 'LOW', 'NORMAL', 11.686],
 [36, 'F', 'HIGH', 'NORMAL', 15.49],
 [18, 'F', 'HIGH', 'HIGH', 37.188],
 [57, 'F', 'NORMAL', 'NORMAL', 25.893],
 [70, 'M', 'HIGH', 'HIGH', 9.849],
 [47, 'M', 'HIGH', 'HIGH', 10.403],
 [65, 'M', 'HIGH', 'NORMAL', 34.997],
 [64, 'M', 'HIGH', 'NORMAL', 20.932],
 [58, 'M', 'HIGH', 'HIGH', 18.991],
 [23, 'M', 'HIGH', 'HIGH', 8.011],
 [72, 'M', 'LOW', 'HIGH', 16.31],
 [72, 'M', 'LOW', 'HIGH', 6.769],
 [46, 'F', 'HIGH', 'HIGH', 34.686],
 [56, 'F', 'LOW', 'HIGH', 11.567],
 [16, 'M', 'LOW', 'HIGH', 12.006],
 [52, 'M', 'NORMAL', 'HIGH', 9.894],
 [40, 'F', 'LOW', 'NORMAL', 11.349]], dtype=object)
```

Encode Categorical Data in Features (One-Hot Encoding)

In [ ]:

```
# Define a ColumnTransformer for applying transformations to specific columns
# - 'encoder': OneHotEncoder is used for one-hot encoding
# - [1, 2, 3]: Columns 1, 2, and 3 are one-hot encoded, specified by their indices
# - 'remainder': 'passthrough' indicates that the remaining columns are passed through without any transformations
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1, 2, 3])], remainder='passthrough')
```

```
# Apply the transformations defined by ColumnTransformer to the feature matrix (X)
X = np.array(ct.fit_transform(X))
```

Out[ ]:
```
array([[1.0, 0.0, 0.0, ..., 0.0, 23, 25.355],
       [0.0, 1.0, 1.0, ..., 0.0, 47, 13.093],
       [0.0, 1.0, 1.0, ..., 0.0, 47, 10.114],
       ...,
       [0.0, 1.0, 1.0, ..., 0.0, 16, 12.006],
       [0.0, 1.0, 1.0, ..., 0.0, 52, 9.894],
       [1.0, 0.0, 1.0, ..., 1.0, 40, 11.349]], dtype=object)
```

Encode Target Data (Label Encoding)

In [ ]:
```
le = LabelEncoder() # Use LabelEncoder to encode the target variable (Y)


Y = np.array(le.fit_transform(Y)) # Transform and overwrite the original target variable (Y) with encoded values

# Display the Target matrix (Y)
Y
```

Out[ ]:
```
array([4, 2, 2, 3, 4, 3, 4, 2, 4, 2, 4, 4, 4, 3, 4, 3, 0, 2, 4, 4, 4, 4,
       4, 4, 4, 4, 3, 4, 4, 3, 1, 3, 4, 3, 3, 0, 3, 3, 3, 4, 1, 4, 3, 3,
       3, 0, 2, 4, 4, 4, 3, 4, 4, 1, 2, 1, 4, 3, 4, 4, 0, 4, 3, 1, 4, 0,
       3, 4, 4, 1, 4, 3, 4, 4, 4, 0, 4, 0, 3, 1, 3, 2, 0, 2, 1, 3, 4, 4,
       4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 4, 0, 0, 2, 3, 4, 3, 3, 4, 1, 4, 0,
       3, 3, 3, 3, 4, 3, 3, 0, 4, 4, 4, 4, 1, 4, 4, 3, 4, 3, 4, 4, 3, 4,
       4, 3, 1, 0, 1, 3, 0, 4, 1, 4, 0, 3, 3, 0, 3, 2, 0, 1, 3, 3, 4, 2,
       0, 4, 2, 3, 3, 1, 3, 4, 4, 4, 4, 3, 4, 0, 3, 3, 4, 0, 4, 0, 4, 4,
       4, 4, 3, 3, 4, 4, 4, 1, 0, 4, 4, 4, 0, 4, 2, 4, 2, 2, 3, 3])
```

1st Experiment

In [ ]:
```
# Define a list of random states which have high variance to ensure Randomization Facotr
random_states = [1736,0, 123, 789, 987, 654]

# Intialize Indicator Variables with -ve values to detect the maximum Accuracy, best experiment, Tree size of the best experiment
max_accuracy = -100
best_experiment = 0
best_treesize = -1
```

```
# Loop Over Random States
for i in range(5):

    # Split the dataset into training and testing sets using a random state
    X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=random_states[i])

    # Create and train a Decision Tree Classifier model
    model = DecisionTreeClassifier()
    model.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = model.predict(X_test)

    # Calculate and print the accuracy of the current experiment
    accuracy = accuracy_score(y_test, y_pred)

    # Update variables if the current experiment has higher accuracy
    if accuracy >= max_accuracy:
        max_accuracy = accuracy
        best_experiment = i+1
        best_treesize = model.tree_.node_count

    # Print Each Experiment with It's Accuracy and Tree Size
    print(f"Experiment {i+1} with Tree Size: {model.tree_.node_count} and Accuracy: {accuracy}")

print("\n")
# Print Details of Experiment hasing best accuracy
print(f"Best Experiment: {best_experiment}\nAccuracy: {max_accuracy}\nTree Size: {best_treesize}")
```

```
Experiment 1 with Tree Size: 15 and Accuracy: 1.0
Experiment 2 with Tree Size: 15 and Accuracy: 0.9661016949152542
Experiment 3 with Tree Size: 15 and Accuracy: 0.8983050847457628
Experiment 4 with Tree Size: 11 and Accuracy: 0.9661016949152542
Experiment 5 with Tree Size: 15 and Accuracy: 0.9661016949152542


Best Experiment: 1
Accuracy: 1.0
Tree Size: 15
```

In [ ]:

```
def run_decision_tree_experiment(X, Y, random_states, trn_size):

    accuracies = []
    tree_sizes = []
```

```
    for i in range(len(random_states)):
        # Split the dataset into training and testing sets using a random state
        X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 1-trn_size, random_state=random_states[i])

        # Create and train a Decision Tree Classifier model
        model = DecisionTreeClassifier()
        model.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = model.predict(X_test)

        # Calculate accuracy of the current experiment
        accuracy = accuracy_score(y_test, y_pred)
        accuracies.append(accuracy)
        tree_sizes.append(model.tree_.node_count)

    # Return details of the best experiment as a tuple
    return np.mean(accuracies), np.max(accuracies) ,np.min(accuracies),np.mean(tree_sizes),np.max(tree_sizes),np.min(tree_sizes)
```

2nd Experiment

In [ ]:

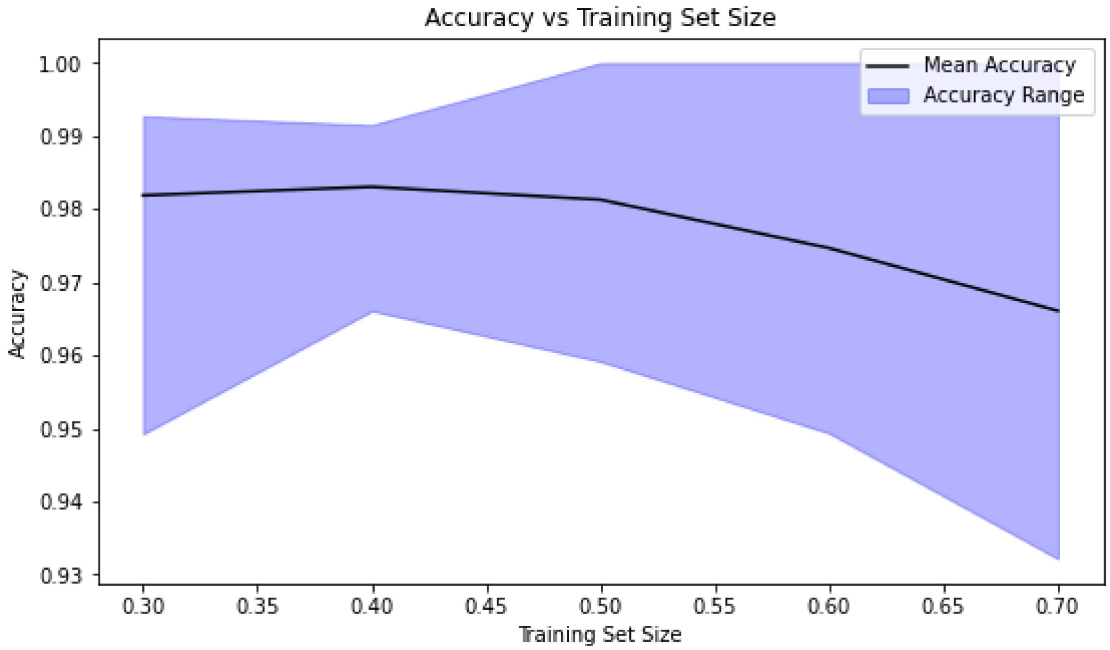
```
train_size = 0.3

# Initialize lists to store statistics
mean_accuracies = []
max_accuracies = []
min_accuracies = []
mean_tree_sizes = []
max_tree_sizes = []
min_tree_sizes = []

# Loop through different training set sizes using while loop
while train_size <= 0.7:

    a_mean, a_max, a_min, t_mean, t_max, t_min = run_decision_tree_experiment(X,Y,random_states,train_size)

    # Calculate mean, max, and min statistics for the current training set size
    mean_accuracies.append(a_mean) # Append Mean of each experiment with specific train_size
    max_accuracies.append(a_max)
    min_accuracies.append(a_min)
    mean_tree_sizes.append(t_mean)
```

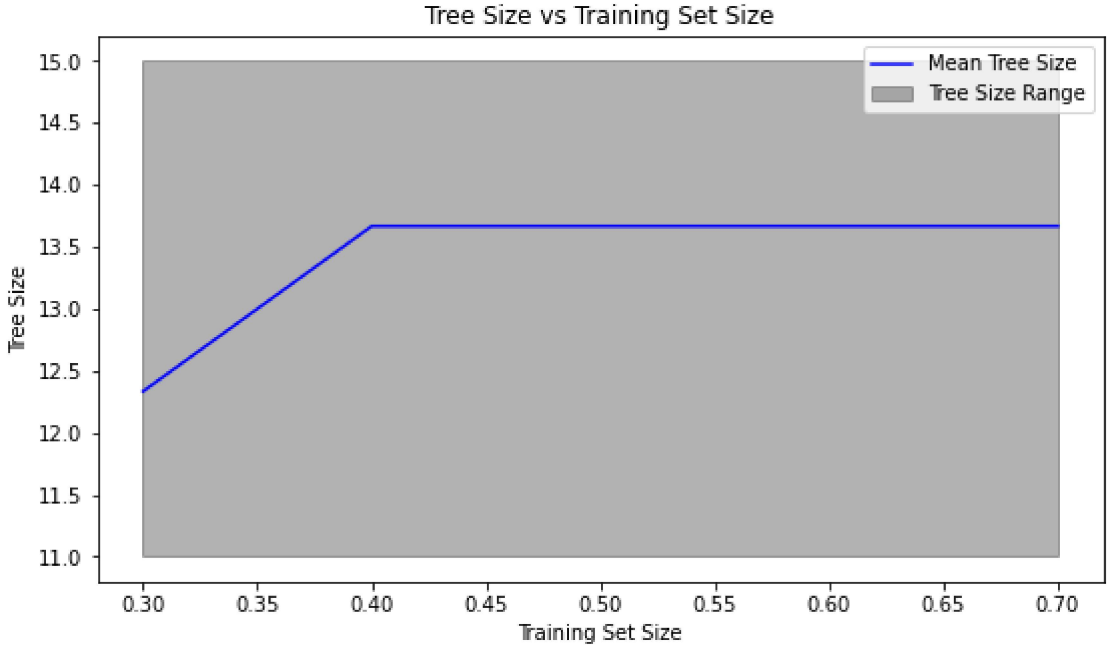
```
    max_tree_sizes.append(t_max)
    min_tree_sizes.append(t_min)

    # Increment training_size
    train_size += 0.1

# Display the statistics
report = pd.DataFrame({
    'Training Set Size': [0.3, 0.4, 0.5, 0.6, 0.7],
    'Mean Accuracy': mean_accuracies,
    'Max Accuracy': max_accuracies,
    'Min Accuracy': min_accuracies,
    'Mean Tree Size': mean_tree_sizes,
    'Max Tree Size': max_tree_sizes,
    'Min Tree Size': min_tree_sizes
})

print(report)

# Define the size of the first plot (accuracy plot) to be 9 units in width and 5 units in height
plt.figure(figsize=(9, 5))

# Create a line plot for mean accuracy with black color and add a legend label
plt.plot([0.3, 0.4, 0.5, 0.6, 0.7], mean_accuracies, label='Mean Accuracy', color='black')

# Fill the area between the minimum and maximum accuracy curves with blue color and transparency, and add a legend label
plt.fill_between([0.3, 0.4, 0.5, 0.6, 0.7], min_accuracies, max_accuracies, alpha=0.3, color='blue', label='Accuracy Range')

# Set the title of the accuracy plot
plt.title('Accuracy vs Training Set Size')

# Label the x-axis as 'Training Set Size'
plt.xlabel('Training Set Size')

# Label the y-axis as 'Accuracy'
plt.ylabel('Accuracy')

# Display the legend in the plot
plt.legend()

# Show the accuracy plot
plt.show()

# Define the size of the second plot (tree size plot) to be 9 units in width and 5 units in height
```

```
plt.figure(figsize=(9, 5))

# Create a line plot for mean tree size with blue color and add a legend label
plt.plot([0.3, 0.4, 0.5, 0.6, 0.7], mean_tree_sizes, label='Mean Tree Size', color='blue')

# Fill the area between the minimum and maximum tree size curves with black color and transparency, and add a legend label
plt.fill_between([0.3, 0.4, 0.5, 0.6, 0.7], min_tree_sizes, max_tree_sizes, alpha=0.3, color='black', label='Tree Size Range')

# Set the title of the tree size plot
plt.title('Tree Size vs Training Set Size')

# Label the x-axis as 'Training Set Size'
plt.xlabel('Training Set Size')

# Label the y-axis as 'Tree Size'
plt.ylabel('Tree Size')

# Display the legend in the plot
plt.legend()

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

	Training Set Size	Mean Accuracy	Max Accuracy	Min Accuracy
0	0.3	0.981884	0.992754	0.949275
1	0.4	0.983051	0.991525	0.966102
2	0.5	0.981293	1.000000	0.959184
3	0.6	0.974684	1.000000	0.949367
4	0.7	0.966102	1.000000	0.932203

	Mean Tree Size	Max Tree Size	Min Tree Size
0	12.333333	15	11
1	13.666667	15	11
2	13.666667	15	11
3	13.666667	15	11
4	13.666667	15	11


Accuracy vs Training Set Size
Mean Accuracy
Accuracy Range
Accuracy
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
Training Set Size


Tree Size vs Training Set Size
Mean Tree Size
Tree Size Range
Tree Size
15.0
14.5
14.0
13.5
13.0
12.5
12.0
11.5
11.0
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
Training Set Size

Problem-2

KNN Class

In [ ]:

```
class k_nearest_neighbors():

    def __init__(self) -> None:
        self.train=list()

    def __euclidean_distance(self,row_1, row_2):
        distance = 0.0
        for i in range(len(row_1)-1):
            distance += (row_1[i] - row_2[i])**2
        return distance**(1/2)


    def __neighbors(self,test_row, k):
        distances = list()
        for train_row in self.train:
                dist = self.__euclidean_distance(test_row, train_row)
                distances.append((train_row, dist))
                distances.sort(key=lambda tup: tup[1])
        neighbors_with_distances=distances[:k]
        return neighbors_with_distances   #Tuples of k neighbors and their distances


    def predict(self, test_row, k):
        nwd = self.__neighbors(test_row, k) #Neighbors with distance
        total_weighted_votes = {}
        total_weights = 0

        for neighbor, dist in nwd:
            weight = 1 / (dist + 0.000001) #to not divide by 0
            total_weights += weight

            class_label = neighbor[-1]

            if class_label in total_weighted_votes:
                total_weighted_votes[class_label] += weight
            else:
```

```
                total_weighted_votes[class_label] = weight

        normalized_votes = {label: weight / total_weights for label, weight in total_weighted_votes.items()} #Weight of every clas
        return max(normalized_votes, key=normalized_votes.get) #Max voted class

    def eval_metric(self,actual, predicted):
        correct = 0

        for i in range(len(actual)):
            if actual[i] == predicted[i]:
                correct += 1
        return correct

    def fit(self,train, test, num_neighbors):
        self.train=train
        predicted_values = list()
        for row in test:
            output = self.predict(row, num_neighbors)
            predicted_values.append(output)
        actual_values = [row[-1] for row in test]
        corr=self.eval_metric(actual_values,predicted_values)
        print("Model fit successfully using:- \nK: {}\nCorrect predicitons: {}\nTest set instances: {}\nAccuracy: {}%".format(num_
```

Preprocessing Class

In [ ]:

```
class preprocessing():

    def train_test_split(dataset,ratio):

        ratio_idx=round(1-ratio*len(dataset))
        train = dataset[:ratio_idx]
        test = dataset[ratio_idx:]
        return train, test

    def normalize(dataset):

        features = [list(map(float, row[:-1])) for row in dataset]
        labels = [row[-1] for row in dataset]

        features_transposed = list(map(list, zip(*features)))
```

```
        # Normalization min max
        normalized_features = []
        for feature_values in features_transposed:
            min_value = min(feature_values)
            max_value = max(feature_values)
            normalized_feature = [(float(value) - min_value) / (max_value - min_value) for value in feature_values]
            normalized_features.append(normalized_feature)

        normalized_features = list(map(list, zip(*normalized_features)))

        normalized_dataset = [normalized_feature + [label] for normalized_feature, label in zip(normalized_features, labels)]

        return normalized_dataset
```

Pandas Class

In [ ]:

```
class pd:

    def read_csv(filename,header=True):
        with open(filename, 'r') as f:
            if header:
                next(f)
            results = []
            for line in f:
                line= line.strip()
                words = line.split(',')
                results.append(words)

        return results
```

Load The Dataset

In [ ]:

```
dataset=pd.read_csv('diabetes.csv')
```

Normalize each feature column separately for training and test objects using Log Transformation or Min-Max Scaling.

In [ ]:
```
dataset=preprocessing.normalize(dataset)
```

Split Dataset into training dataset and test dataset

In [ ]:
```
train,test=preprocessing.train_test_split(dataset,0.3)
```

Train Dataset into KNN Classifier

In [ ]:
```
knn=k_nearest_neighbors()
knn.fit(train,test,5)
```

```
Model fit successfully using:-
K: 5
Correct predicitons: 173
Test set instances: 229
Accuracy: 75.55%
```

Evaluate With Different values for K

In [ ]:
```
for k in [3,6,9,12,14]:
    knn.fit(train,test,k)
    print('—' * 20)
```

```
Model fit successfully using:-
K: 3
Correct predicitons: 175
Test set instances: 229
Accuracy: 76.42%
————————————————————
Model fit successfully using:-
K: 6
Correct predicitons: 176
Test set instances: 229
Accuracy: 76.86%
————————————————————
Model fit successfully using:-
```

```
K: 9
Correct predicitons: 171
Test set instances: 229
Accuracy: 74.67%
--------------------
Model fit successfully using:-
K: 12
Correct predicitons: 177
Test set instances: 229
Accuracy: 77.29%
--------------------
Model fit successfully using:-
K: 14
Correct predicitons: 178
Test set instances: 229
Accuracy: 77.73%
--------------------
```