```
from google.colab import drive
drive.mount('/content/drive')
```

```
    Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

```
#importing required modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
#Importing warnings
import warnings
warnings.filterwarnings('ignore')
```

```
#reading csv file
data = pd.read_csv('/content/drive/MyDrive/new_election_dataset (1).csv')
data.head()
```

	TimeElapsed	time	territoryName	totalMandates	availableMandates	numParis
0	0	8	0	0	16	
1	0	8	0	0	16	
2	0	8	0	0	16	
3	0	8	0	0	16	
4	0	8	0	0	16	

5 rows × 29 columns

```
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
```

```
# Preparing Data set
# dropping Final Mandate variable from X
#assign the value of y for training
x = data.drop(columns=['FinalMandates'])
y = data[["FinalMandates"]]
y = y.values.reshape(-1, 1)  # Reshape to make it a 2D array
```

```
#Standardizing value of x by using standardscalar to make the data normally distr
sc = StandardScaler()
a = sc.fit_transform(x)
df_new_x = pd.DataFrame(a,columns=x.columns)
df_new_x.head()
```

	TimeElapsed	time	territoryName	totalMandates	availableMandates	numPa
0	-1.752045	-1.206238	-1.741356	-0.767282	0.979379	-(
1	-1.752045	-1.206238	-1.741356	-0.767282	0.979379	-(
2	-1.752045	-1.206238	-1.741356	-0.767282	0.979379	-(
3	-1.752045	-1.206238	-1.741356	-0.767282	0.979379	-(
4	-1.752045	-1.206238	-1.741356	-0.767282	0.979379	-(

5 rows × 28 columns

```
#Splitting the data into training and testing data
x_train,x_test,y_train,y_test=train_test_split(df_new_x,y,test_size=0.20,random_s
```

Without Hyper parameter tuning

```
model= DecisionTreeRegressor(random_state=42)
model.fit(x_train,y_train)
score=model.score(x_train,y_train)
predm=model.predict(x_test)
MSE_before_tuning = mean_absolute_error(y_test,predm)
print('Score of',model,'is:',score)
print('MAE:',mean_absolute_error(y_test,predm))
print('MSE:',mean_squared_error(y_test,predm))
print('RMSE:',np.sqrt(mean_squared_error(y_test,predm)))
print('R2 score:',r2_score(y_test,predm))
print('*'*100)
print('\n')
```

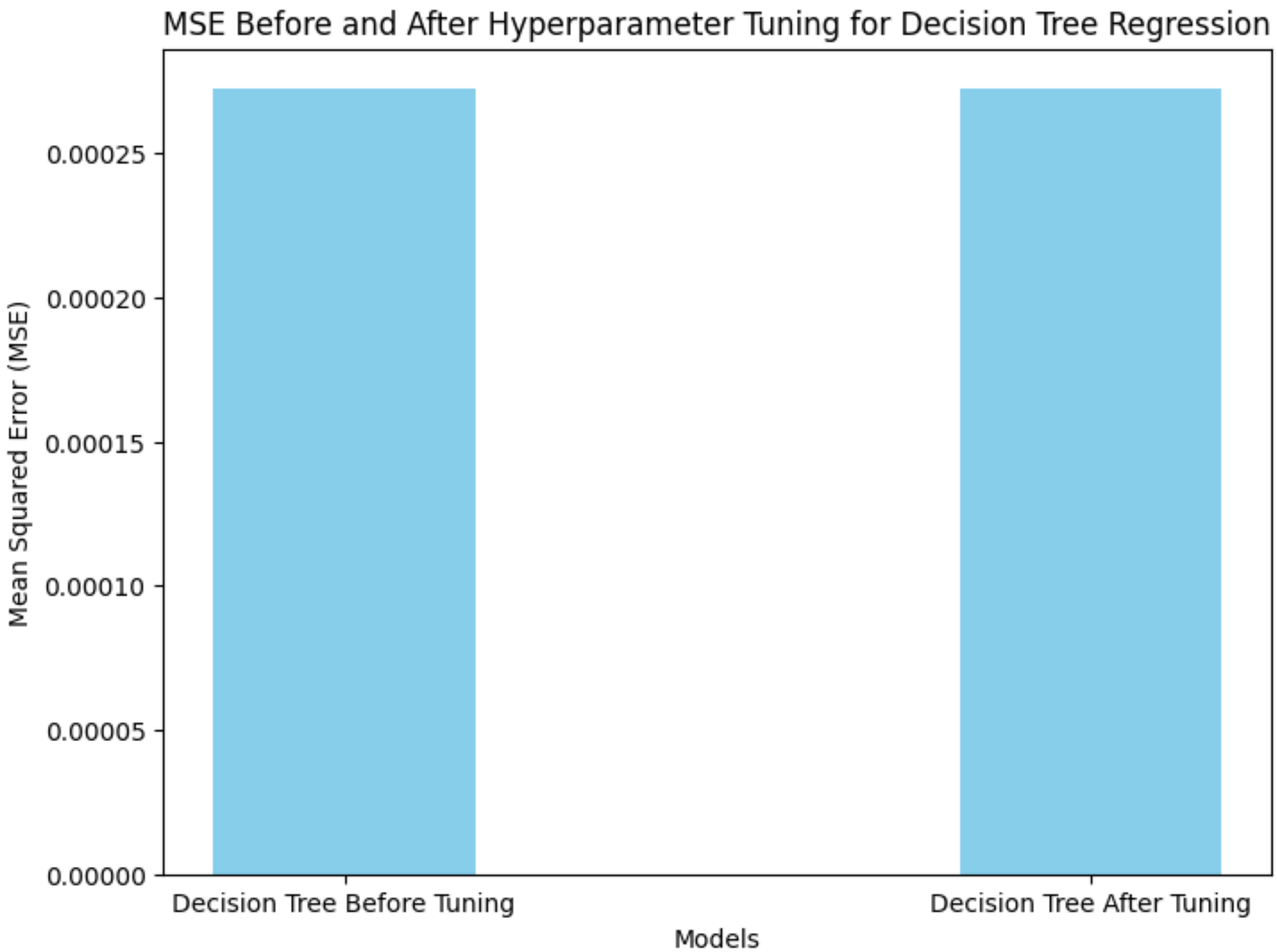
```
Score of DecisionTreeRegressor(random_state=42) is: 1.0
MAE: 0.0002727024815925825
MSE: 0.0002727024815925825
RMSE: 0.016513705870960113
R2 score: 0.9998700090217355
*****************************************************************************
```

With Hyper Parameter Tuning

```
model1 = DecisionTreeRegressor(random_state=42)
# Using GridSearchCV for HyperParameter Tuning
grid_search = GridSearchCV(estimator=model1, param_grid={'max_depth': [None, 10, 20
grid_search.fit(x_train, y_train)

# Retreiving the best model with optimal hyperparameters
best_model = grid_search.best_estimator_

# Making Predtions with the best model
predm1 = best_model.predict(x_test)

mse_after_tuning = mean_squared_error(y_test, predm1)

# printing Results and Evaluation Metrics
print(f'Best parameters for {model1}: {grid_search.best_params_}')
print('MAE:', mean_absolute_error(y_test, predm))
print('MSE:', mean_squared_error(y_test, predm))
print('RMSE:', np.sqrt(mean_squared_error(y_test, predm)))
print('R2 score:', r2_score(y_test, predm))
print('*' * 100)
print('\n')
```

```
Best parameters for DecisionTreeRegressor(random_state=42): {'max_depth': None
MAE: 0.0002727024815925825
MSE: 0.0002727024815925825
RMSE: 0.016513705870960113
R2 score: 0.9998700090217355
*****************************************************************************
```

```
# Bar plot
models_names = ['Decision Tree Before Tuning', 'Decision Tree After Tuning']

plt.figure(figsize=(8, 6))
bar_width = 0.35
index = np.arange(len(models_names))

plt.bar(index, [MSE_before_tuning, mse_after_tuning], width=bar_width, color='skybl

plt.xlabel('Models')
plt.ylabel('Mean Squared Error (MSE)')
plt.title('MSE Before and After Hyperparameter Tuning for Decision Tree Regression'
plt.xticks(index, models_names)
plt.show()
```



XGB Regressor without Hyper parameter Tuning

```
xgb_before_tuning = XGBRegressor(random_state=42)
xgb_before_tuning.fit(x_train, y_train)
y_pred_before = xgb_before_tuning.predict(x_test)
mse_before_tuning_XGB = mean_squared_error(y_test, y_pred_before)
print(mse_before_tuning_XGB)
```

```
0.0003445863762973193
```

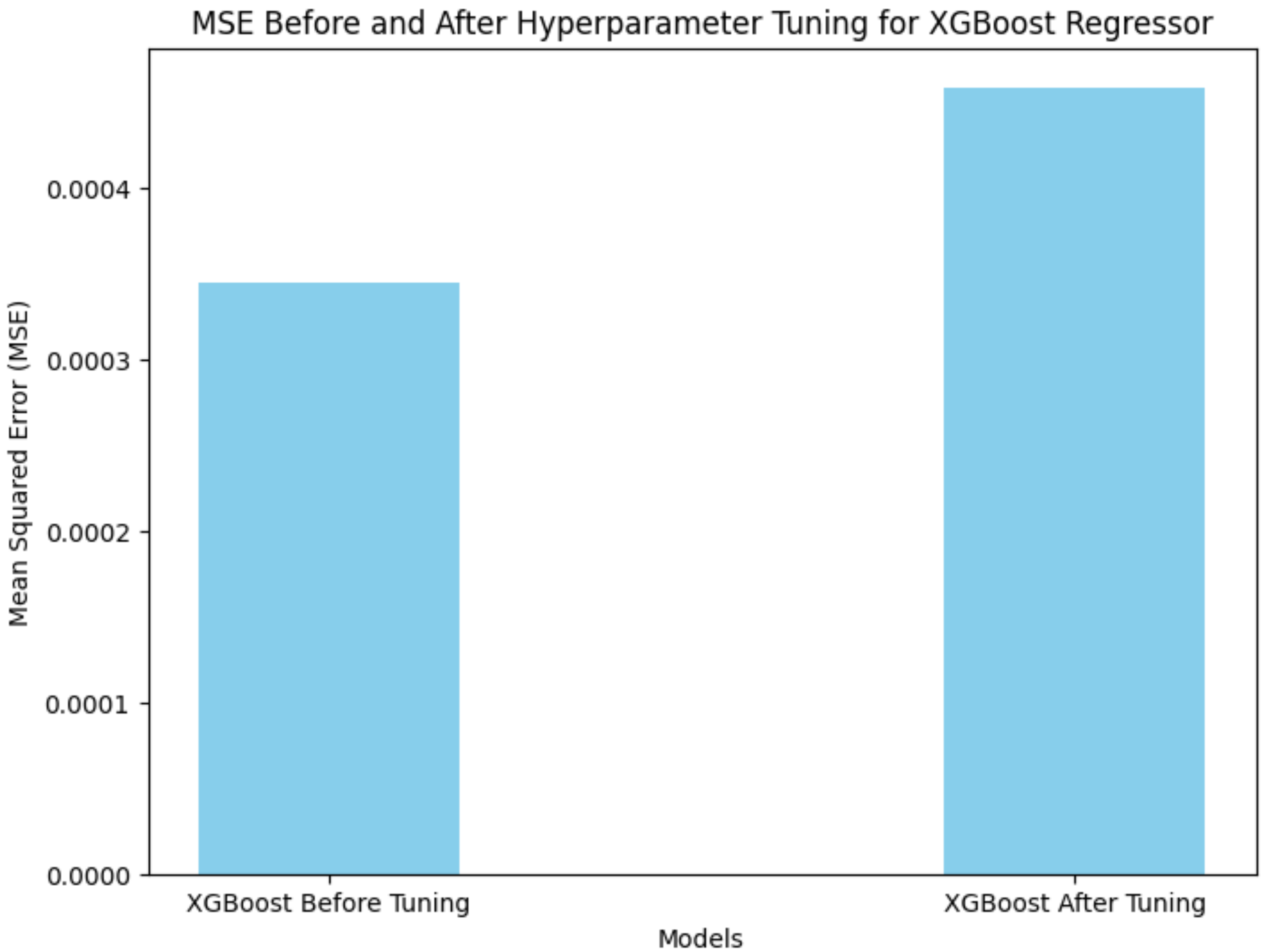
XGB Regressor with Hyper parameter Tuning

```
grid_search = GridSearchCV(XGBRegressor(random_state=42), param_grid={'learning_r
grid_search.fit(x_train, y_train)
best_xgb_after_tuning = grid_search.best_estimator_
y_pred_after_tuning = best_xgb_after_tuning.predict(x_test)
mse_after_tuning_XGB = mean_squared_error(y_test, y_pred_after_tuning)
```

```
print(mse_after_tuning_XGB)
```

```
0.0004586255743918887
```

```
# Bar plot
models_names = ['XGBoost Before Tuning', 'XGBoost After Tuning']

plt.figure(figsize=(8, 6))
bar_width = 0.35
index = np.arange(len(models_names))

plt.bar(index, [mse_before_tuning_XGB, mse_after_tuning_XGB], width=bar_width, co

plt.xlabel('Models')
plt.ylabel('Mean Squared Error (MSE)')
plt.title('MSE Before and After Hyperparameter Tuning for XGBoost Regressor')
plt.xticks(index, models_names)
plt.show()
```



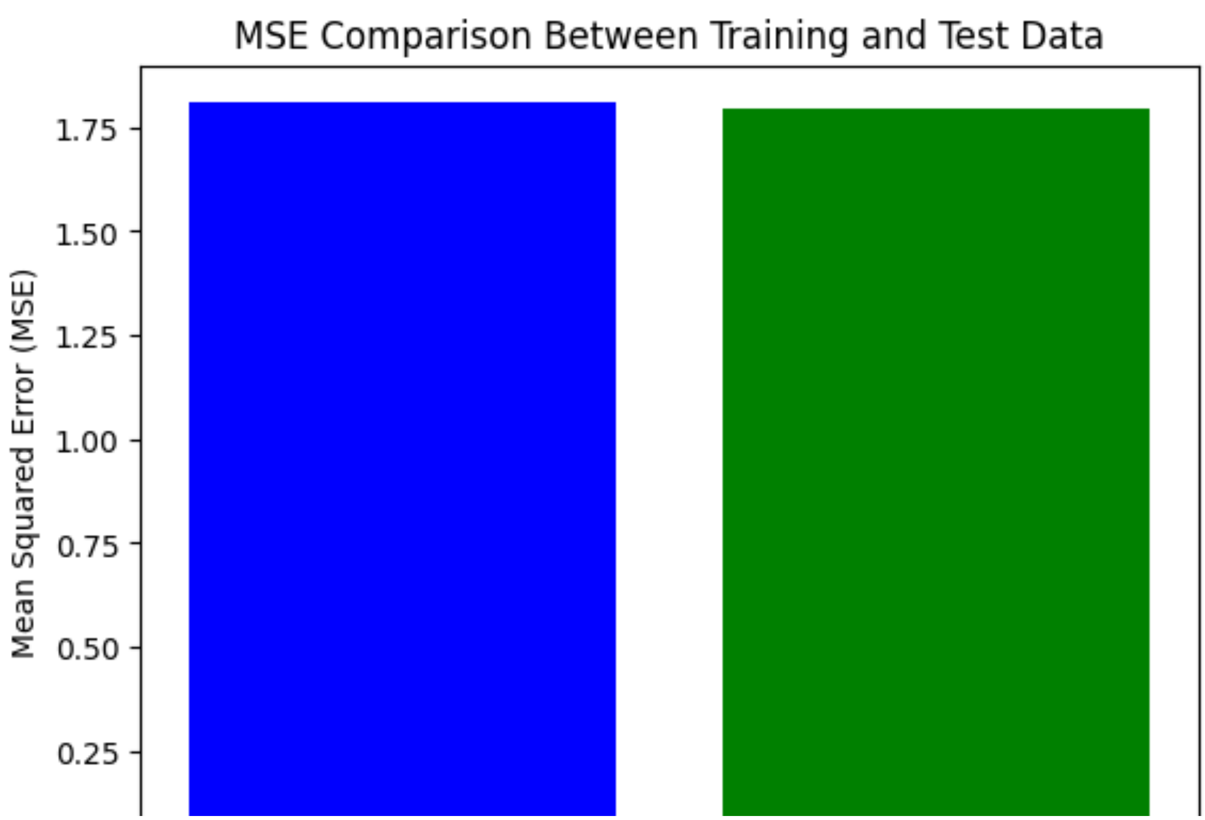
Extreme Learning Machine

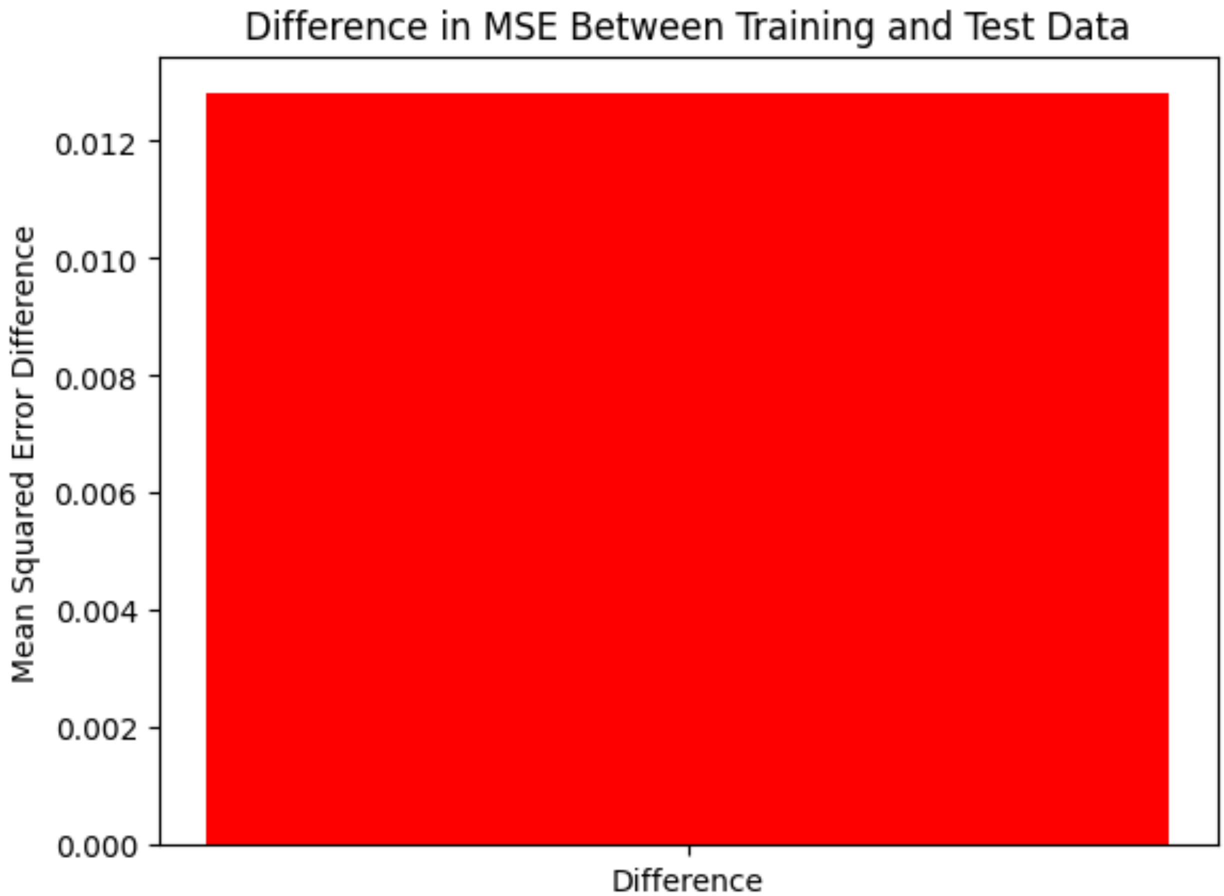
```
class ELMRegressor:
    def __init__(self, n_input, n_hidden, activation_function=np.tanh):
        self.n_input = n_input
        self.n_hidden = n_hidden
        self.activation_function = activation_function
        self.weights_input_hidden = None
        self.bias_hidden = None
        self.weights_hidden_output = None

    def _initialize_weights(self):
        self.weights_input_hidden = np.random.rand(self.n_input, self.n_hidden)
        self.bias_hidden = np.random.rand(1, self.n_hidden)
        self.weights_hidden_output = np.random.rand(self.n_hidden, 1)

    def _activation(self, x):
        return self.activation_function(x)

    def train(self, X, y):
        self._initialize_weights()

        # Calculate hidden layer output
        hidden_output = self._activation(np.dot(X, self.weights_input_hidden) + s

        # Calculate output layer weights using the Moore-Penrose pseudoinverse
        self.weights_hidden_output = np.dot(np.linalg.pinv(hidden_output), y)

    def predict(self, X):
        hidden_output = self._activation(np.dot(X, self.weights_input_hidden) + s
        output = np.dot(hidden_output, self.weights_hidden_output)
        return output
    def mse(self, y_true, y_pred):
        return np.mean((y_true - y_pred) ** 2)


elm = ELMRegressor(n_input = x_train.shape[1], n_hidden=50)
elm.train(x_train, y_train)


y_pred_train_ELM = elm.predict(x_train)
y_pred_test_ELM = elm.predict(x_test)
```

```
mse_train = elm.mse(y_train, y_pred_train_ELM)
print(mse_train)
mse_test = elm.mse(y_test, y_pred_test_ELM)
print(mse_test)
```

```
1.8094103259568297
1.7966060903506333
```

```
# Plot bar chart for MSE
labels = ['Training Data', 'Test Data']
mse_values = [mse_train, mse_test]

plt.bar(labels, mse_values, color=['blue', 'green'])
plt.ylabel('Mean Squared Error (MSE)')
plt.title('MSE Comparison Between Training and Test Data')
plt.show()

# Plot the difference in MSE between training and test data
mse_difference = np.abs(mse_train - mse_test)
plt.bar(['Difference'], [mse_difference], color='red')
plt.ylabel('Mean Squared Error Difference')
plt.title('Difference in MSE Between Training and Test Data')
plt.show()
```





A Basic Deep Learning Model with two layers

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

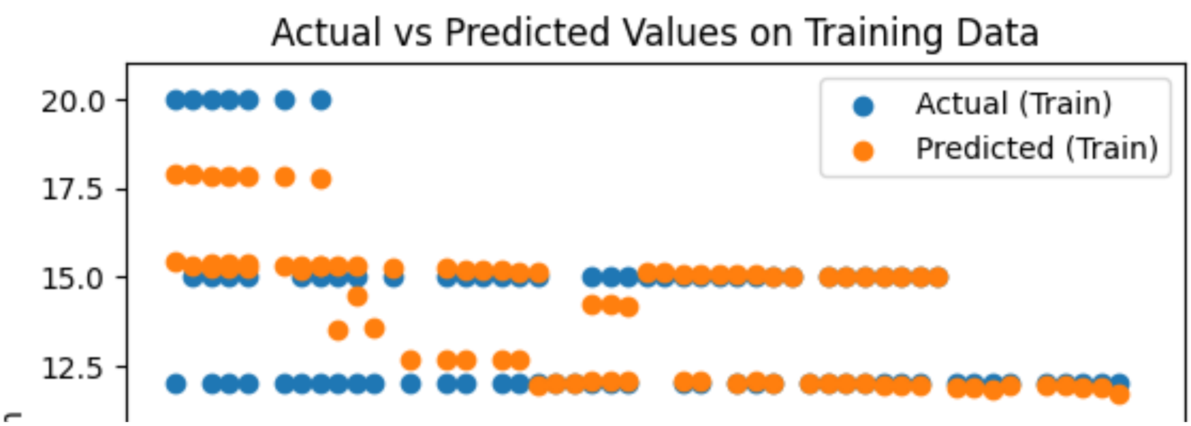
```
# Build the model
model = Sequential([
    # Input layer (specify the input shape for the first layer)
    Dense(units=10, activation='relu', input_shape=(x_train.shape[1],)),

    # Hidden layer
    Dense(units=5, activation='relu'),

    # Output layer
    Dense(units=1, activation='linear')  # Assuming it's a regression task
])

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')  # Assuming it's a reg

# Print the model summary
model.summary()
```

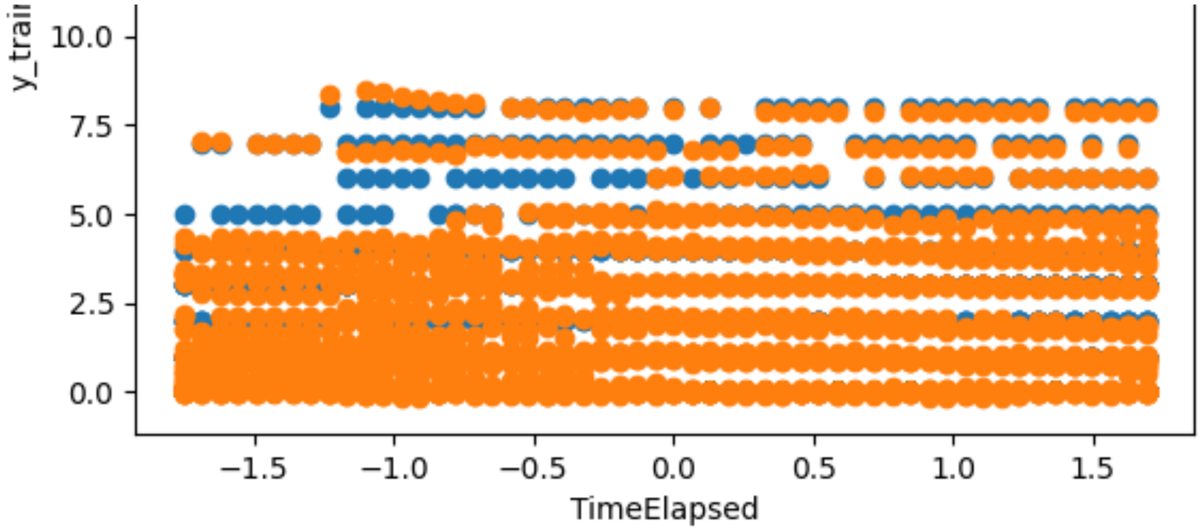
```
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_21 (Dense)            (None, 10)                290

 dense_22 (Dense)            (None, 5)                 55

 dense_23 (Dense)            (None, 1)                 6

=================================================================
Total params: 351 (1.37 KB)
Trainable params: 351 (1.37 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

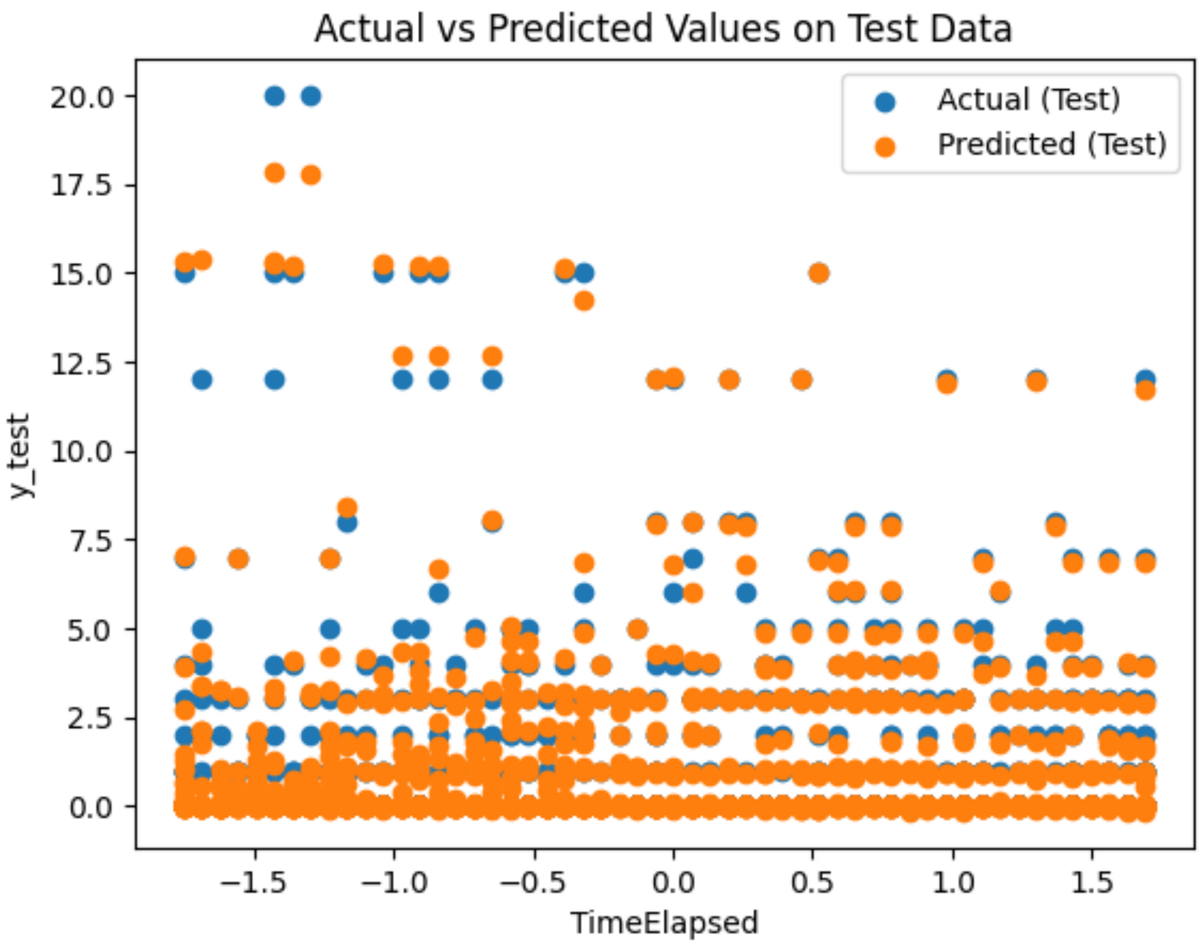
```
# Train the model
history = model.fit(x_train, y_train, epochs=100, batch_size=32, verbose=0)

# Make predictions on training and test data
y_pred_train = model.predict(x_train).flatten()
y_pred_test = model.predict(x_test).flatten()

# Calculate Mean Squared Error (MSE) on training and test data
mse_train = np.mean((y_train - y_pred_train)**2)
```

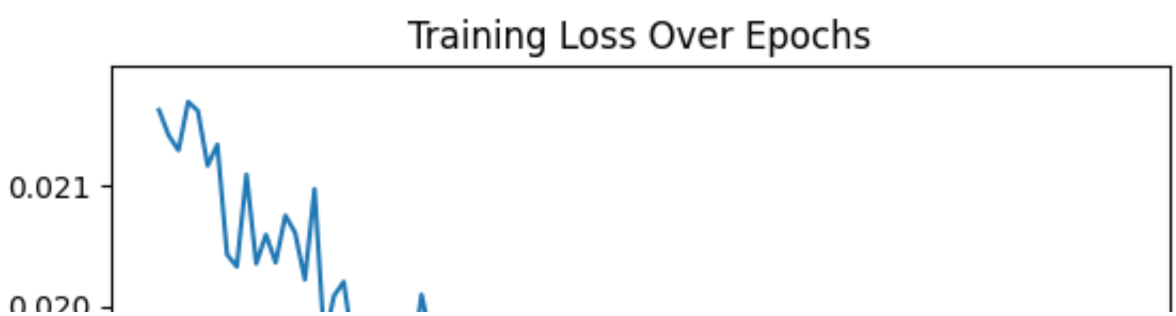
```
mse_test = np.mean((y_test - y_pred_test)**2)

print("Mean Squared Error (MSE) on training data:", mse_train)
print("Mean Squared Error (MSE) on test data:", mse_test)

# Plot actual vs predicted values on training data
plt.scatter(x_train.iloc[:, 0], y_train, label='Actual (Train)')
plt.scatter(x_train.iloc[:, 0], y_pred_train, label='Predicted (Train)')
plt.xlabel(x_train.columns[0])
plt.ylabel('y_train')
plt.legend()
plt.title('Actual vs Predicted Values on Training Data')
plt.show()

# Plot actual vs predicted values on test data
plt.scatter(x_test.iloc[:, 0], y_test, label='Actual (Test)')
plt.scatter(x_test.iloc[:, 0], y_pred_test, label='Predicted (Test)')
plt.xlabel(x_test.columns[0])
plt.ylabel('y_test')
plt.legend()
plt.title('Actual vs Predicted Values on Test Data')
plt.show()

# Plot training loss over epochs
plt.plot(history.history['loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss Over Epochs')
plt.show()
```

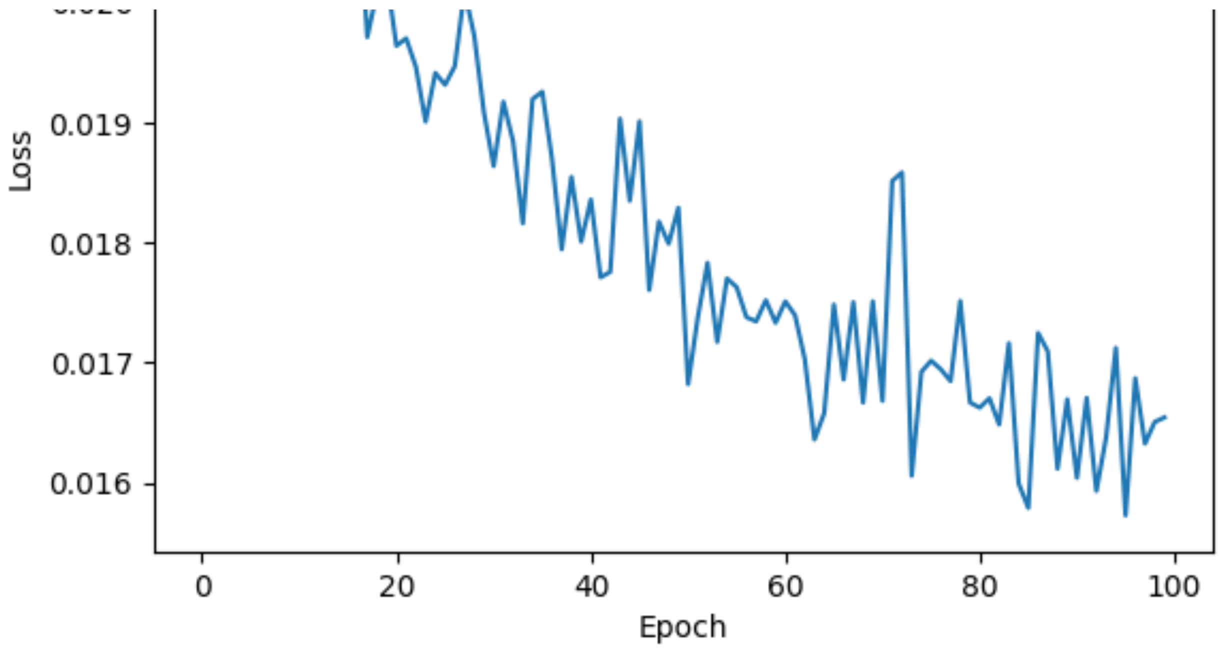
```
459/459 [==============================] - 1s 2ms/step
115/115 [==============================] - 0s 2ms/step
Mean Squared Error (MSE) on training data: 4.068193624997948
Mean Squared Error (MSE) on test data: 4.204130928743757
```




y_trai
10.0
7.5
5.0
2.5
0.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
TimeElapsed


Actual vs Predicted Values on Test Data
Actual (Test)
Predicted (Test)
y_test
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
TimeElapsed


Training Loss Over Epochs
0.021
0.020



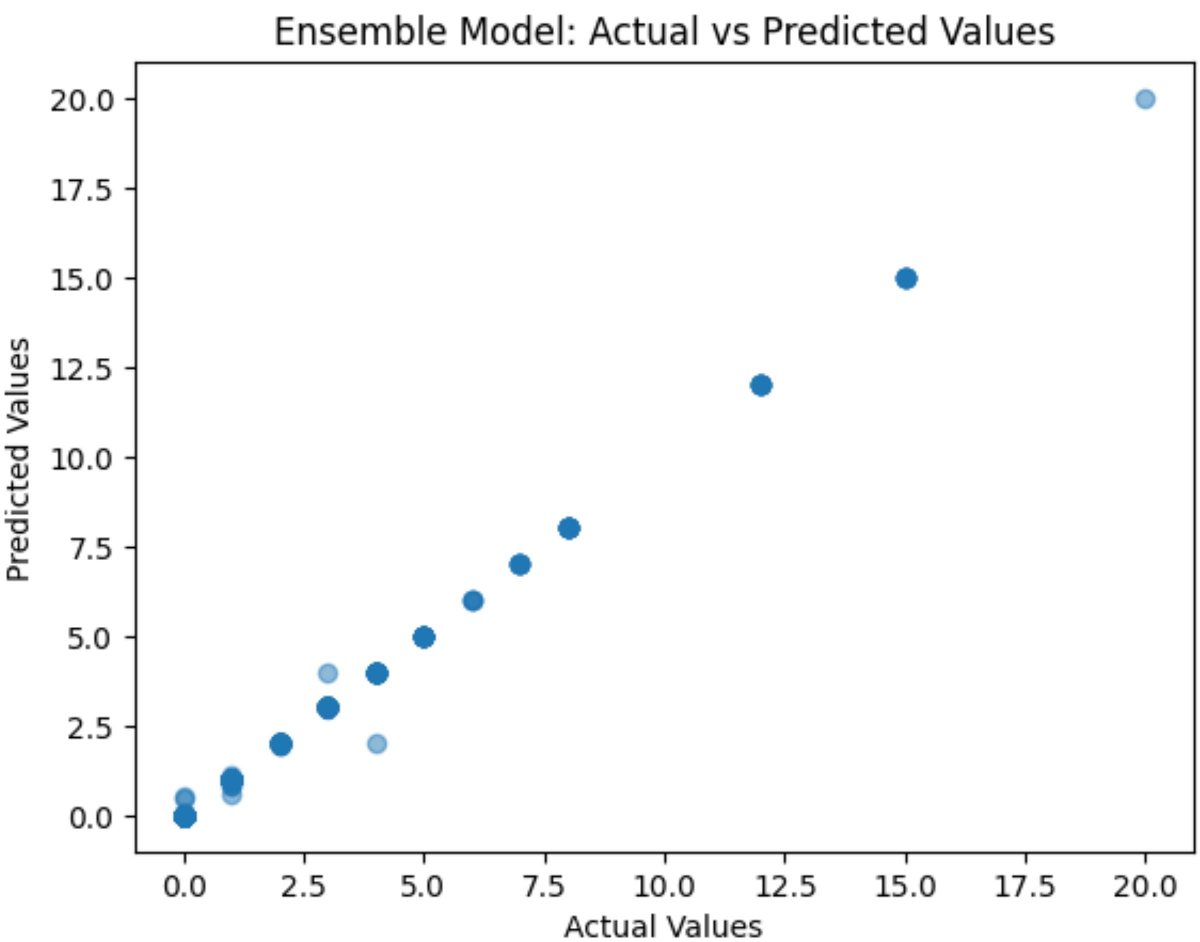

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import VotingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
import pandas as pd

# Load the data
data = pd.read_csv('/content/drive/MyDrive/new_election_dataset (1).csv')

# Preparing the dataset
X = data.drop(columns=['FinalMandates'])
y = data['FinalMandates']

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, r

# Model 1: RandomForestRegressor with Hyperparameter Tuning
rf_params = {'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20], 'min_sa
rf_model = RandomForestRegressor(random_state=42)
```

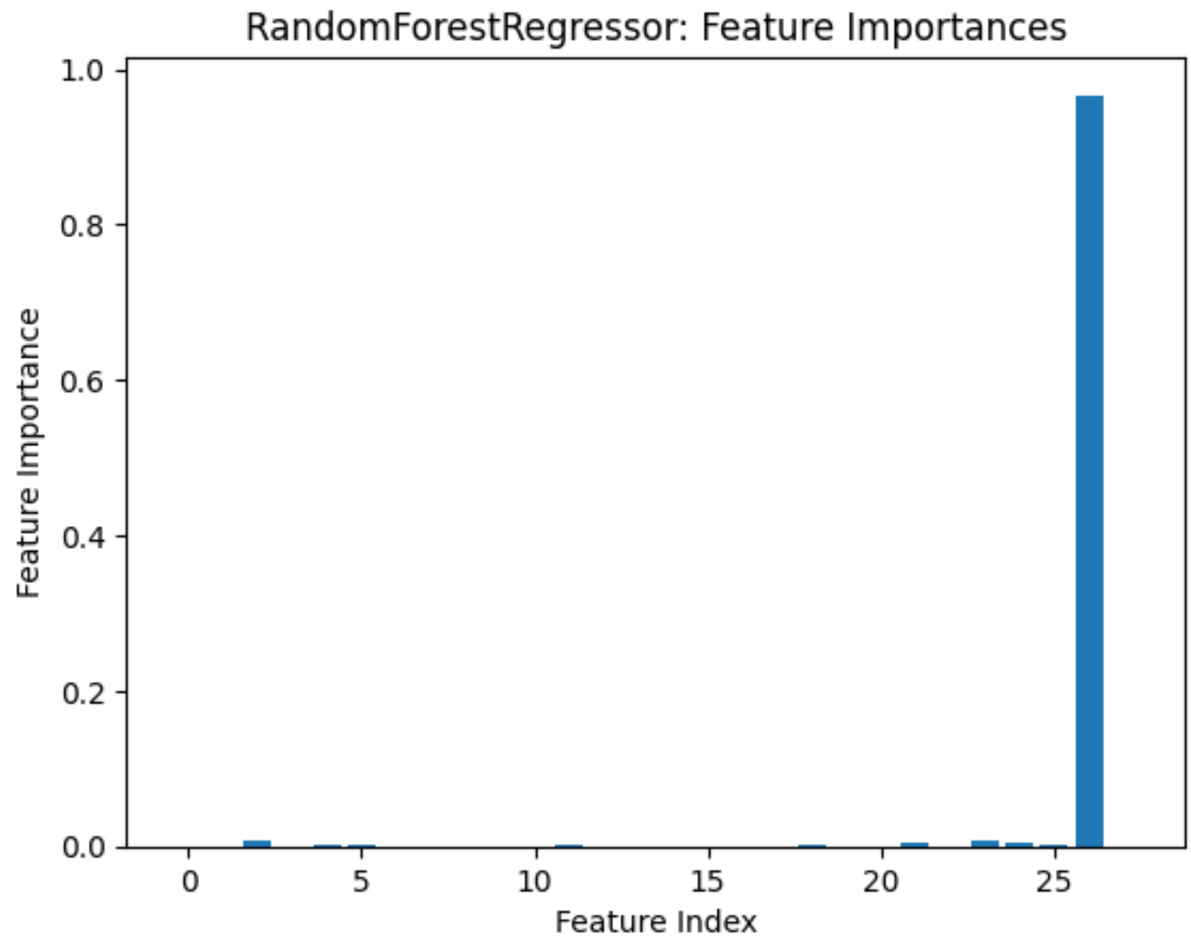
```
grid_search_rf = GridSearchCV(rf_model, rf_params, cv=5)
grid_search_rf.fit(X_train, y_train)
best_rf_model = grid_search_rf.best_estimator_

# Model 2: DecisionTreeRegressor with Hyperparameter Tuning
dt_params = {'max_depth': [None, 10, 20], 'min_samples_split': [2, 5, 10]}
dt_model = DecisionTreeRegressor(random_state=42)
grid_search_dt = GridSearchCV(dt_model, dt_params, cv=5)
grid_search_dt.fit(X_train, y_train)
best_dt_model = grid_search_dt.best_estimator_

# Model 3: XGBRegressor with Hyperparameter Tuning
xgb_params = {'n_estimators': [50, 100, 200], 'max_depth': [3, 5, 7], 'learning_r
xgb_model = XGBRegressor(random_state=42)
grid_search_xgb = GridSearchCV(xgb_model, xgb_params, cv=5)
grid_search_xgb.fit(X_train, y_train)
best_xgb_model = grid_search_xgb.best_estimator_

# Ensemble model using VotingRegressor
ensemble_model = VotingRegressor(estimators=[
    ('rf', best_rf_model),
    ('dt', best_dt_model),
    ('xgb', best_xgb_model)
])

# Fit the ensemble model
ensemble_model.fit(X_train, y_train)

# Make predictions on the test set
ensemble_preds = ensemble_model.predict(X_test)

# Evaluate the ensemble model
ensemble_mse = mean_squared_error(y_test, ensemble_preds)
print("Ensemble Model Mean Squared Error (MSE):", ensemble_mse)
```

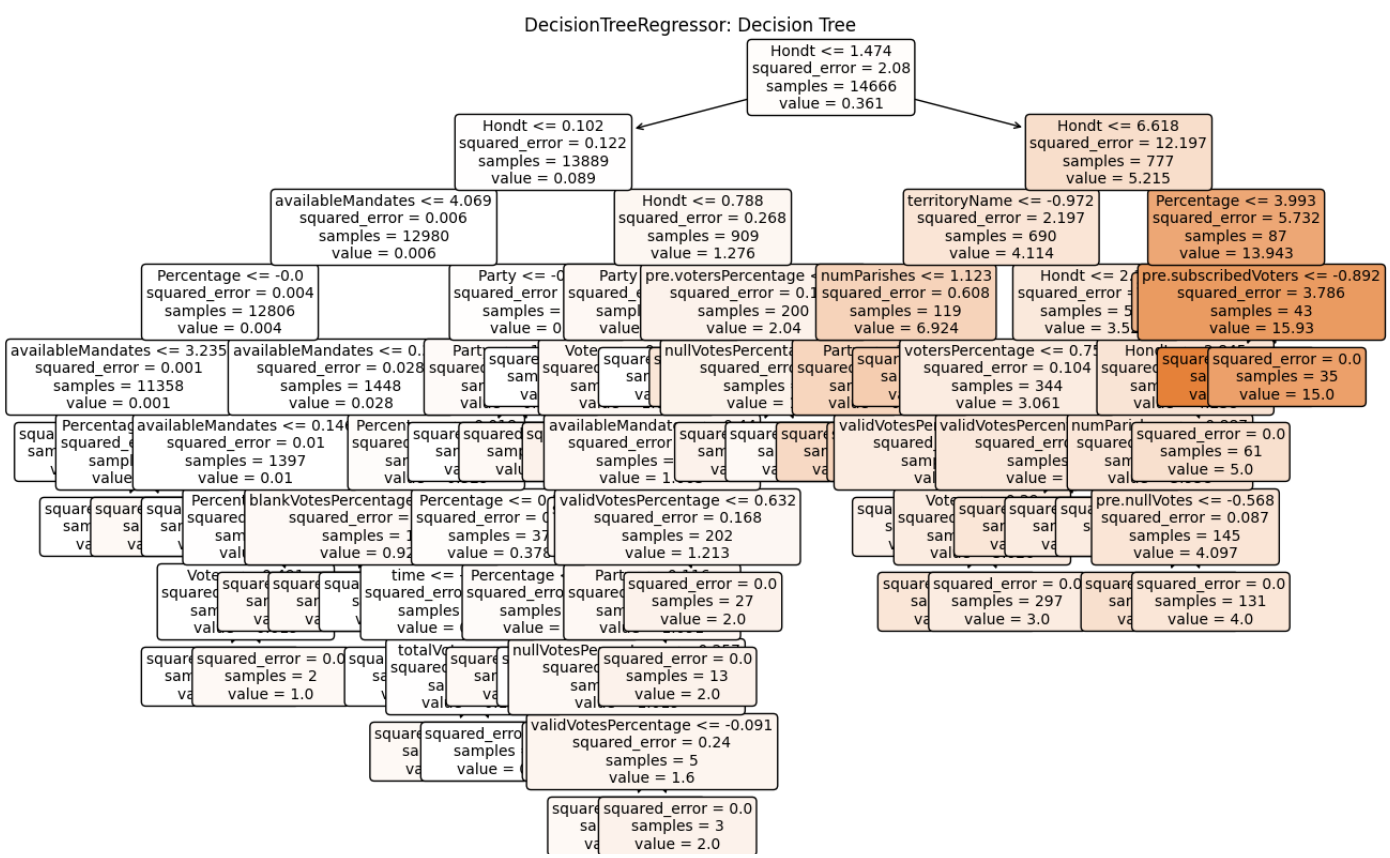
```
Ensemble Model Mean Squared Error (MSE): 0.0015516642879219696
```

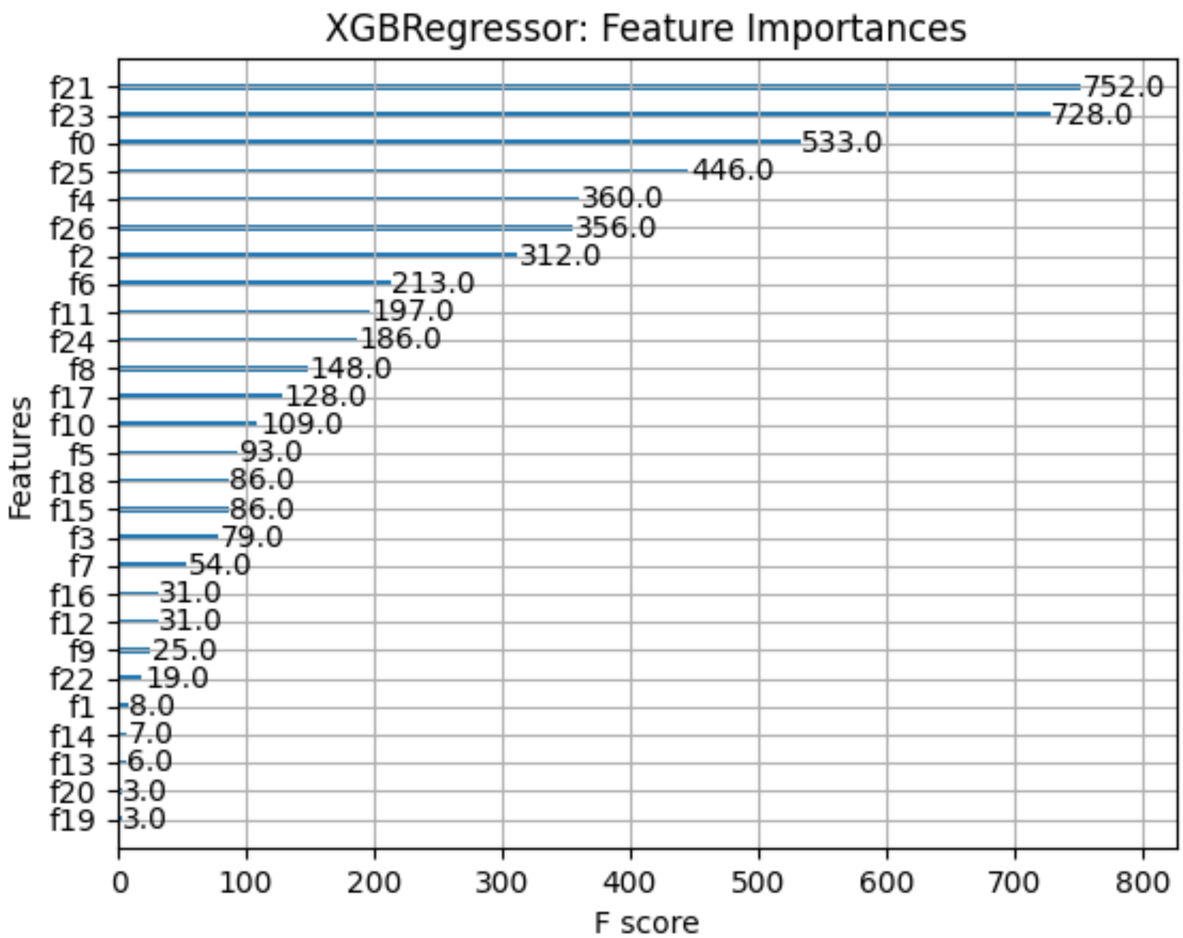
```
from xgboost import plot_importance
from sklearn.tree import plot_tree
# Plot actual vs predicted values for the ensemble model
plt.scatter(y_test, ensemble_preds, alpha=0.5)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Ensemble Model: Actual vs Predicted Values")
```

```
plt.title("Ensemble Model: Actual vs Predicted Values")
plt.show()

# Plot feature importances for RandomForestRegressor
feature_importances_rf = best_rf_model.feature_importances_
plt.bar(range(len(feature_importances_rf)), feature_importances_rf)
plt.xlabel("Feature Index")
plt.ylabel("Feature Importance")
plt.title("RandomForestRegressor: Feature Importances")
plt.show()

# Plot the tree from DecisionTreeRegressor
plt.figure(figsize=(15, 10))
plot_tree(best_dt_model, filled=True, feature_names=X.columns, rounded=True, fontsi
plt.title("DecisionTreeRegressor: Decision Tree")
plt.show()

# Plot feature importances for XGBRegressor
plot_importance(best_xgb_model)
plt.title("XGBRegressor: Feature Importances")
plt.show()
```




RandomForestRegressor: Feature Importances
Feature Importance
Feature Index
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
25


DecisionTreeRegressor: Decision Tree
Hondt <= 1.474
squared_error = 2.08
samples = 14666
value = 0.361
Hondt <= 0.102
squared_error = 0.122
samples = 13889
value = 0.089
Hondt <= 6.618
squared_error = 12.197
samples = 777
value = 5.215
availableMandates <= 4.069
squared_error = 0.006
samples = 12980
value = 0.006
Hondt <= 0.788
squared_error = 0.268
samples = 909
value = 1.276
territoryName <= -0.972
squared_error = 2.197
samples = 690
value = 4.114
Percentage <= 3.993
squared_error = 5.732
samples = 87
value = 13.943
Percentage <= -0.0
squared_error = 0.004
samples = 12806
value = 0.004
numParishes <= 1.123
squared_error = 0.608
samples = 119
value = 6.924
pre.subscribedVoters <= -0.892
squared_error = 3.786
samples = 43
value = 15.93
availableMandates <= 3.235
squared_error = 0.001
samples = 11358
value = 0.001
squared_error = 0.0
samples = 35
value = 15.0
squared_error = 0.0
samples = 61
value = 5.0
validVotesPercentage <= 0.632
squared_error = 0.168
samples = 202
value = 1.213
pre.nullVotes <= -0.568
squared_error = 0.087
samples = 145
value = 4.097
squared_error = 0.0
samples = 27
value = 2.0
squared_error = 0.0
samples = 131
value = 4.0
squared_error = 0.0
samples = 2
value = 1.0
squared_error = 0.0
samples = 13
value = 2.0
validVotesPercentage <= -0.091
squared_error = 0.24
samples = 5
value = 1.6
squared_error = 0.0
samples = 3
value = 2.0


XGBRegressor: Feature Importances
Features
F score
f21
f23
f0
f25
f4
f26
f2
f6
f11
f24
f8
f17
f10
f5
f18
f15
f3
f7
f16
f12
f9
f22
f1
f14
f13
f20
f19
752.0
728.0
533.0
446.0
360.0
356.0
312.0
213.0
197.0
186.0
148.0
128.0
109.0
93.0
86.0
86.0
79.0
54.0
31.0
31.0
25.0
19.0
8.0
7.0
6.0
3.0
3.0
0
100
200
300
400
500
600
700
800