Fish Weight Prediction using various ML Models and comparison

by

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(GitHub Link: https://github.com/aman4computing/Fish_Weight_Prediction)

DATA ANALYTICS

MCSE615L

OBJECTIVE:

The objective of this project is to develop a machine-learning model to predict the weight of fish based on various features. The main goals of the project include:

1. Data Cleaning: Preprocess the dataset by handling missing values, removing duplicates, and addressing any inconsistencies in the data.
2. Feature Selection: Identify the most relevant features that have a significant impact on predicting the fish's weight. Use feature selection techniques to select the subset of features that contribute the most to the model's performance.
3. Model Building: Build machine learning models to predict fish weight based on the selected features.
4. Model Evaluation: Assess the performance of the models using evaluation metrics such as RMSE, MSE, MAE, and R2 score. Compare the performance of the different models to determine which one performs the best.
5. Visualization: Visualize the data, model predictions, and evaluation metrics to gain insights and effectively communicate the results.

The ultimate objective is to create an accurate and reliable model that can predict the weight of fish based on the given set of features.

DATASET:

Dataset Link: https://www.kaggle.com/datasets/aungpyaeap/fish-market

This dataset is a record of 7 common different fish species in fish market sales. With this dataset, a predictive model can be performed using machine-friendly data, and estimate the weight of fish can be predicted.

DESCRIPTION OF WORK:

Here I am using three ML Models:

1. Decision Tree
2. Random Forest
3. Linear Regression

And comparing them based on RMSE and R2 scores.

Following Steps are used here:

Step 1: Importing Libraries

Step 2: Read the Dataset

Step 3: Data cleaning and preprocessing

Step 4: Feature selection and elimination

1. Identify the features that are most relevant for predicting fish weight.
2. Use Recursive Feature Elimination (RFE) with the DecisionTreeRegressor.

Step 5: Select the root node

Step 6: Build models

Step 7: Evaluation and visualization

Step8: Comparisons of ML Models

IMPLEMENTATION & VISUALIZATION:

Step 1: Importing Libraries

Step 1: Importing Libraries

```
[ ]  import pandas as pd
     import numpy as np
     import seaborn as sns
     import matplotlib.pyplot as plt
     from sklearn.model_selection import train_test_split
     from sklearn.tree import DecisionTreeRegressor, plot_tree
     from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
     from sklearn.feature_selection import RFE
     from sklearn.preprocessing import LabelEncoder, OneHotEncoder, MinMaxScaler
```

Step 2: Read the Dataset

Step 2: Read Dataset

```
[ ]  df=pd.read_csv('/content/Fish.csv')
```

```
[ ]  df
```

	Species	Weight	Length1	Length2	Length3	Height	Width
0	Bream	242.0	23.2	25.4	30.0	11.5200	4.0200
1	Bream	290.0	24.0	26.3	31.2	12.4800	4.3056
2	Bream	340.0	23.9	26.5	31.1	12.3778	4.6961
3	Bream	363.0	26.3	29.0	33.5	12.7300	4.4555
4	Bream	430.0	26.5	29.0	34.0	12.4440	5.1340
...	...	...	...	...	...	...	...
154	Smelt	12.2	11.5	12.2	13.4	2.0904	1.3936
155	Smelt	13.4	11.7	12.4	13.5	2.4300	1.2690
156	Smelt	12.2	12.1	13.0	13.8	2.2770	1.2558
157	Smelt	19.7	13.2	14.3	15.2	2.8728	2.0672
158	Smelt	19.9	13.8	15.0	16.2	2.9322	1.8792

159 rows × 7 columns

Step 3: Data cleaning and preprocessing

Step 3: Data cleaning and preprocessing

```
[ ] # Check for missing values
    print(df.isnull().sum())
```

```
Species    0
Weight     0
Length1    0
Length2    0
Length3    0
Height     0
Width      0
dtype: int64
```

Here no missing value in dataset & also data is already cleaned so no need to do preprocessing and cleaning here

Step 4: Feature selection and elimination

1. Identify the features that are most relevant for predicting fish weight.

2. Use Recursive Feature Elimination (RFE) with the DecisionTreeRegressor.

Step 4: Feature selection and elimination

1. Identify the features that are most relevant for predicting fish weight.

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```
[ ] # Select the features and target
    features = df.drop(['Weight'], axis=1)
    target = df['Weight']
```

```
[ ] # Convert categorical features to numerical representation using one-hot encoding
    categorical_features = ['Species']
    numeric_features = ['Length1', 'Length2', 'Length3', 'Height', 'Width']
```

```
[ ] # Perform one-hot encoding on categorical features
    encoder = OneHotEncoder(sparse=False)
    encoded_features = encoder.fit_transform(features[categorical_features])
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `spar
  warnings.warn(
```

```
[ ] # Combine encoded features with numerical features
    X = np.concatenate((encoded_features, features[numeric_features].values), axis=1)
    X=pd.DataFrame(X)
```

```
[ ] print(X)
```

```
       0    1    2    3    4    5    6     7     8     9        10      11
0    1.0  0.0  0.0  0.0  0.0  0.0  0.0  23.2  25.4  30.0  11.5200  4.0200
1    1.0  0.0  0.0  0.0  0.0  0.0  0.0  24.0  26.3  31.2  12.4800  4.3056
2    1.0  0.0  0.0  0.0  0.0  0.0  0.0  23.9  26.5  31.1  12.3778  4.6961
3    1.0  0.0  0.0  0.0  0.0  0.0  0.0  26.3  29.0  33.5  12.7300  4.4555
4    1.0  0.0  0.0  0.0  0.0  0.0  0.0  26.5  29.0  34.0  12.4440  5.1340
..   ...  ...  ...  ...  ...  ...  ...   ...   ...   ...      ...     ...
154  0.0  0.0  0.0  0.0  0.0  1.0  0.0  11.5  12.2  13.4   2.0904  1.3936
155  0.0  0.0  0.0  0.0  0.0  1.0  0.0  11.7  12.4  13.5   2.4300  1.2690
156  0.0  0.0  0.0  0.0  0.0  1.0  0.0  12.1  13.0  13.8   2.2770  1.2558
157  0.0  0.0  0.0  0.0  0.0  1.0  0.0  13.2  14.3  15.2   2.8728  2.0672
158  0.0  0.0  0.0  0.0  0.0  1.0  0.0  13.8  15.0  16.2   2.9322  1.8792

[159 rows x 12 columns]
```

```
[ ] # Perform Recursive Feature Elimination (RFE) with DecisionTreeRegressor
    estimator = DecisionTreeRegressor()
    selector = RFE(estimator, n_features_to_select=3, step=1)
    X_selected = selector.fit_transform(X, target)
```

```
[ ] # Get the selected feature indices
    X_selected
```

```
array([[30.    , 11.52  ,  4.02  ],
       [31.2   , 12.48  ,  4.3056],
       [31.1   , 12.3778,  4.6961],
       [33.5   , 12.73  ,  4.4555],
       [34.    , 12.444 ,  5.134 ],
       [34.7   , 13.6024,  4.9274],
       [34.5   , 14.1795,  5.2785],
       [35.    , 12.67  ,  4.69  ],
       [35.1   , 14.0049,  4.8438],
       [36.2   , 14.2266,  4.9594],
       [36.2   , 14.2628,  5.1042],
       [36.2   , 14.3714,  4.8146],
       [36.4   , 13.7592,  4.368 ],
       [37.3   , 13.9129,  5.0728],
       [37.2   , 14.9544,  5.1708],
       [37.2   , 15.438 ,  5.58  ],
       [38.3   , 14.8604,  5.2854],
       [38.5   , 14.938 ,  5.1975],
       [38.6   , 15.633 ,  5.1338],
```

Step 5: Select the root node

Step 5: Select the root node

```
[ ] root_feature = X_selected[:,0]
```

```
[ ] root_feature
```

```
array([30. , 31.2, 31.1, 33.5, 34. , 34.7, 34.5, 35. , 35.1, 36.2, 36.2,
       36.2, 36.4, 37.3, 37.2, 37.2, 38.3, 38.5, 38.6, 38.7, 39.5, 39.2,
       39.7, 40.6, 40.5, 40.9, 40.6, 41.5, 41.6, 42.6, 44.1, 44. , 45.3,
       45.9, 46.5, 16.2, 20.3, 21.2, 22.2, 22.2, 22.8, 23.1, 23.7, 24.7,
       24.3, 25.3, 25. , 25. , 27.2, 26.7, 26.8, 27.9, 29.2, 30.6, 35. ,
       28.7, 29.3, 30.8, 34. , 39.6, 43.5, 16.5, 17.4, 19.8, 21.3, 22.4,
       23.2, 23.2, 24.1, 25.8, 28. , 29. ,  8.8, 14.7, 16. , 17.2, 18.5,
       19.2, 19.4, 20.2, 20.8, 21. , 22.5, 22.5, 22.5, 22.8, 23.5, 23.5,
       23.5, 23.5, 23.5, 24. , 24. , 24.2, 24.5, 25. , 25.5, 25.5, 26.2,
       26.5, 27. , 28. , 28.7, 28.9, 28.9, 28.9, 29.4, 30.1, 31.6, 34. ,
       36.5, 37.3, 39. , 38.3, 39.4, 39.3, 41.4, 41.4, 41.3, 42.3, 42.5,
       42.4, 42.5, 44.6, 45.2, 45.5, 46. , 46.6, 34.8, 37.8, 38.8, 39.8,
       40.5, 41. , 45.5, 45.5, 45.8, 48. , 48.7, 51.2, 55.1, 59.7, 64. ,
       64. , 68. , 10.8, 11.6, 11.6, 12. , 12.4, 12.6, 13.1, 13.1, 13.2,
       13.4, 13.5, 13.8, 15.2, 16.2])
```

Step 6: Build models

1. DT MODEL

```
[ ] # Split the dataset into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_selected, target, test_size=0.2, random_state=42)
```

```
[ ] # Normalize numerical features using Min-Max scaling
    scaler = MinMaxScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
```

```
[ ] # Build a Decision Tree model
    model = DecisionTreeRegressor(random_state=42)
    model.fit(X_train_scaled, y_train)
```

```
DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

2. RF MODEL

```
[ ]  from sklearn.ensemble import RandomForestRegressor
```

```
[ ]  # Build a Random Forest Regressor model
     rf_model = RandomForestRegressor(random_state=42)
     rf_model.fit(X_train_scaled, y_train)
```

```
▾        RandomForestRegressor
RandomForestRegressor(random_state=42)
```

```
[ ]  # Make predictions on the test set using Random Forest model
     rf_y_pred = rf_model.predict(X_test_scaled)
```

3. LINEAR REGRESSION

```
[ ]  from sklearn.linear_model import LinearRegression

     # Build a Linear Regression model
     lr_model = LinearRegression()
     lr_model.fit(X_train_scaled, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
[ ]  # Make predictions on the test set using Linear Regression model
     lr_y_pred = lr_model.predict(X_test_scaled)
```

Step 7: Evaluation and visualization

1.DT MODEL

Step 7: Evaluation and visualization

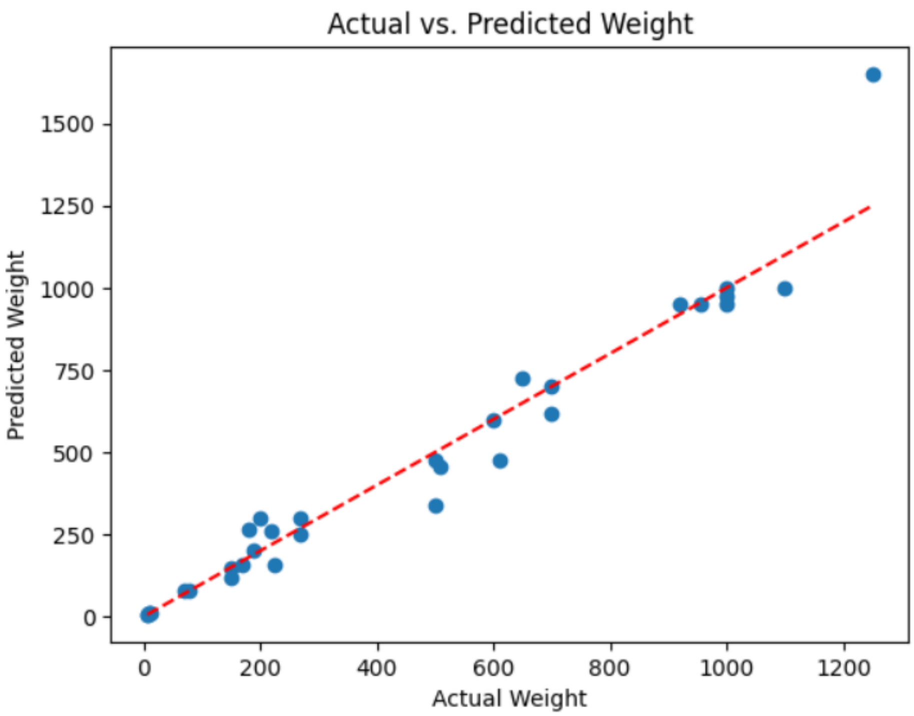
```
[ ] # Make predictions on the test set
    y_pred = model.predict(X_test_scaled)
```

```
[ ] df = pd.DataFrame({'Real':y_test, 'Predicted':y_pred})
    df
```

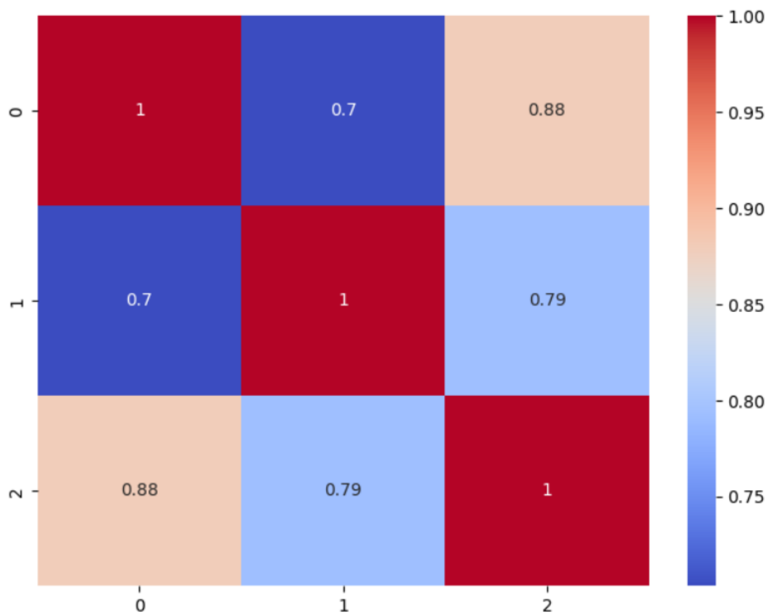
	Real	Predicted
78	78.0	80.0
155	13.4	12.2
128	200.0	300.0
55	270.0	300.0
94	150.0	150.0
29	1000.0	975.0
147	7.0	7.5
51	180.0	265.0
98	188.0	200.0

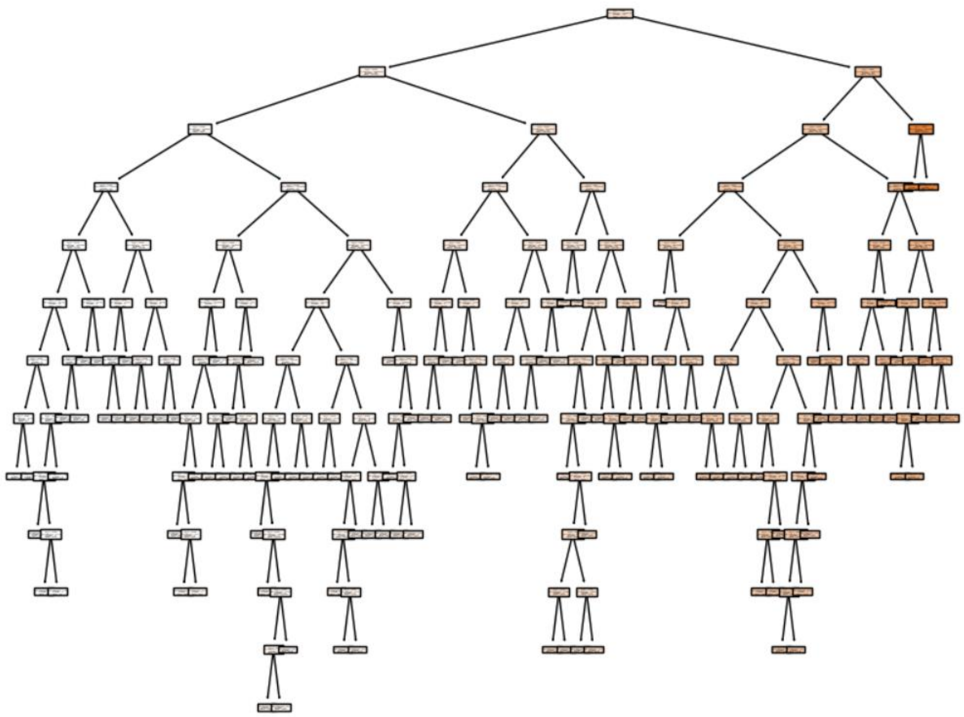
```
[ ] # Calculate evaluation metrics
    dt_mae = mean_absolute_error(y_test, y_pred)
    dt_mse = mean_squared_error(y_test, y_pred)
    dt_rmse = np.sqrt(dt_mse)
    dt_r2 = r2_score(y_test, y_pred)

    print("Mean Absolute Error (MAE):", dt_mae)
    print("Mean Squared Error (MSE):", dt_mse)
    print("Root Mean Squared Error (RMSE):", dt_rmse)
    print("R-squared (R2) Score:", dt_r2)
```

```
Mean Absolute Error (MAE): 48.368750000000006
Mean Squared Error (MSE): 8100.168125
Root Mean Squared Error (RMSE): 90.00093402293112
R-squared (R2) Score: 0.943052525745978
```




```
<function matplotlib.pyplot.title(label, fontdict=None, loc=None, pad=None, *, y=None, **kwargs)>
```





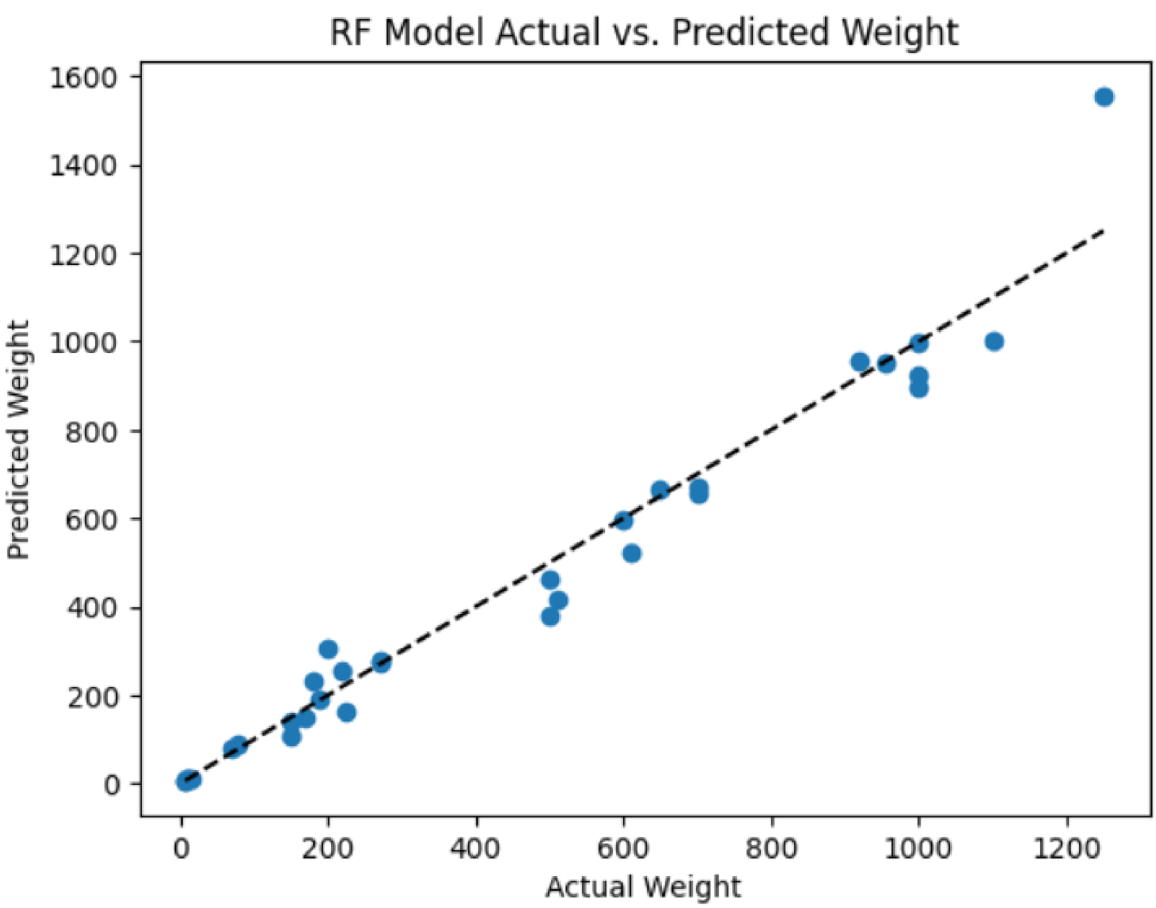
2. RF MODEL

```
df = pd.DataFrame({'Real':y_test, 'Predicted':rf_y_pred})
df
```

	Real	Predicted
78	78.0	89.400000
155	13.4	11.361000
128	200.0	306.760000
55	270.0	276.170000
94	150.0	138.670000
29	1000.0	923.050000
147	7.0	8.226000
51	180.0	233.240000
98	188.0	191.670000
141	1250.0	1555.908333
19	650.0	667.340000
60	1000.0	897.450000

```python
# Calculate evaluation metrics for Random Forest model
rf_mae = mean_absolute_error(y_test, rf_y_pred)
rf_mse = mean_squared_error(y_test, rf_y_pred)
rf_rmse = np.sqrt(rf_mse)
rf_r2 = r2_score(y_test, rf_y_pred)

print("Mean Absolute Error (MAE):", rf_mae)
print("Mean Squared Error (MSE):", rf_mse)
print("Root Mean Squared Error (RMSE):", rf_rmse)
print("R-squared (R2) Score:",rf_r2)
```

```
Mean Absolute Error (MAE): 44.49804166666666
Mean Squared Error (MSE): 5573.728655805551
Root Mean Squared Error (RMSE): 74.65740857949432
R-squared (R2) Score: 0.9608144220925796
```



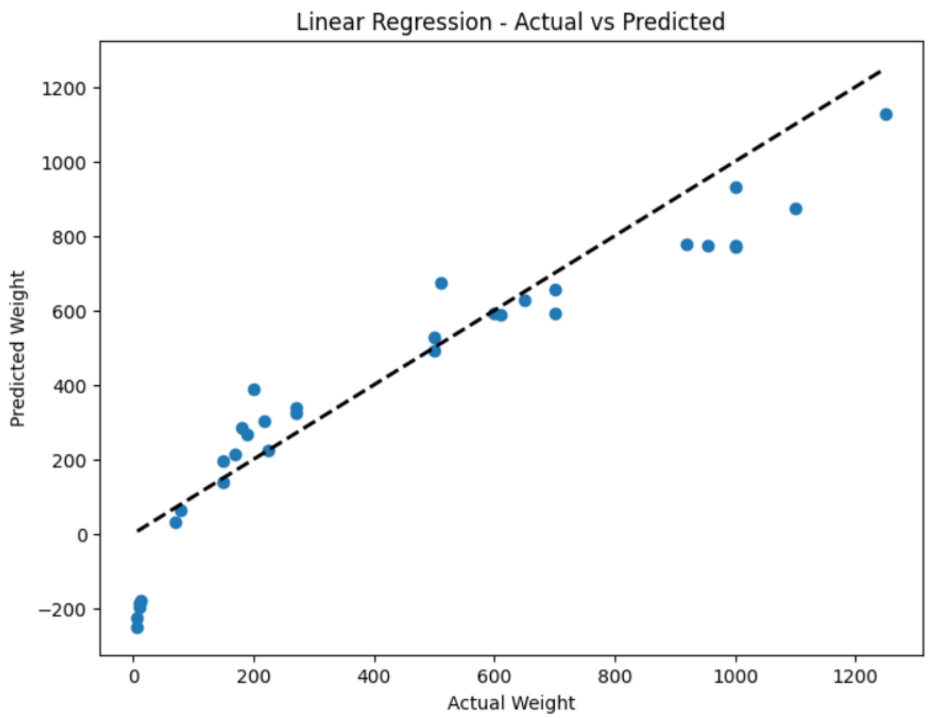
3. LINEAR REGRESSION

```
[ ] df = pd.DataFrame({'Real':y_test, 'Predicted':lr_y_pred})
    df
```

	Real	Predicted
78	78.0	62.373863
155	13.4	-180.411377
128	200.0	386.885877
55	270.0	325.423377
94	150.0	197.318826
29	1000.0	769.134371
147	7.0	-227.027368
51	180.0	285.605085
98	188.0	268.387362
141	1250.0	1127.061612
19	650.0	628.927875

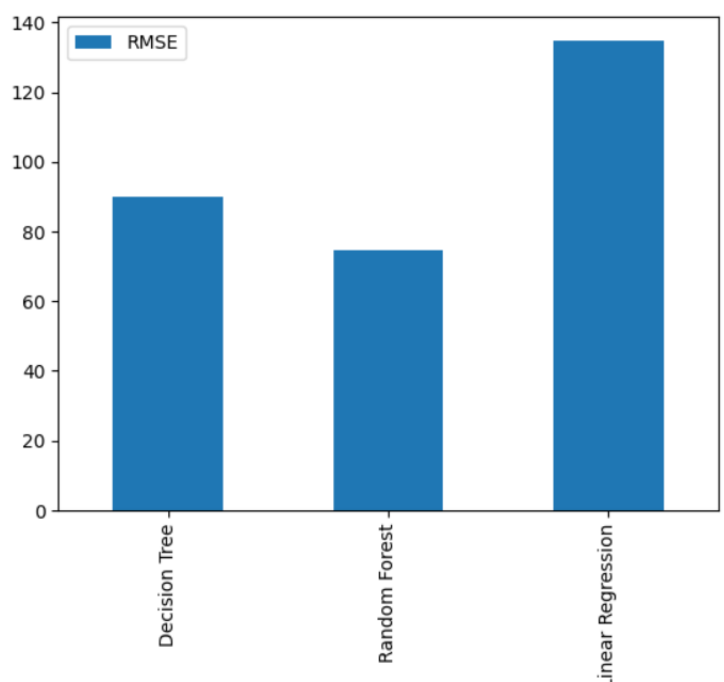
```
[ ] # Calculate evaluation metrics for Linear Regression model
    lr_mae = mean_absolute_error(y_test, lr_y_pred)
    lr_mse = mean_squared_error(y_test, lr_y_pred)
    lr_rmse = np.sqrt(lr_mse)
    lr_r2 = r2_score(y_test, lr_y_pred)

    print("Mean Absolute Error (MAE):", lr_mae)
    print("Mean Squared Error (MSE):", lr_mse)
    print("Root Mean Squared Error (RMSE):", lr_rmse)
    print("R-squared (R2) Score:", lr_r2)
```

```
Mean Absolute Error (MAE): 106.94110171832082
Mean Squared Error (MSE): 18176.402480858458
Root Mean Squared Error (RMSE): 134.81988904037289
R-squared (R2) Score: 0.8722125027115497
```

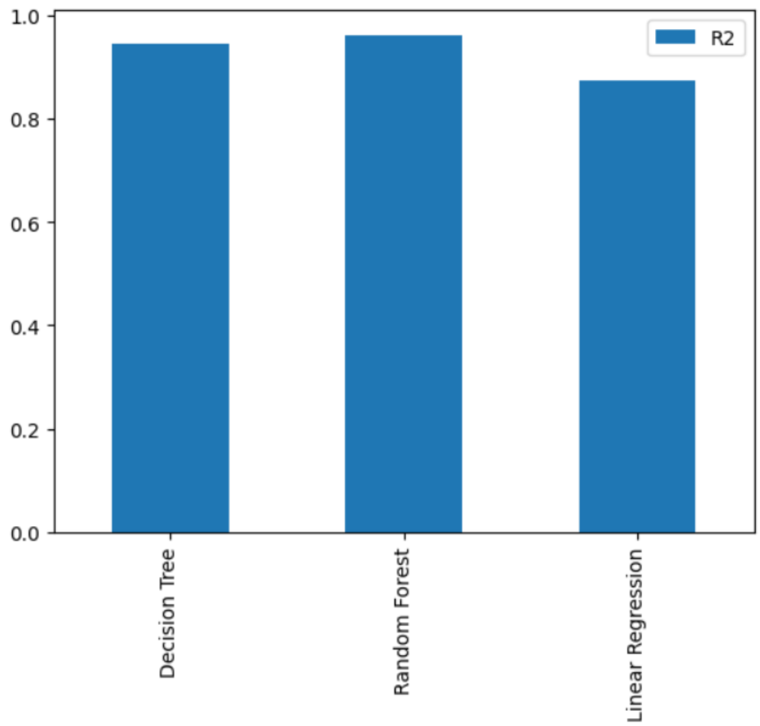


Step8: Comparisons of ML Models

```
# Create a bar plot to compare RMSE for the models
metrics = {'RMSE':[dt_rmse,rf_rmse,lr_rmse]}
score=pd.DataFrame(metrics,index=['Decision Tree','Random Forest','Linear Regression'])
plot=score.plot.bar()
```



```
[ ] # Create a bar plot to compare R2 score for the models
    metrics = {'R2':[dt_r2,rf_r2,lr_r2]}
    score=pd.DataFrame(metrics,index=['Decision Tree','Random Forest','Linear Regression'])
    plot=score.plot.bar()
```



Conclusion:

Model	RMSE	R2
DT	90.00	0.94
RF	74.65	0.96
Linear Regression	134.81	0.87

1. Random Forest Model has the lowest RMSE value which implies that the majority of predicted ratings are close to the actual ratings compared to the other two models.

2. And Random Forest Model has the highest R2 score which says the RF Model fits data better compared to the other two models.

So by the above two statements we can say Random Forest Model performed better compared to the other two models and also give more accurate predictions if we compared it with others.