old-car-price-pred

April 3, 2024

1 Old Car Price Prediction

[1]:
```
# Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
```

[2]:
```
# Reading the dataset
df=pd.read_csv(r'C:\Users\ntpc\Desktop\car_prediction_data.csv')
df.head()
```

[2]:
```
  Car_Name  Year  Selling_Price  Present_Price  Kms_Driven Fuel_Type  \
0     ritz  2014           3.35           5.59       27000    Petrol
1      sx4  2013           4.75           9.54       43000    Diesel
2     ciaz  2017           7.25           9.85        6900    Petrol
3  wagon r  2011           2.85           4.15        5200    Petrol
4    swift  2014           4.60           6.87       42450    Diesel

  Seller_Type Transmission  Owner
0      Dealer       Manual      0
1      Dealer       Manual      0
2      Dealer       Manual      0
3      Dealer       Manual      0
4      Dealer       Manual      0
```

[3]:
```
## Checking missing value
df.isnull().sum()
```

[3]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
```

```
Owner             0
dtype: int64
```

[4]:
```
# checking datatypes for each column name
df.dtypes
```

[4]:
```
Car_Name          object
Year               int64
Selling_Price    float64
Present_Price    float64
Kms_Driven         int64
Fuel_Type         object
Seller_Type       object
Transmission      object
Owner              int64
dtype: object
```

1.1 Now converting Categorical columns to numerical using Label Encoder

1.1.1 Car_Name

[5]:
```
car_name_le=LabelEncoder()
df['Car_Name']=car_name_le.fit_transform(df['Car_Name'])
```

1.1.2 Fuel_Type

[6]:
```
Fuel_Type_le=LabelEncoder()
df['Fuel_Type']=Fuel_Type_le.fit_transform(df['Fuel_Type'])
```

1.1.3 Seller_Type

[7]:
```
Seller_Type_le=LabelEncoder()
df['Seller_Type']=Seller_Type_le.fit_transform(df['Seller_Type'])
```

1.1.4 Transmission

[8]:
```
Transmission_le=LabelEncoder()
df['Transmission']=Transmission_le.fit_transform(df['Transmission'])
```

[9]:
```
df.head()
```

[9]:
```
   Car_Name  Year  Selling_Price  Present_Price  Kms_Driven  Fuel_Type  \
0        90  2014           3.35           5.59       27000          2
1        93  2013           4.75           9.54       43000          1
2        68  2017           7.25           9.85        6900          2
3        96  2011           2.85           4.15        5200          2
```

```
4         92  2014           4.60           6.87       42450            1

   Seller_Type  Transmission  Owner
0            0             1      0
1            0             1      0
2            0             1      0
3            0             1      0
4            0             1      0
```

1.2 Separating features and target variable

[10]:
```python
X = df.drop('Selling_Price', axis=1)
y = df['Selling_Price']
```

[11]:
```python
from sklearn.preprocessing import StandardScaler
```

[12]:
```python
ss=StandardScaler()
X= pd.DataFrame(ss.fit_transform(X),columns=X.columns)
```

[13]:
```python
from sklearn.model_selection import train_test_split
```

[14]:
```python
# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[15]:
```python
## Applying various ML models to deal with this regression type of problem
from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
```

[16]:
```python
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

[17]:
```python
lr=LinearRegression()
lr.fit(X_train,y_train)
lr.score(X_train,y_train)*100,lr.score(X_test,y_test)*100
```

[17]: (88.40630578239453, 84.65539666857805)

[18]:
```python
lr1=Lasso(alpha=0.05)
lr1.fit(X_train,y_train)
lr1.score(X_train,y_train)*100,lr1.score(X_test,y_test)*100
```

[18]: (88.35433202380113, 84.42023265451037)

[19]:
```
lr2=Ridge(alpha=0.05)
lr2.fit(X_train,y_train)
lr2.score(X_train,y_train)*100,lr2.score(X_test,y_test)*100
```

[19]: (88.40630230556692, 84.65323174459922)

[20]:
```
lr3=ElasticNet(alpha=0.05)
lr3.fit(X_train,y_train)
lr3.score(X_train,y_train)*100,lr3.score(X_test,y_test)*100
```

[20]: (88.33239931760652, 84.24688675401035)

[21]:
```
dt=DecisionTreeRegressor(max_depth=10)
dt.fit(X_train,y_train)
dt.score(X_train,y_train)*100,dt.score(X_test,y_test)*100
```

[21]: (99.96116535900154, 94.77674801512742)

[22]:
```
mean_squared_error(y_test,dt.predict(X_test)),mean_absolute_error(y_test,dt.
  ↪predict(X_test))
```

[22]: (1.2032066256830605, 0.6830054644808742)

[23]:
```
rf=RandomForestRegressor(n_estimators=100)
rf.fit(X_train,y_train)
rf.score(X_train,y_train)*100,rf.score(X_test,y_test)*100
```

[23]: (98.1835007242522, 95.7721695448578)

[24]:
```
mean_squared_error(y_test,rf.predict(X_test)),mean_absolute_error(y_test,rf.
  ↪predict(X_test))
```

[24]: (0.9739054578688531, 0.6012016393442626)

[25]:
```
sv=SVR()
sv.fit(X_train,y_train)
sv.score(X_train,y_train)*100,sv.score(X_test,y_test)*100
```

[25]: (66.00840380338376, 78.48466914602926)

[26]:
```
kn=KNeighborsRegressor(n_neighbors=3)
kn.fit(X_train,y_train)
kn.score(X_train,y_train)*100,kn.score(X_test,y_test)*100
```

[26]: (94.44132806227177, 93.19938751062641)

[27]:
```
mean_squared_error(y_test,kn.predict(X_test)),mean_absolute_error(y_test,kn.
↪predict(X_test))
```

[27]: (1.5665608378870677, 0.763551912568306)

[28]:
```
# Now applying testing
rf.predict([[-1.275759 ,        0.821718 ,        -0.817924 ,        -0.333500␣
↪,        0.500183 ,        1.356327 ,        -2.554408 ,        -0.174501]])
```

```
C:\Python312\Lib\site-packages\sklearn\base.py:493: UserWarning: X does not have
valid feature names, but RandomForestRegressor was fitted with feature names
  warnings.warn(
```

[28]: array([0.4399])

[29]:
```
new_data=pd.DataFrame([['ritz',2014,5.
↪59,27000,        'Petrol','Dealer','Manual',0]],columns=X_train.columns)
```

[30]:
```
new_data['Car_Name']=car_name_le.transform(new_data['Car_Name'])
new_data['Fuel_Type']=Fuel_Type_le.transform(new_data['Fuel_Type'])
new_data['Seller_Type']=Seller_Type_le.transform(new_data['Seller_Type'])
new_data['Transmission']=Transmission_le.transform(new_data['Transmission'])
```

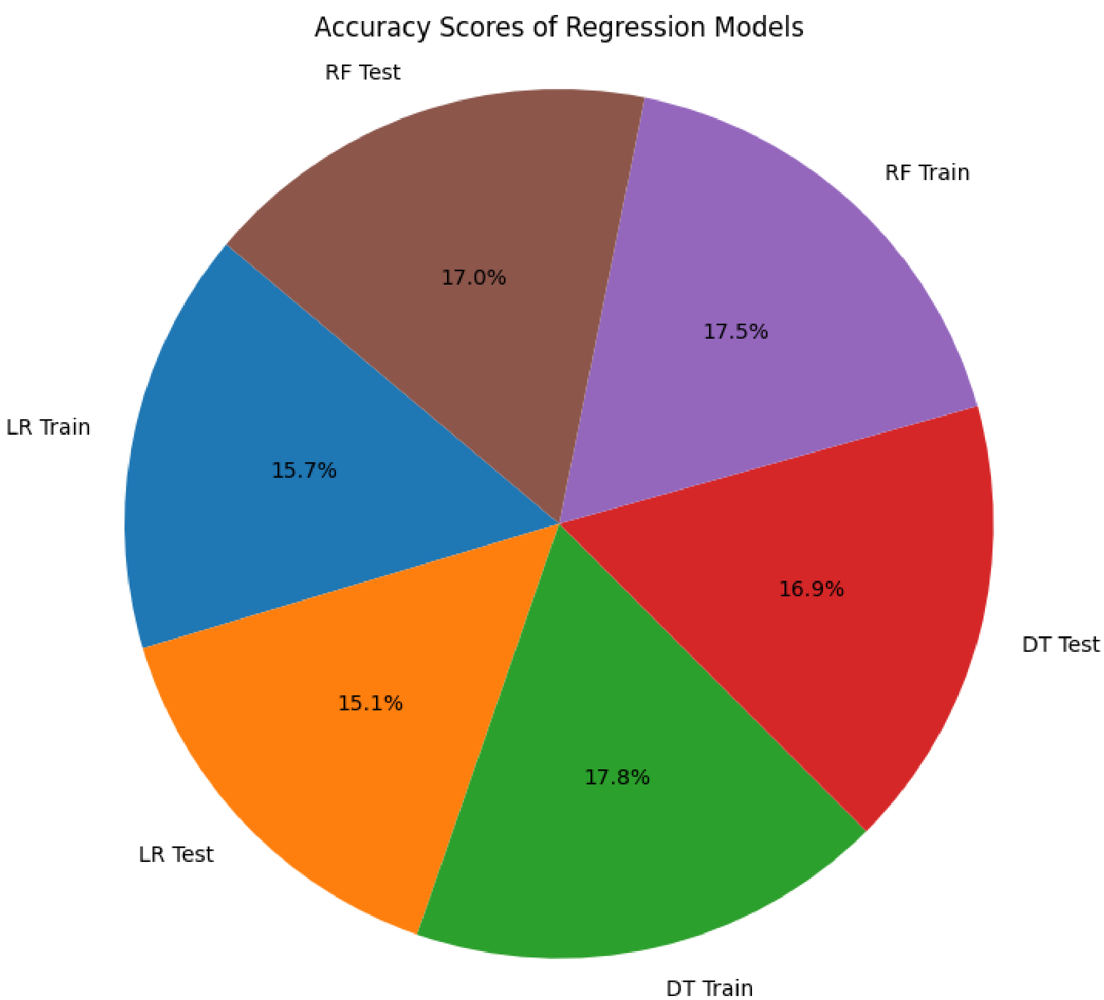
[31]:
```
#Scaling the values for new data
new_data=pd.DataFrame(ss.transform(new_data),columns=new_data.columns)
```

[32]:
```
rf.predict(new_data)
```

[32]: array([3.9155])

[33]:
```
## Now Visualizing the ML models
# Calculate accuracy scores
lr_train_score = lr.score(X_train, y_train) * 100
lr_test_score = lr.score(X_test, y_test) * 100

dt_train_score = dt.score(X_train, y_train) * 100
dt_test_score = dt.score(X_test, y_test) * 100

rf_train_score = rf.score(X_train, y_train) * 100
rf_test_score = rf.score(X_test, y_test) * 100

# Labels and corresponding scores for the pie chart
labels = ['LR Train', 'LR Test', 'DT Train', 'DT Test', 'RF Train', 'RF Test']
scores = [lr_train_score, lr_test_score, dt_train_score, dt_test_score,␣
↪rf_train_score, rf_test_score]

# Create a pie chart
```

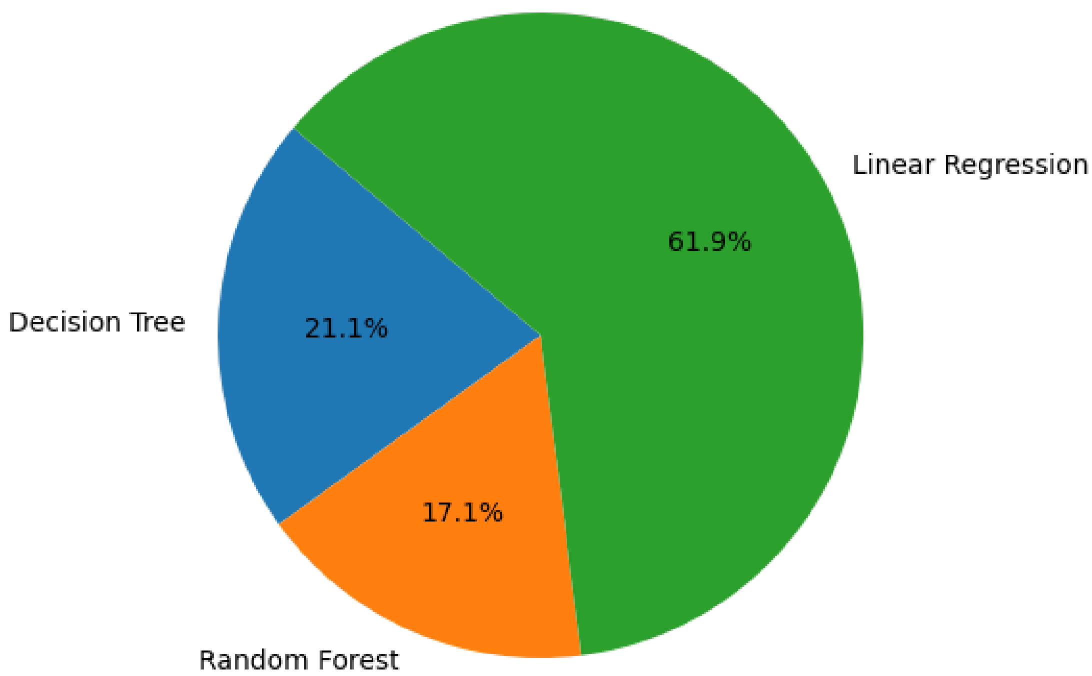
```
plt.figure(figsize=(8, 8))
plt.pie(scores, labels=labels, autopct='%1.1f%%', startangle=140)
plt.title('Accuracy Scores of Regression Models')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

# Display the pie chart
plt.show()
```



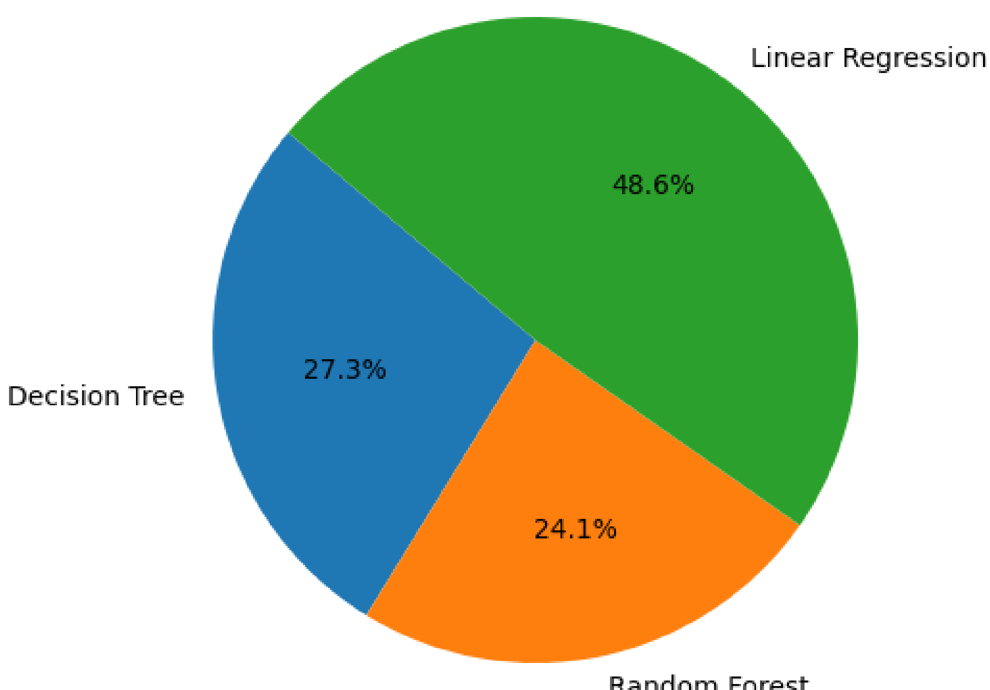
[34]:
```
# Calculate MSE and MAE for each model
dt_mse = mean_squared_error(y_test, dt.predict(X_test))
dt_mae = mean_absolute_error(y_test, dt.predict(X_test))

rf_mse = mean_squared_error(y_test, rf.predict(X_test))
rf_mae = mean_absolute_error(y_test, rf.predict(X_test))

lr_mse = mean_squared_error(y_test, lr.predict(X_test))
```

```
lr_mae = mean_absolute_error(y_test, lr.predict(X_test))

# Labels and corresponding error metrics for the pie charts
models = ['Decision Tree', 'Random Forest', 'Linear Regression']
mse_values = [dt_mse, rf_mse, lr_mse]
mae_values = [dt_mae, rf_mae, lr_mae]

# Create pie charts for MSE and MAE
fig, axs = plt.subplots(2, 1, figsize=(10, 12))

# Pie chart for MSE
axs[0].pie(mse_values, labels=models, autopct='%1.1f%%', startangle=140)
axs[0].set_title('Mean Squared Error (MSE) of Regression Models on Test Data')

# Pie chart for MAE
axs[1].pie(mae_values, labels=models, autopct='%1.1f%%', startangle=140)
axs[1].set_title('Mean Absolute Error (MAE) of Regression Models on Test Data')

# Display the pie charts
plt.show()
```

Mean Squared Error (MSE) of Regression Models on Test Data



Mean Absolute Error (MAE) of Regression Models on Test Data



1.3 Conclusion : Among all these Random Forest Gives Better accuracy score with low error