Task

Car Price Prediction

with Machine Learning The price of a car depends on a lot of factors like the goodwill of the brand of the car, features of the car, horsepower and the mileage it gives and many more. Car price prediction is one of the major research areas in machine learning.

Imports Librarys

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
```

Load the dataset

```
df = pd.read_csv("car data.csv")
```

Basic information

```
df.head()
```

```
  Car_Name  Year  Selling_Price  Present_Price  Driven_kms 
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
```

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

```
df.nunique()
```

```
Car_Name          98
Year              16
Selling_Price    156
Present_Price    148
Driven_kms       206
Fuel_Type          3
Selling_type       2
Transmission       2
Owner              3
dtype: int64
```

```
df.shape
```

```
(301, 9)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Driven_kms     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Selling_type   301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

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

```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
```

```
Selling_type      0
Transmission      0
Owner             0
dtype: int64
```

Handle categorical variables

```
categorical_features = ['Fuel_Type', 'Selling_type', 'Transmission']
ohe = OneHotEncoder(drop='first', sparse_output=False)
categorical_data = ohe.fit_transform(df[categorical_features])
categorical_df = pd.DataFrame(categorical_data,
columns=ohe.get_feature_names_out())
```

Combine numerical and categorical data

```
df = df.drop(columns=categorical_features)
df = pd.concat([df, categorical_df], axis=1)
```

Define features and target variable

```
X = df.drop(columns=['Selling_Price', 'Car_Name'])
y = df['Selling_Price']
```

Split 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)
```

Scale numerical features

```
# Scale numerical features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

Train a Linear Regression model

```
model = LinearRegression()
model.fit(X_train, y_train)
```

```
LinearRegression()
```

Make predictions

```
y_pred = model.predict(X_test)
```

Evaluate the model

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
print(f'R2 Score: {r2}')
```

```
MAE: 1.3148837577539134
MSE: 3.5526176797354854
RMSE: 1.8848389002075179
R2 Score: 0.8457769683853144
```

Visualize predictions

```
# Visualize predictions
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel("Actual Selling Price")
plt.ylabel("Predicted Selling Price")
plt.title("Actual vs Predicted Selling Price")
plt.show()
```

Train a Random Forest Regressor model

```
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

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

Make predictions

```
y_pred = model.predict(X_test)
```

Evaluate the model

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

```python
print(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
print(f'R2 Score: {r2}')
```

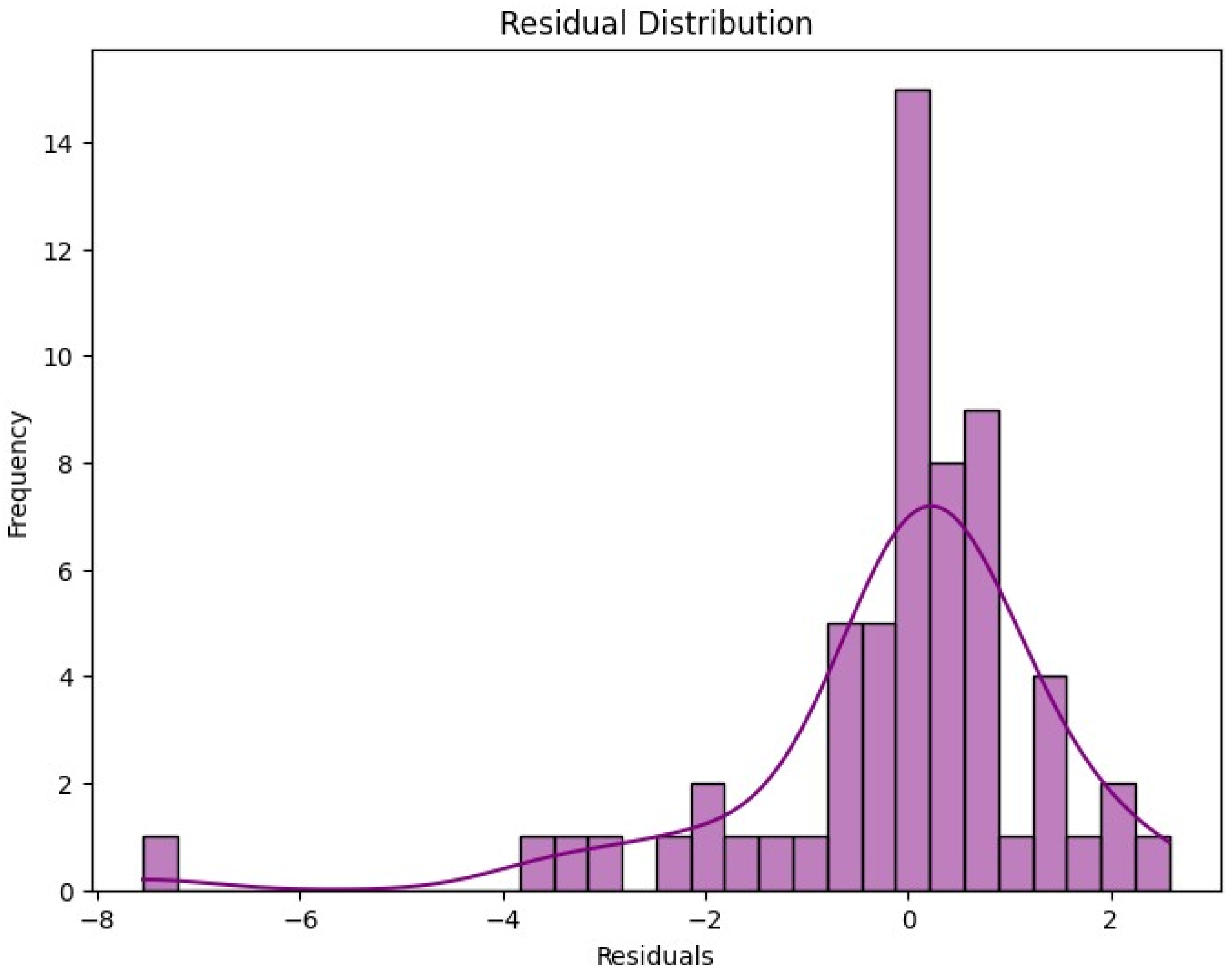
```
MAE: 0.9776049180327874
MSE: 2.429239694590164
RMSE: 1.5586018396595598
R2 Score: 0.8945440393557005
```

```python
# Visualize predictions
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel("Actual Selling Price")
plt.ylabel("Predicted Selling Price")
plt.title("Actual vs Predicted Selling Price")
plt.show()
```


```python
# Shows the errors (residuals = actual - predicted), ideally centered
around zero.
import seaborn as sns

residuals = y_test - y_pred
```

```
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True, bins=30, color="purple")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Residual Distribution")
plt.show()
```

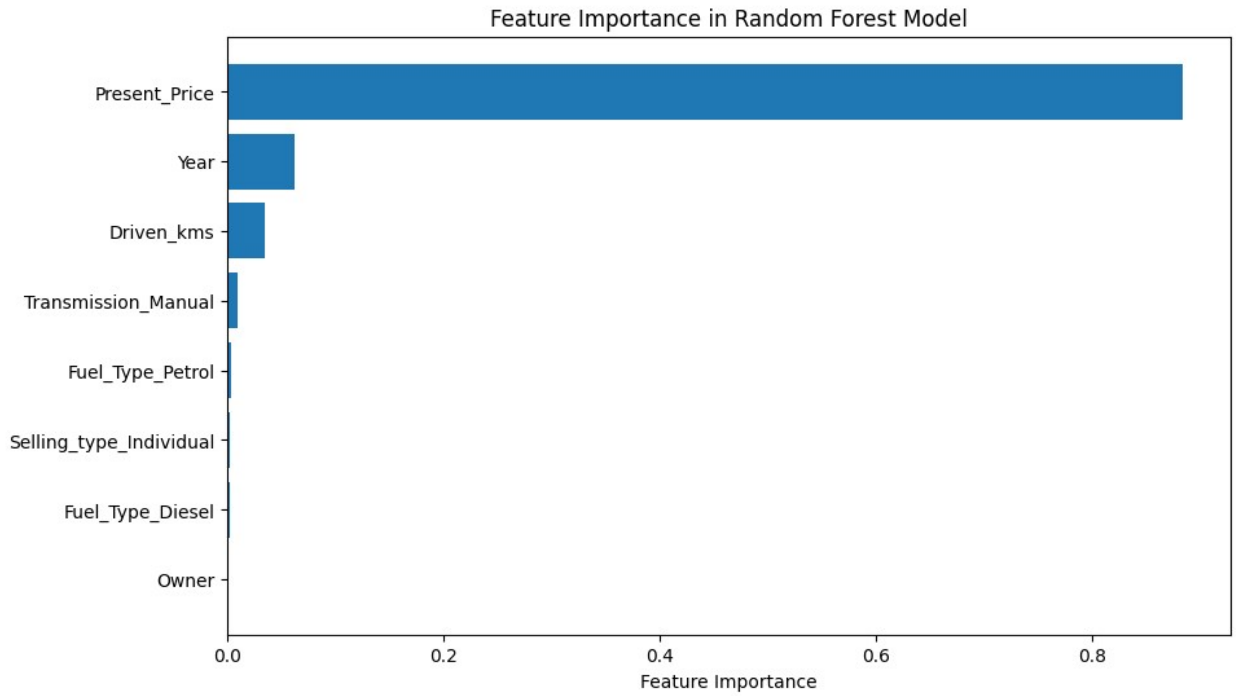



```
import numpy as np

feature_importances = model.feature_importances_
features = X.columns

sorted_idx = np.argsort(feature_importances)
plt.figure(figsize=(10, 6))
plt.barh(range(len(sorted_idx)), feature_importances[sorted_idx],
align="center")
plt.yticks(range(len(sorted_idx)), np.array(features)[sorted_idx])
plt.xlabel("Feature Importance")
```

```python
plt.title("Feature Importance in Random Forest Model")
plt.show()
```




```python
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.5, color="blue")
plt.xlabel("Actual Selling Price")
plt.ylabel("Predicted Selling Price")
plt.title("Actual vs Predicted Selling Price")
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
color="red", linestyle="--")  # Perfect fit line
plt.show()
```

Conclusion:Linear Regression vs. Random Forest Regressor

In My Car Price Prediction project, I compared Linear Regression and Random Forest Regressor. Here's how they performed:

Metric Linear Regression Random Forest Regressor

MAE 1.31 0.98 (Better)
MSE 3.55 2.43 (Better)
RMSE 1.88 1.56 (Better)
R^2 Score 0.85 0.89 (Better)

Key Takeaways

Random Forest Regressor performs better than Linear Regression in all metrics.
Lower MAE and RMSE mean the Random Forest model makes more accurate price predictions.
Higher R^2 Score (0.89 vs. 0.85) means Random Forest explains more variance in car prices.
Linear Regression assumes a linear relationship, while Random Forest captures complex patterns and interactions better.