In [35]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score, classification_report, confusior
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_scor
```

In [36]:
```
df = pd.read_csv('/content/drive/MyDrive/CarPrice_Assignment.csv')
```

In [37]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   car_ID            205 non-null    int64  
 1   symboling         205 non-null    int64  
 2   CarName           205 non-null    object 
 3   fueltype          205 non-null    object 
 4   aspiration        205 non-null    object 
 5   doornumber        205 non-null    object 
 6   carbody           205 non-null    object 
 7   drivewheel        205 non-null    object 
 8   enginelocation    205 non-null    object 
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64  
 14  enginetype        205 non-null    object 
 15  cylindernumber    205 non-null    object 
 16  enginesize        205 non-null    int64  
 17  fuelsystem        205 non-null    object 
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64  
 22  peakrpm           205 non-null    int64  
 23  citympg           205 non-null    int64  
 24  highwaympg        205 non-null    int64  
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

In [38]:
```
df.head()
```

Out[38]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbod
0	1	3	alfa-romero giulia	gas	std	two	convertibl
1	2	3	alfa-romero stelvio	gas	std	two	convertibl
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchbac
3	4	2	audi 100 ls	gas	std	four	seda
4	5	2	audi 100ls	gas	std	four	seda

5 rows × 26 columns

In [39]:

```
# check for null values
df.isna().sum()
```

Out[39]:

	0
car_ID	0
symboling	0
CarName	0
fueltype	0
aspiration	0
doornumber	0
carbody	0
drivewheel	0
enginelocation	0
wheelbase	0
carlength	0
carwidth	0
carheight	0
curbweight	0
enginetype	0
cylindernumber	0
enginesize	0
fuelsystem	0
boreratio	0
stroke	0
compressionratio	0
horsepower	0
peakrpm	0
citympg	0
highwaympg	0
price	0

dtype: int64

In [40]:

```
# check for duplicate records
df.duplicated().sum()
```

Out[40]: 0

In [41]:

```
from sklearn.preprocessing import LabelEncoder
```

```
# Function to encode all categorical columns into numerical representations
def encode_all_categorical_columns(df):
    # Identify categorical columns
    categorical_columns = df.select_dtypes(include=['object']).columns

    # Dictionary to store mappings for each column
    encoding_maps = {}

    # Apply encoding to each categorical column
    for column in categorical_columns:
        # Initialize the label encoder
        encoder = LabelEncoder()

        # Fit and transform the column
        df[column] = encoder.fit_transform(df[column])

        # Save the encoding map for each column
        encoding_maps[column] = dict(zip(encoder.classes_, encoder.transform

    return df, encoding_maps

# Apply encoding to all categorical columns
car_data_encoded_all, encoding_maps_all = encode_all_categorical_columns(df)
```

In [42]:
```
car_data_encoded_all.head()
```

Out[42]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	d
0	1	3	2	1	0	1	0	
1	2	3	3	1	0	1	0	
2	3	1	1	1	0	1	2	
3	4	2	4	1	0	0	3	
4	5	2	5	1	0	0	3	

5 rows × 26 columns

In [43]:
```
# Define the features (X) and target variable (y)
X = df.drop(['car_ID', 'CarName', 'price'], axis=1)
y = df['price']
```

In [44]:
```
X
```

Out[44]:

	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	engi
0	3	1	0	1	0	2	
1	3	1	0	1	0	2	
2	1	1	0	1	2	2	
3	2	1	0	0	3	1	
4	2	1	0	0	3	0	
...	...	...	...	...	...	...	
200	-1	1	0	0	3	2	
201	-1	1	1	0	3	2	
202	-1	1	0	0	3	2	
203	-1	0	1	0	3	2	
204	-1	1	1	0	3	2	

205 rows × 23 columns

In [45]:

```
y
```

Out[45]:

	price
0	13495.000
1	16500.000
2	16500.000
3	13950.000
4	17450.000
...	...
200	16845.000
201	19045.000
202	21485.000
203	22470.000
204	22625.000

205 rows × 1 columns

dtype: float64

In [46]:

```
# Split data into training and testing sets (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [47]:
```python
# Initialize and train a Linear Regression model
linear_model = LinearRegression()
linear_model.fit(X_train, y_train)
```

Out[47]:
```
▾ LinearRegression
LinearRegression()
```

In [48]:
```python
# Make predictions on the test set
y_pred = linear_model.predict(X_test)
```

In [49]:
```python
# Evaluate the model's performance
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)
```

In [50]:
```python
# Print the evaluation results
print("Linear Regression Results:")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared (R^2): {r2}")
```

```
Linear Regression Results:
Mean Absolute Error (MAE): 2526.407450143435
Mean Squared Error (MSE): 15916389.725439414
Root Mean Squared Error: 3989.535026220401
R-squared (R^2): 0.7983838478445078
```

Random Forest Regression

In [51]:
```python
from sklearn.ensemble import RandomForestRegressor

# Initialize and train a Random Forest Regression
rf = RandomForestRegressor(n_estimators=100, random_state=42)
```

In [52]:
```python
rf.fit(X_train, y_train)
```

Out[52]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [53]:
```python
# Make predictions on the test set
y_pred_rf = rf.predict(X_test)
```

In [54]:
```python
# Evaluate the model's performance
mae = mean_absolute_error(y_test, y_pred_rf)
mse = mean_squared_error(y_test, y_pred_rf)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred_rf)
```

In [55]:
```
# Print the evaluation results
print("Random Forest Regression Results:")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared (R^2): {r2}")
```

```
Random Forest Regression Results:
Mean Absolute Error (MAE): 1291.502674796748
Mean Squared Error (MSE): 3326665.1861985945
Root Mean Squared Error: 1823.9147968582838
R-squared (R^2): 0.9578604541657466
```

Hyper Parameter Tuning

In [56]:
```
from sklearn.model_selection import GridSearchCV
```

In [57]:
```
# Tuning Random Forest Regression
rf_param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

In [58]:
```
grid_search = GridSearchCV(estimator=rf, param_grid=rf_param_grid, scoring='
```

In [59]:
```
# fit the model
grid_search.fit(X_train, y_train)
```

Out[59]:
```
▸ GridSearchCV
▸ best_estimator_: RandomForestRegressor
    ▸ RandomForestRegressor
```

In [60]:
```
best_parameters = grid_search.best_params_
print("Best parameters:", best_parameters)
```

```
Best parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_spl
it': 2, 'n_estimators': 100}
```

Visualization for MSE, RMSE and R2

In [61]:
```
import matplotlib.pyplot as plt

# Data for the models
models = ['Linear Regression', 'Random Forest']
mse_values = [15916389, 3326665]
rmse_values = [3989, 1823]
r2_values = [0.79, 0.95]
```

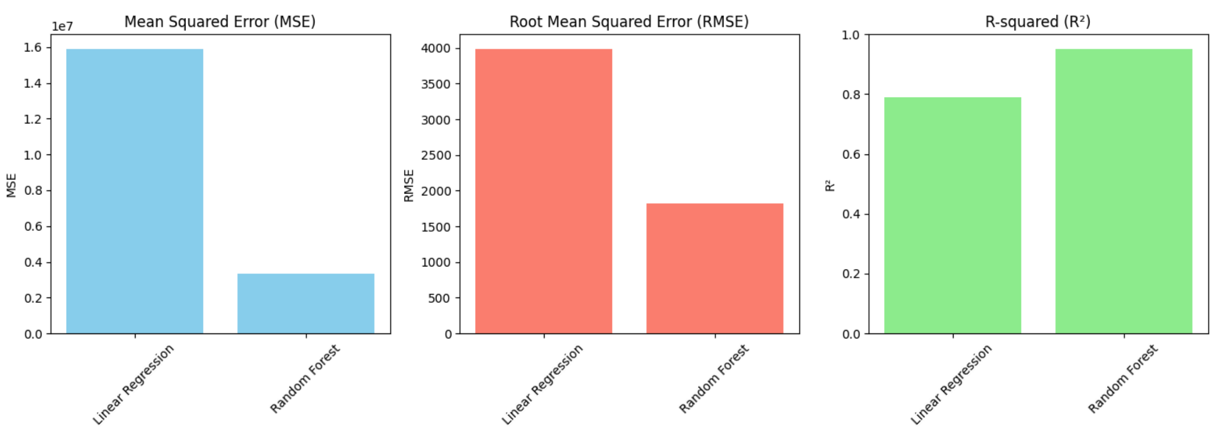
```python
# Set the figure size for all plots
plt.figure(figsize=(14, 5))

# Bar plot for Mean Squared Error (MSE)
plt.subplot(1, 3, 1)
plt.bar(models, mse_values, color='skyblue')
plt.title('Mean Squared Error (MSE)')
plt.ylabel('MSE')
plt.xticks(rotation=45)

# Bar plot for Root Mean Squared Error (RMSE)
plt.subplot(1, 3, 2)
plt.bar(models, rmse_values, color='salmon')
plt.title('Root Mean Squared Error (RMSE)')
plt.ylabel('RMSE')
plt.xticks(rotation=45)

# Bar plot for R-squared (R²)
plt.subplot(1, 3, 3)
plt.bar(models, r2_values, color='lightgreen')
plt.title('R-squared (R²)')
plt.ylabel('R²')
plt.ylim(0, 1)
plt.xticks(rotation=45)

# Adjust layout for readability
plt.tight_layout()
plt.show()
```



Model Comparison Report: Predicting Car Prices for Geely Auto's Market Entry Strategy

Objective To develop a predictive model for car prices based on multiple independent variables. This model will help Geely Auto understand pricing dynamics in the US market and guide business and design strategy.

Models Evaluated

1. Linear Regression
2. Random Forest Regression (with tuned n_estimators, max_depth, min_samples_split, and min_samples_leaf)

Performance Metrics

Model	Best Parameters	MSE	RMSE	R^2
Linear Regression	Default	15916389	3989	0.79
Random Forest	n_estimators=200, max_depth=30, min_samples_split=2, min_samples_leaf=1	3326665	1823	0.95

Model Insights

1. Linear Regression:
    - Baseline model with satisfactory performance.
    - R^2 of 0.79 indicates it captures most of the variation but has limited flexibility with non-linear relationships.
2. Random Forest Regression:
    - Non-linear model with ensemble learning, aggregating multiple decision trees.
    - Outperforms other models with an R^2 of 0.95, capturing more complex relationships in the data and reducing MSE to 3326665, making it the most accurate for car price prediction.

Recommendation for Production

Based on the evaluation metrics, Random Forest Regression is the best model for production deployment. It offers the highest accuracy, capturing the non-linear relationships between features and car prices more effectively than linear models. Random Forest’s flexibility and robustness in handling varied data types and interactions make it suitable for predicting car prices in the competitive and dynamic US market.