price-prediction-with-10-ml-models

February 25, 2025

[ ]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

[1]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

[3]:
```python
df = pd.read_csv("/kaggle/input/mobile-phones-dataset-specs-prices-and-trends/
↪Mobiles Dataset (2025).csv", encoding="latin-1")
```

[4]:
```python
df.head()
```

[4]:
```
  Company Name            Model Name Mobile Weight  RAM Front Camera  \
0        Apple       iPhone 16 128GB          174g  6GB         12MP
1        Apple       iPhone 16 256GB          174g  6GB         12MP
2        Apple       iPhone 16 512GB          174g  6GB         12MP
3        Apple  iPhone 16 Plus 128GB          203g  6GB         12MP
4        Apple  iPhone 16 Plus 256GB          203g  6GB         12MP

  Back Camera   Processor Battery Capacity Screen Size  \
0        48MP  A17 Bionic         3,600mAh  6.1 inches
1        48MP  A17 Bionic         3,600mAh  6.1 inches
2        48MP  A17 Bionic         3,600mAh  6.1 inches
3        48MP  A17 Bionic         4,200mAh  6.7 inches
4        48MP  A17 Bionic         4,200mAh  6.7 inches

  Launched Price (Pakistan) Launched Price (India) Launched Price (China)  \
0               PKR 224,999             INR 79,999             CNY 5,799
1               PKR 234,999             INR 84,999             CNY 6,099
2               PKR 244,999             INR 89,999             CNY 6,499
3               PKR 249,999             INR 89,999             CNY 6,199
4               PKR 259,999             INR 94,999             CNY 6,499

  Launched Price (USA) Launched Price (Dubai)  Launched Year
0              USD 799              AED 2,799           2024
1              USD 849              AED 2,999           2024
2              USD 899              AED 3,199           2024
3              USD 899              AED 3,199           2024
4              USD 949              AED 3,399           2024
```

[5]:
```python
df.isnull().sum()
```

[5]:
```
Company Name                 0
Model Name                   0
Mobile Weight                0
RAM                          0
Front Camera                 0
Back Camera                  0
Processor                    0
Battery Capacity             0
Screen Size                  0
```

```
Launched Price (Pakistan)    0
Launched Price (India)       0
Launched Price (China)       0
Launched Price (USA)         0
Launched Price (Dubai)       0
Launched Year                0
dtype: int64
```

[6]:
```python
df.shape
```

[6]: (930, 15)

[7]:
```python
df.duplicated().sum()
```

[7]: 15

[8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 930 entries, 0 to 929
Data columns (total 15 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Company Name               930 non-null    object
 1   Model Name                 930 non-null    object
 2   Mobile Weight              930 non-null    object
 3   RAM                        930 non-null    object
 4   Front Camera               930 non-null    object
 5   Back Camera                930 non-null    object
 6   Processor                  930 non-null    object
 7   Battery Capacity           930 non-null    object
 8   Screen Size                930 non-null    object
 9   Launched Price (Pakistan)  930 non-null    object
 10  Launched Price (India)     930 non-null    object
 11  Launched Price (China)     930 non-null    object
 12  Launched Price (USA)       930 non-null    object
 13  Launched Price (Dubai)     930 non-null    object
 14  Launched Year              930 non-null    int64
dtypes: int64(1), object(14)
memory usage: 109.1+ KB
```

[9]:
```python
df.describe()
```

[9]:

	Launched Year
count	930.000000
mean	2023.161290
std	29.629971

```
min      2014.000000
25%      2021.000000
50%      2023.000000
75%      2024.000000
max      2924.000000
```

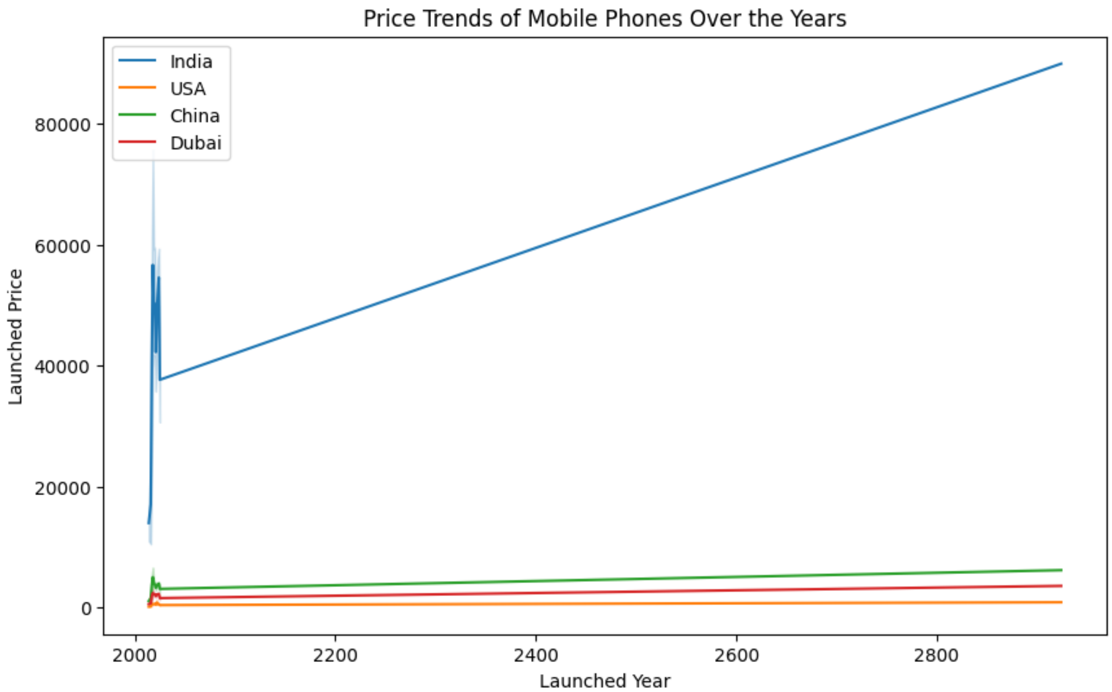
[10]:
```
def clean_numeric(value):
    if isinstance(value, str):
        value = ''.join([c for c in value if c.isdigit() or c == '.'])
        parts = value.split('.')
        if len(parts) > 2:
            value = parts[0] + '.' + parts[1]
        return float(value) if value else np.nan
    return value
```

[11]:
```
numeric_columns = [
    "Mobile Weight", "RAM", "Front Camera", "Back Camera",
    "Battery Capacity", "Screen Size", "Launched Price (Pakistan)",
    "Launched Price (India)", "Launched Price (China)",
    "Launched Price (USA)", "Launched Price (Dubai)"
]
```

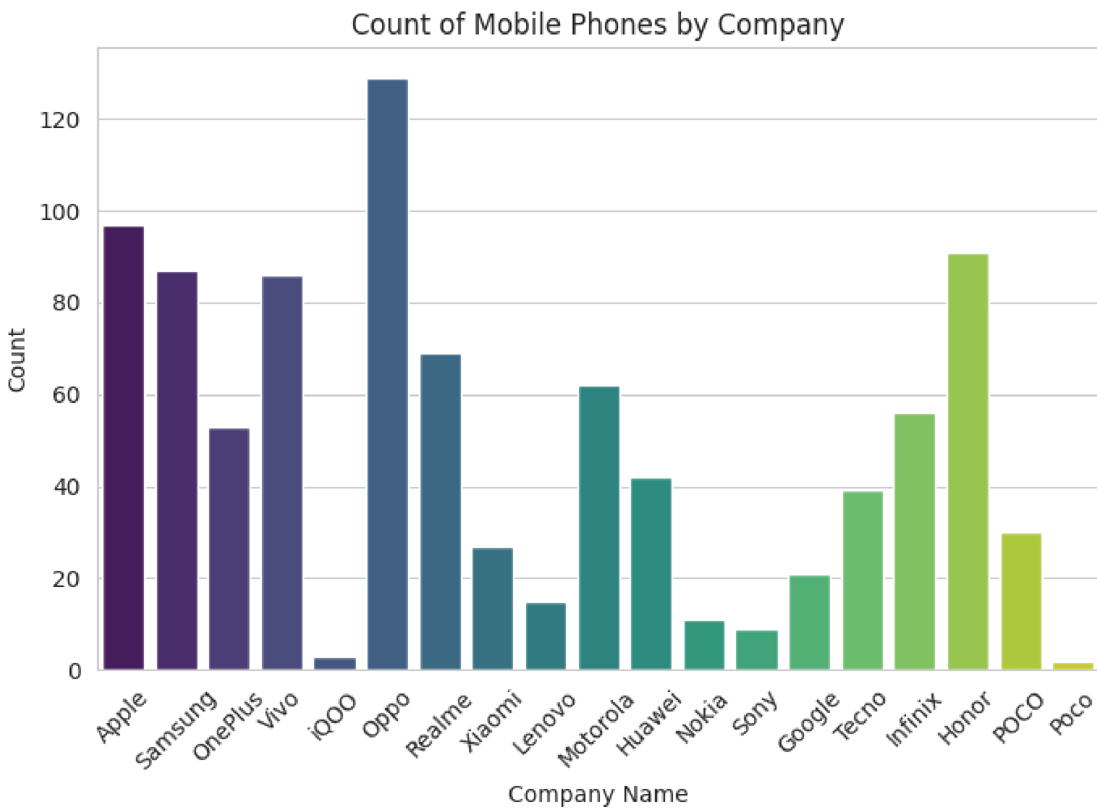
[12]:
```
numeric_columns = [col for col in numeric_columns if col in df.columns]
```

[13]:
```
df[numeric_columns] = df[numeric_columns].applymap(clean_numeric)
df.dropna(inplace=True)
```

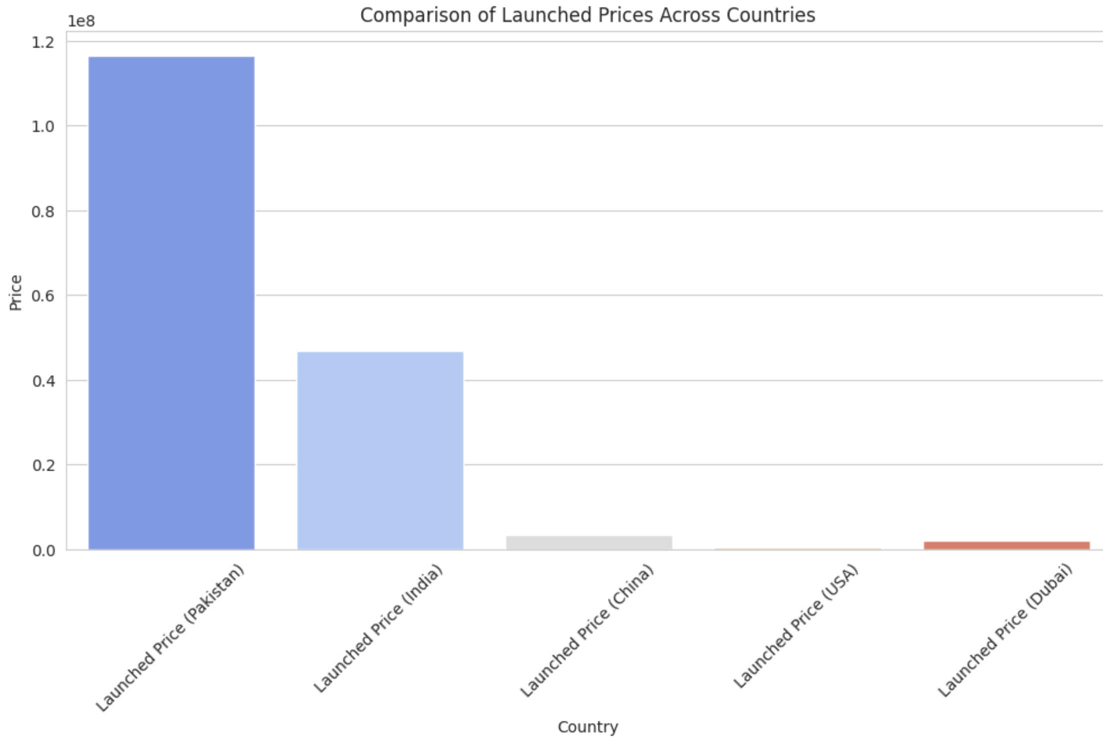
[14]:
```
plt.figure(figsize=(10, 6))
sns.lineplot(x='Launched Year', y='Launched Price (India)', data=df,␣
 ↪label='India')
sns.lineplot(x='Launched Year', y='Launched Price (USA)', data=df, label='USA')
sns.lineplot(x='Launched Year', y='Launched Price (China)', data=df,␣
 ↪label='China')
sns.lineplot(x='Launched Year', y='Launched Price (Dubai)', data=df,␣
 ↪label='Dubai')
plt.title("Price Trends of Mobile Phones Over the Years")
plt.xlabel("Launched Year")
plt.ylabel("Launched Price")
plt.legend()
plt.show()
```



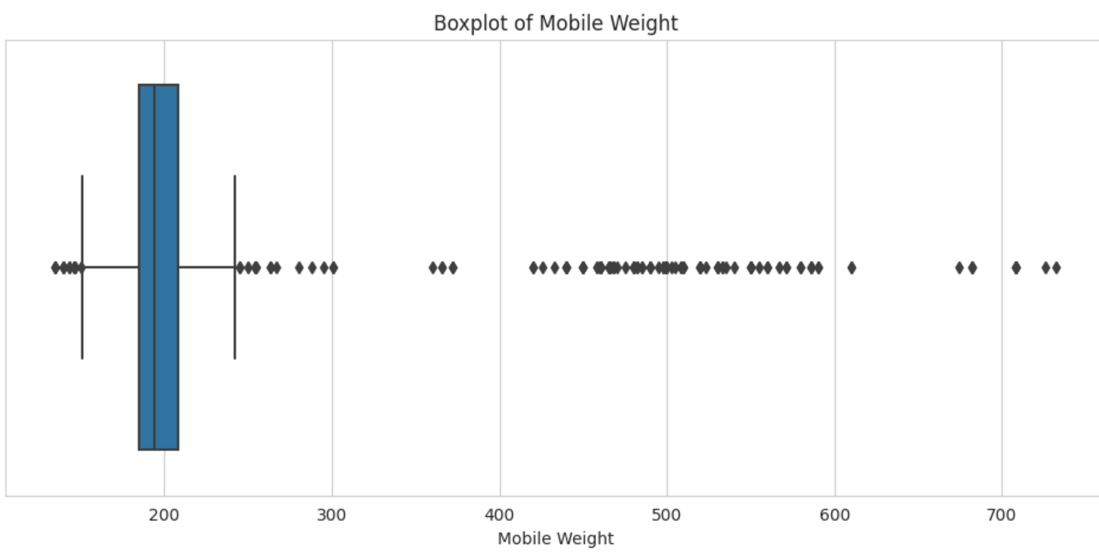
[31]:
```
# Set Seaborn style
sns.set_style("whitegrid")

# Countplot for Company Name
plt.figure(figsize=(8, 5))
sns.countplot(x='Company Name', data=df, palette='viridis')
plt.title("Count of Mobile Phones by Company")
plt.xlabel("Company Name")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```



[32]:
```
# Bar plot for price comparisons across different countries
plt.figure(figsize=(12, 6))
price_columns = [
    "Launched Price (Pakistan)", "Launched Price (India)",
    "Launched Price (China)", "Launched Price (USA)", "Launched Price (Dubai)"
]
data_melted = df.melt(id_vars=["Model Name"], value_vars=price_columns,␣
↪var_name="Country", value_name="Price")

sns.barplot(x="Country", y="Price", data=data_melted, estimator=sum, ci=None,␣
↪palette="coolwarm")
plt.title("Comparison of Launched Prices Across Countries")
plt.xticks(rotation=45)
plt.ylabel("Price")
plt.show()
```

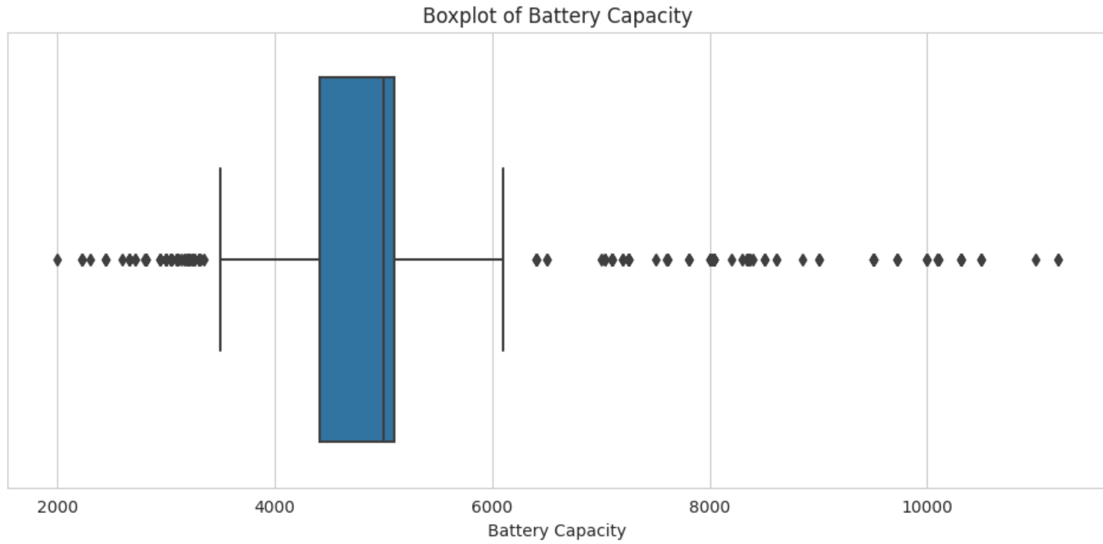


[33]:
```python
# Boxplot for numerical distributions
plt.figure(figsize=(12, 5))
sns.boxplot(x=df["Mobile Weight"])
plt.title("Boxplot of Mobile Weight")
plt.show()
```



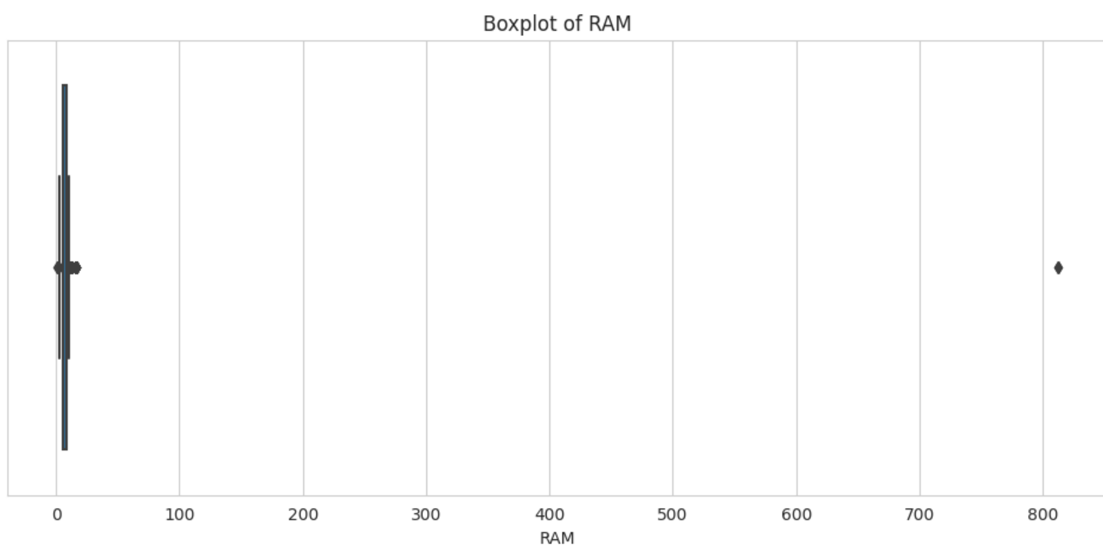
[34]:

```
plt.figure(figsize=(12, 5))
sns.boxplot(x=df["Battery Capacity"])
plt.title("Boxplot of Battery Capacity")
plt.show()
```

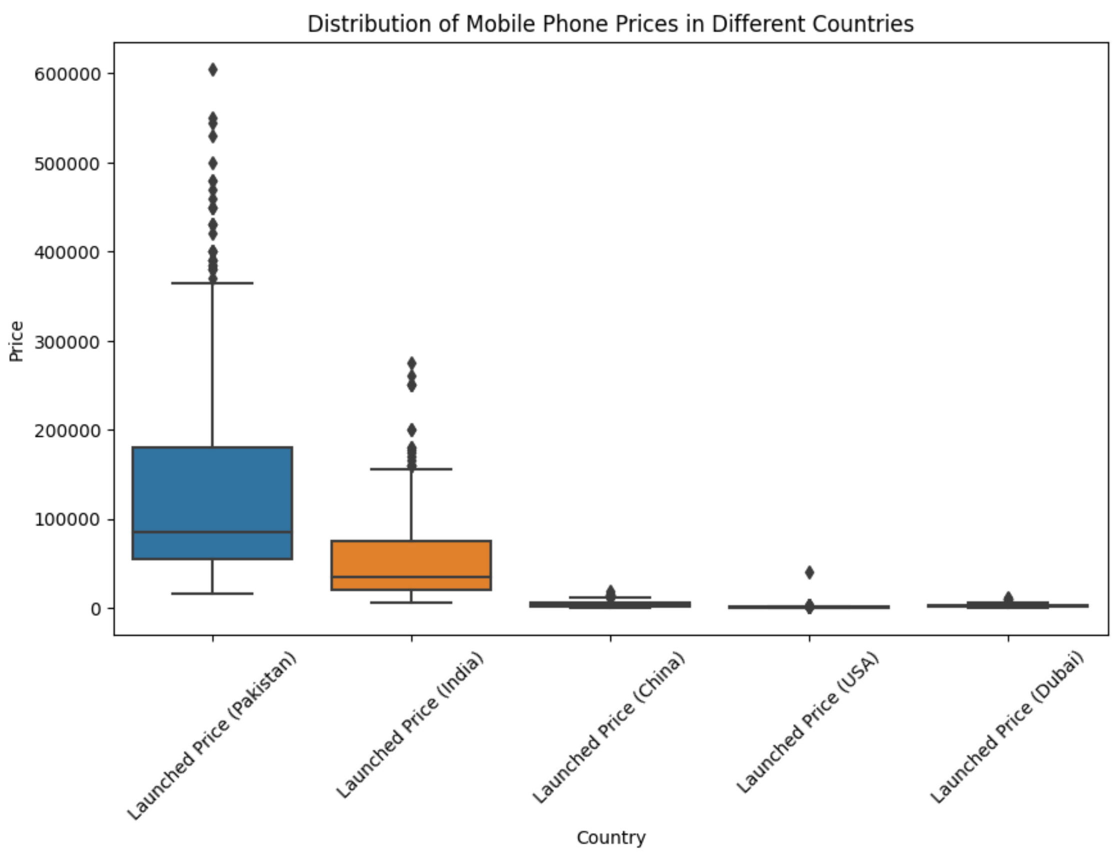


[35]:

```
plt.figure(figsize=(12, 5))
sns.boxplot(x=df["RAM"])
plt.title("Boxplot of RAM")
plt.show()
```

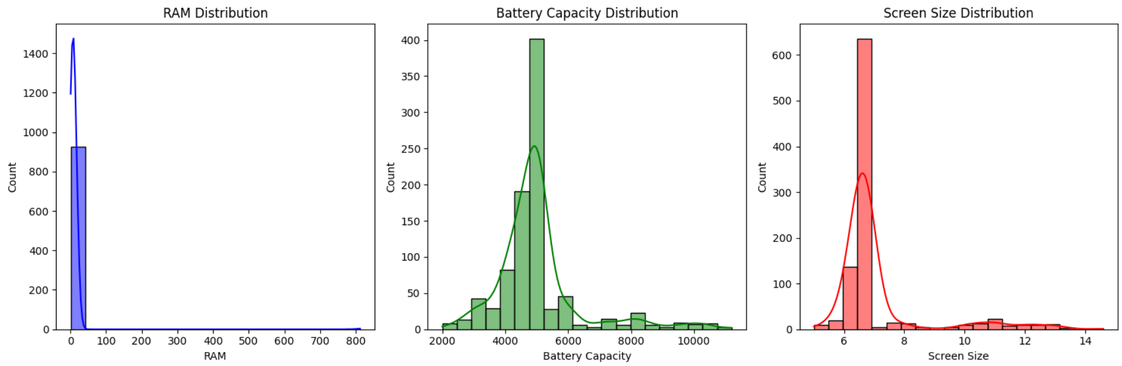


[15]:
```
plt.figure(figsize=(10, 6))
price_cols = ['Launched Price (Pakistan)', 'Launched Price (India)',
              'Launched Price (China)', 'Launched Price (USA)', 'Launched Price␣
 ↪(Dubai)']
df_melted = df.melt(id_vars=['Launched Year'], value_vars=price_cols,␣
 ↪var_name='Country', value_name='Price')
sns.boxplot(x='Country', y='Price', data=df_melted)
plt.xticks(rotation=45)
plt.title("Distribution of Mobile Phone Prices in Different Countries")
plt.show()
```

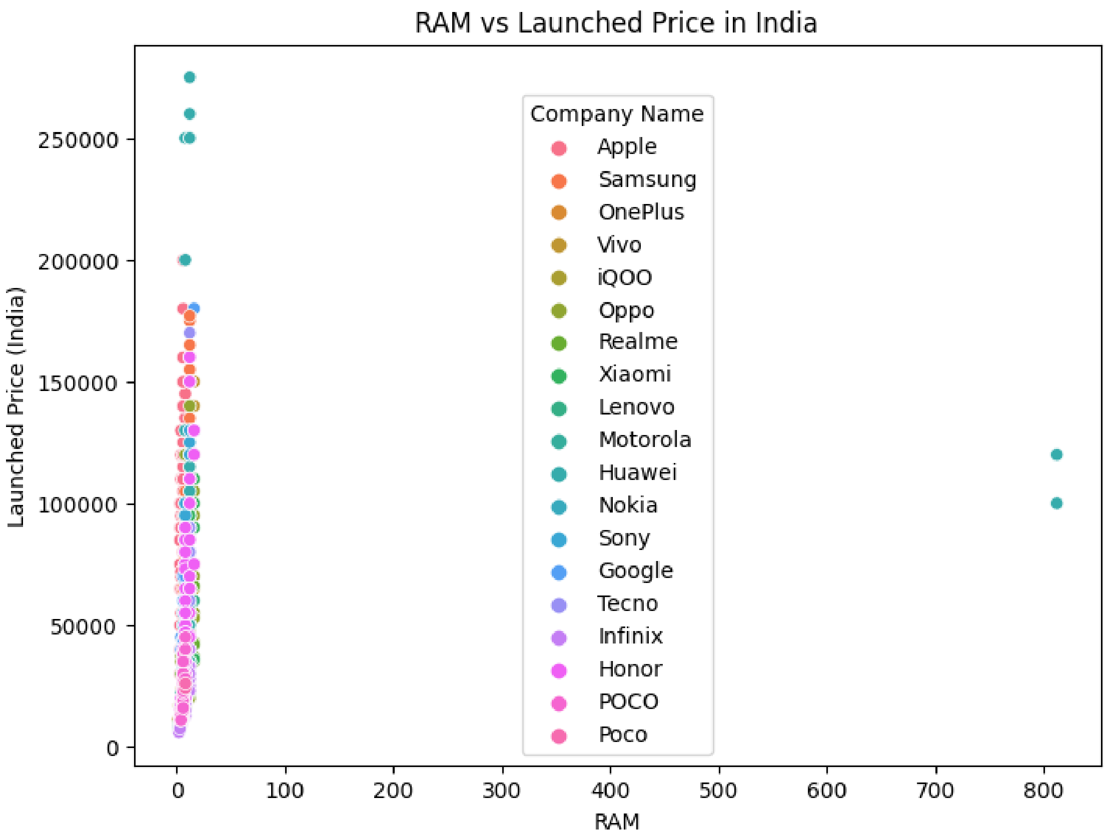


[16]:
```
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

sns.histplot(df['RAM'], bins=20, kde=True, ax=axes[0], color='blue')
axes[0].set_title("RAM Distribution")

sns.histplot(df['Battery Capacity'], bins=20, kde=True, ax=axes[1],␣
 ↪color='green')
axes[1].set_title("Battery Capacity Distribution")
```

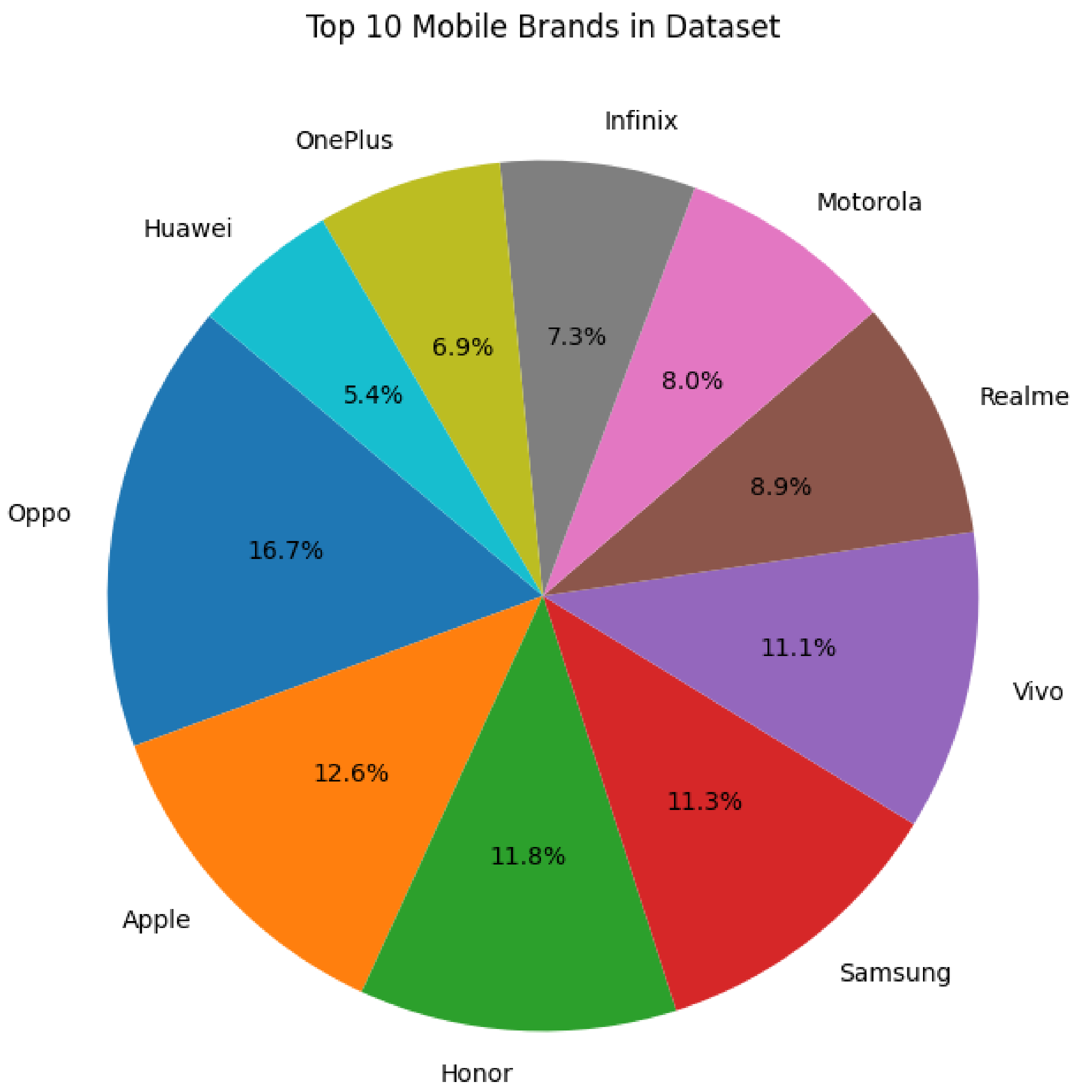
```
sns.histplot(df['Screen Size'], bins=20, kde=True, ax=axes[2], color='red')
axes[2].set_title("Screen Size Distribution")

plt.tight_layout()
plt.show()
```



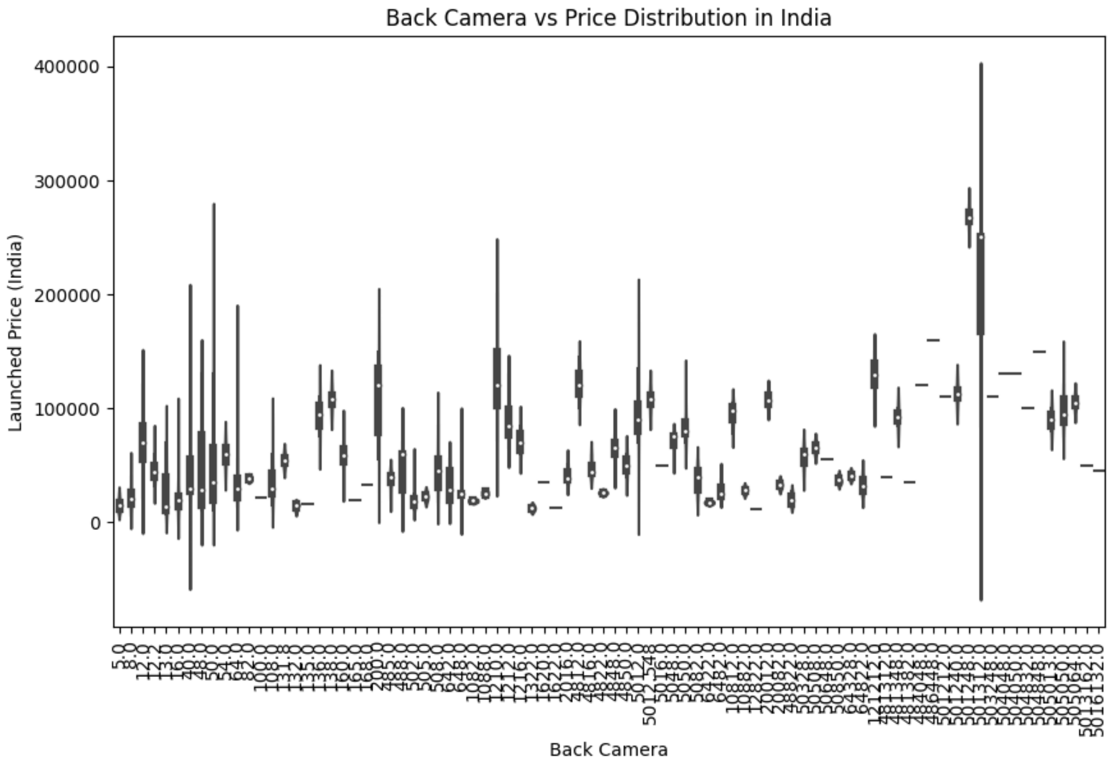
[17]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='RAM', y='Launched Price (India)', data=df, hue='Company␣
↪Name')
plt.title("RAM vs Launched Price in India")
plt.show()
```



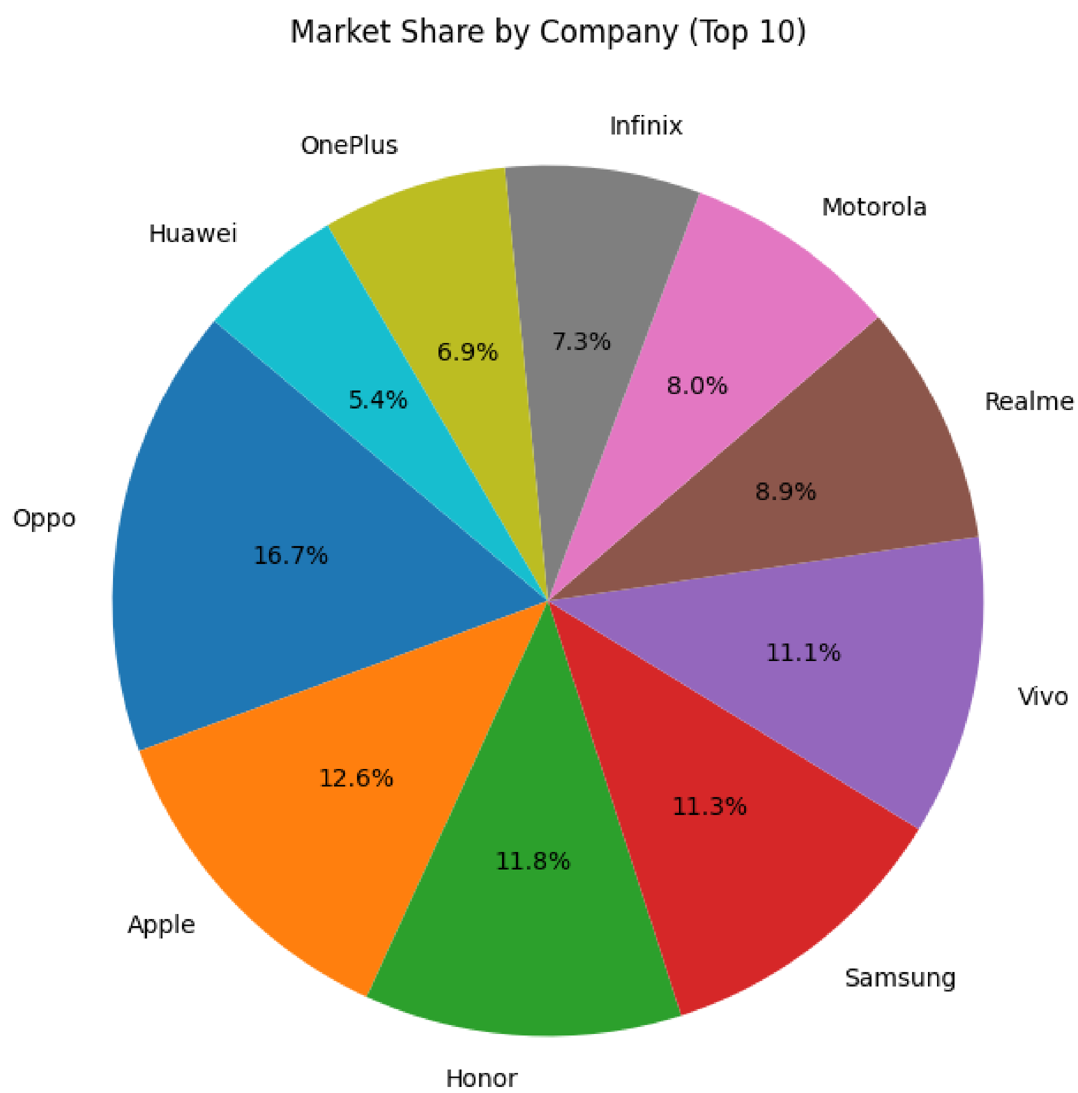
[18]:
```
brand_counts = df['Company Name'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(brand_counts[:10], labels=brand_counts.index[:10], autopct='%1.1f%%',
    startangle=140)
plt.title("Top 10 Mobile Brands in Dataset")
plt.show()
```



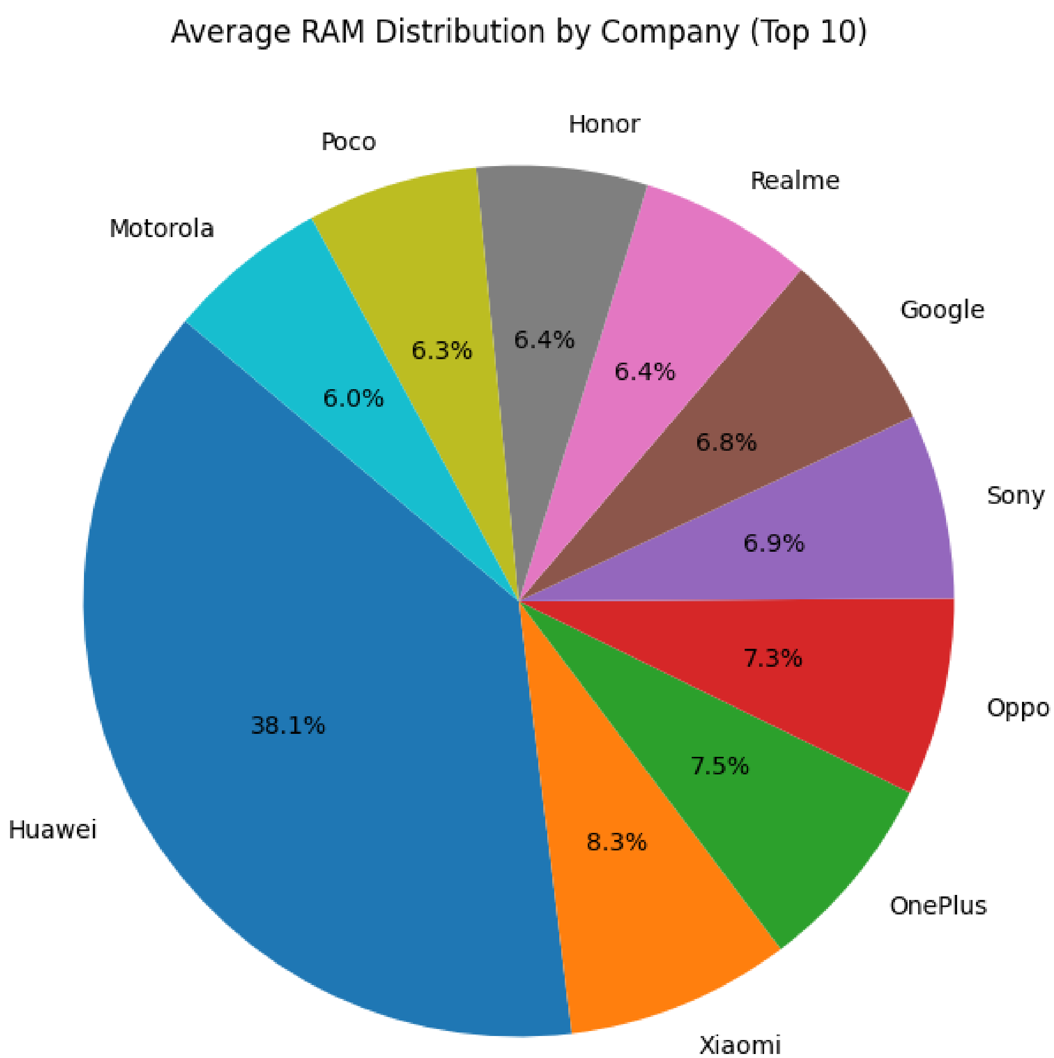
[20]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(x='Back Camera', y='Launched Price (India)', data=df)
plt.xticks(rotation=90)
plt.title("Back Camera vs Price Distribution in India")
plt.show()
```



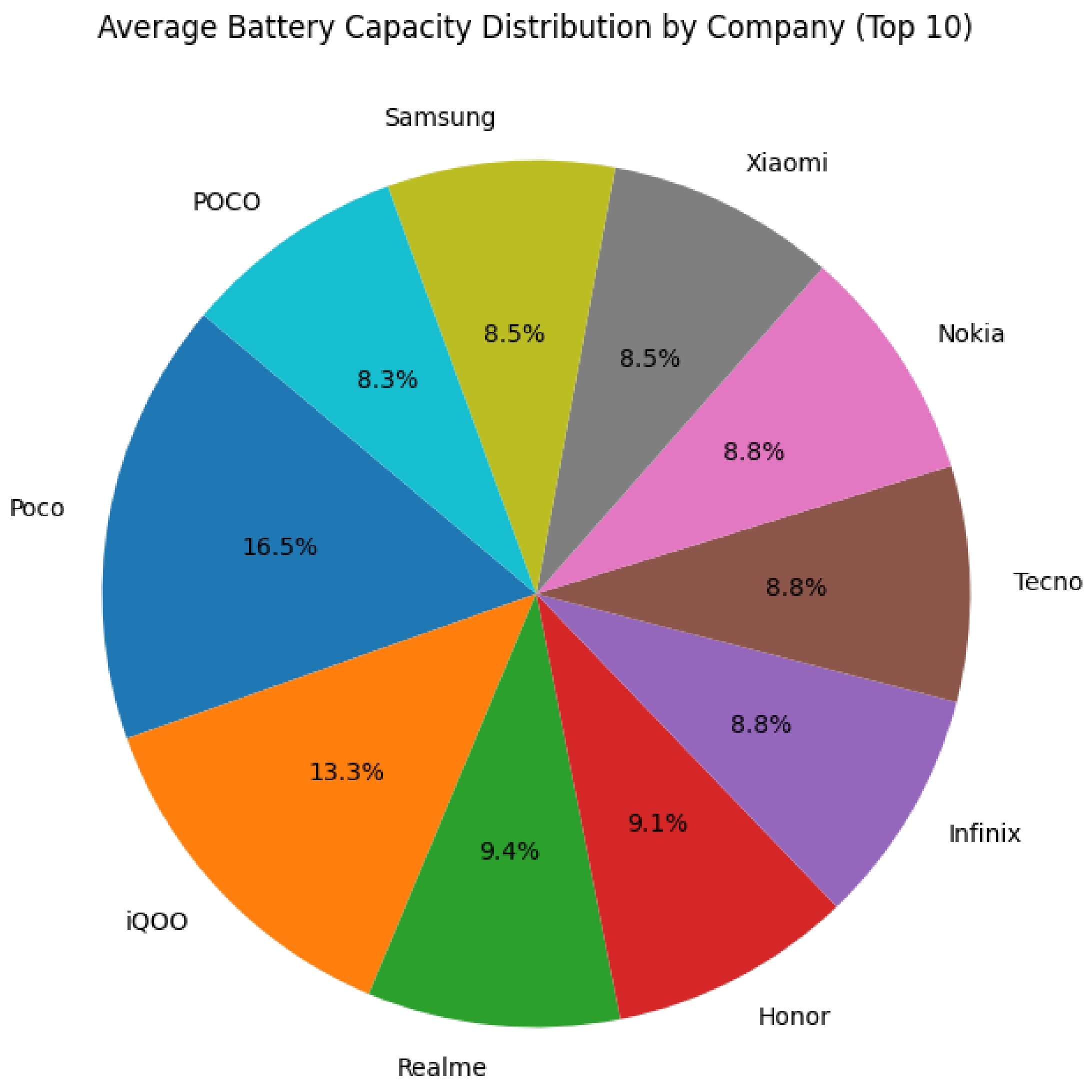
[21]:
```
company_counts = df["Company Name"].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(company_counts[:10], labels=company_counts.index[:10], autopct='%1.
 ↪1f%%', startangle=140)
plt.title("Market Share by Company (Top 10)")
plt.show()
```



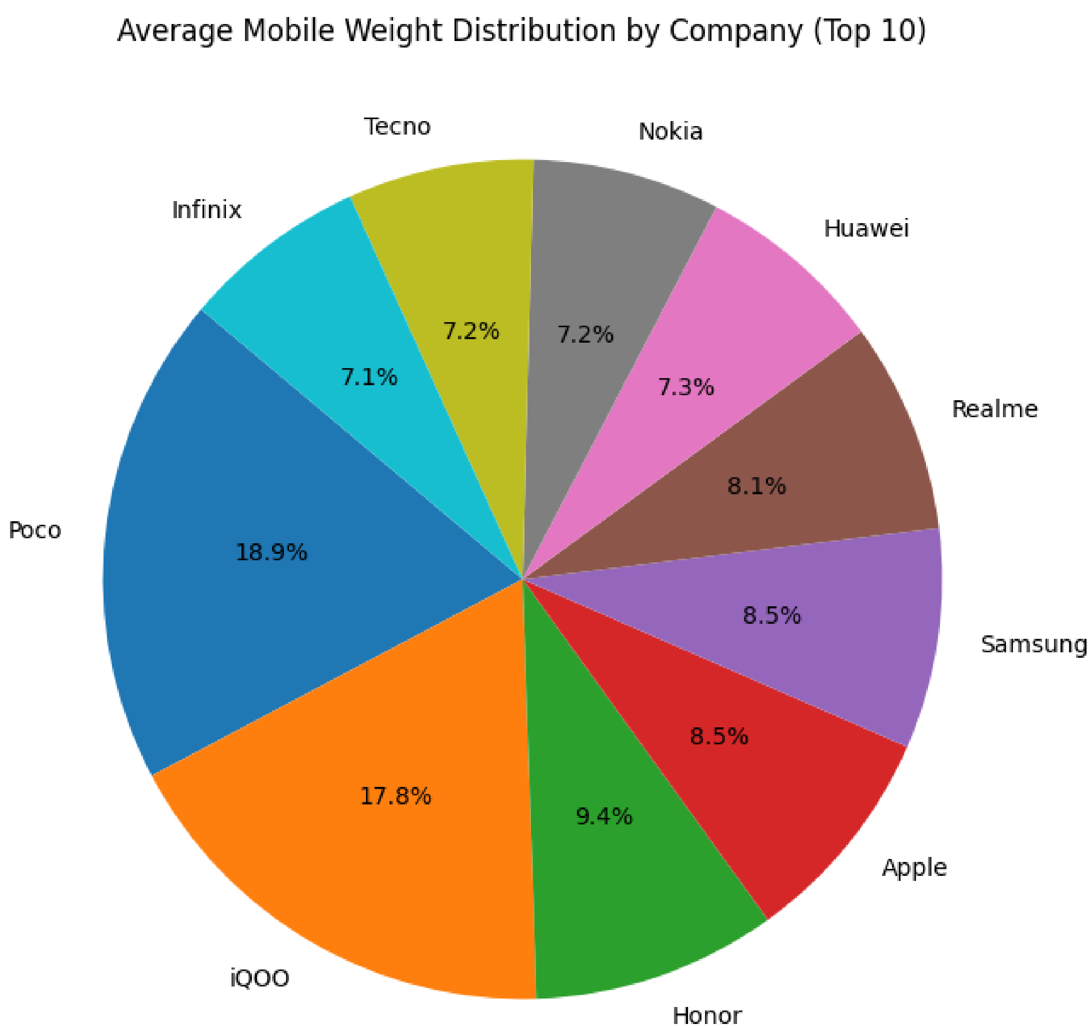
[22]:
```
avg_ram = df.groupby("Company Name")["RAM"].mean().
  ↪sort_values(ascending=False)[:10]
plt.figure(figsize=(8, 8))
plt.pie(avg_ram, labels=avg_ram.index, autopct='%1.1f%%', startangle=140)
plt.title("Average RAM Distribution by Company (Top 10)")
plt.show()
```



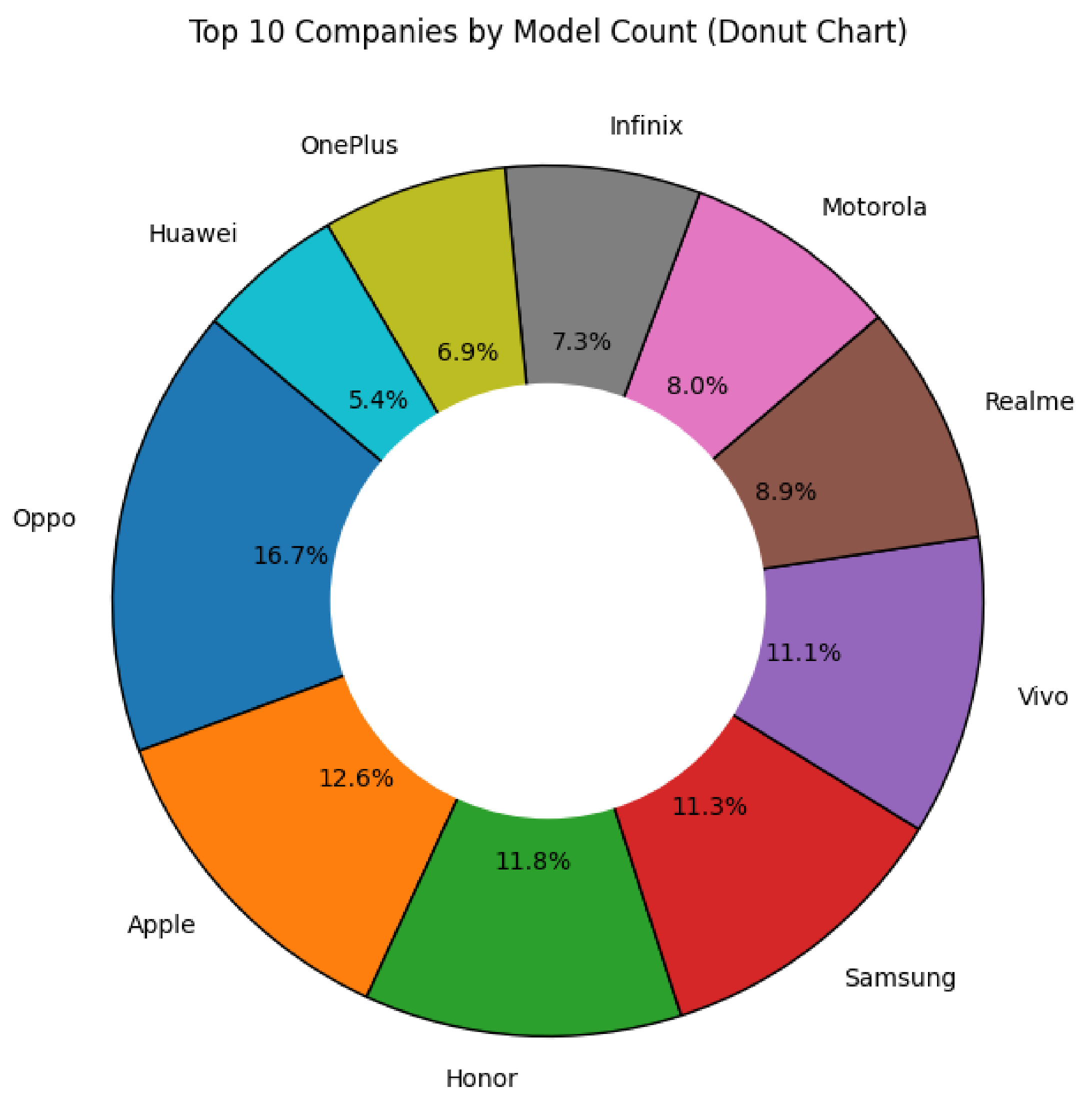
[23]:
```
avg_battery = df.groupby("Company Name")["Battery Capacity"].mean().
    ↪sort_values(ascending=False)[:10]
plt.figure(figsize=(8, 8))
plt.pie(avg_battery, labels=avg_battery.index, autopct='%1.1f%%',␣
    ↪startangle=140)
plt.title("Average Battery Capacity Distribution by Company (Top 10)")
plt.show()
```



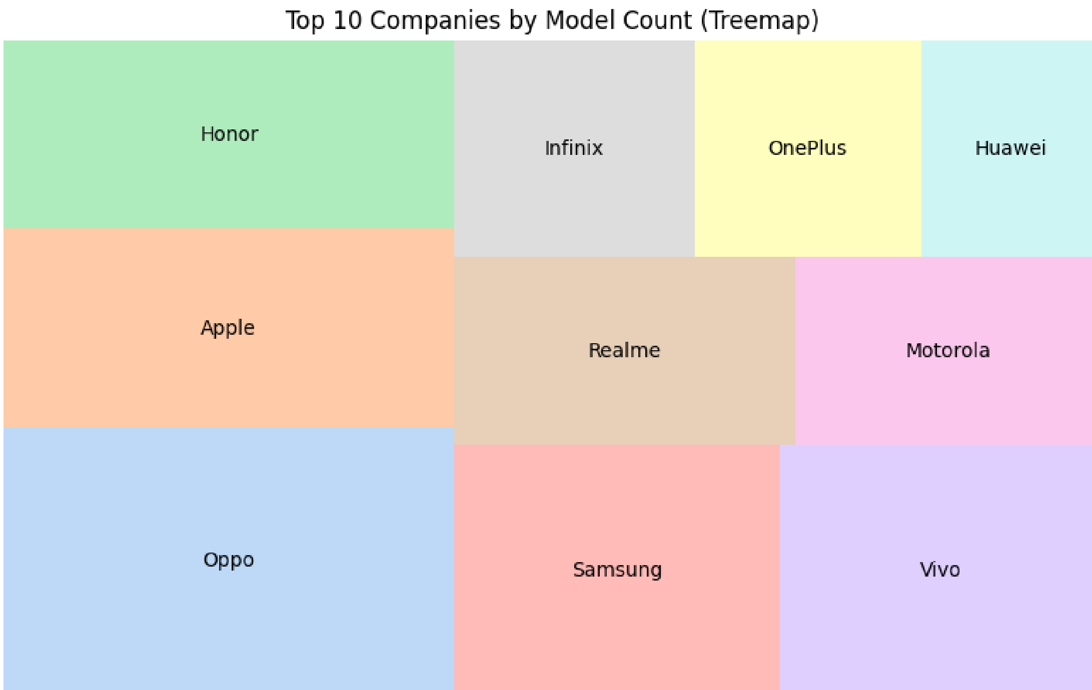
[24]:
```
avg_weight = df.groupby("Company Name")["Mobile Weight"].mean().
  ↪sort_values(ascending=False)[:10]
plt.figure(figsize=(8, 8))
plt.pie(avg_weight, labels=avg_weight.index, autopct='%1.1f%%', startangle=140)
plt.title("Average Mobile Weight Distribution by Company (Top 10)")
plt.show()
```



[25]:
```
plt.figure(figsize=(8, 8))
company_counts = df["Company Name"].value_counts().head(10)
plt.pie(company_counts, labels=company_counts.index, autopct='%1.1f%%',␣
↪startangle=140, wedgeprops={'edgecolor': 'black'})
plt.gca().add_artist(plt.Circle((0, 0), 0.5, fc='white'))  # Create the donut␣
↪effect
plt.title("Top 10 Companies by Model Count (Donut Chart)")
plt.show()
```

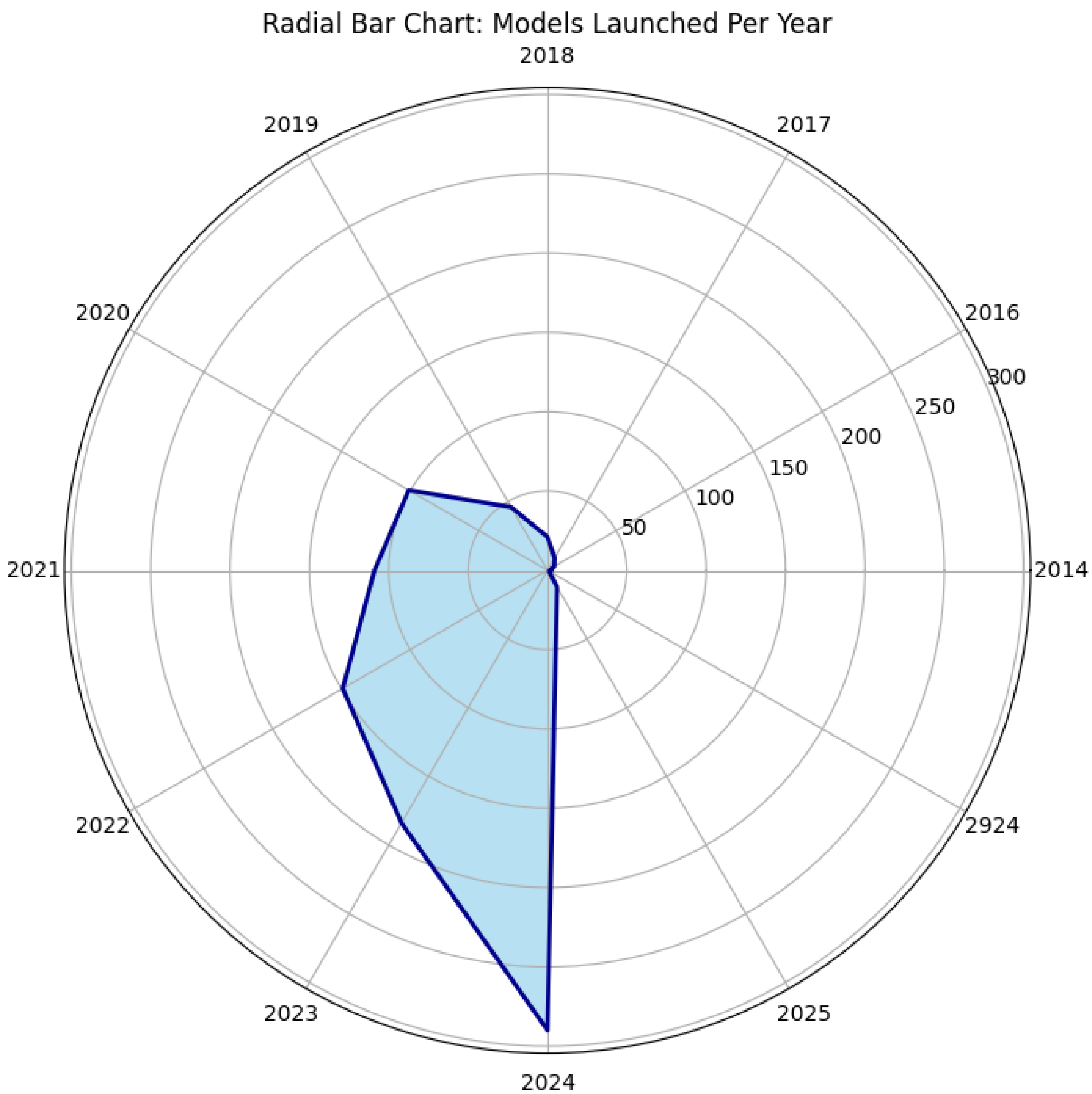


[26]:
```
import squarify

company_counts = df["Company Name"].value_counts().head(10)
plt.figure(figsize=(10, 6))
squarify.plot(sizes=company_counts, label=company_counts.index, alpha=0.7,␣
↪color=sns.color_palette("pastel"))
plt.title("Top 10 Companies by Model Count (Treemap)")
plt.axis("off")
plt.show()
```

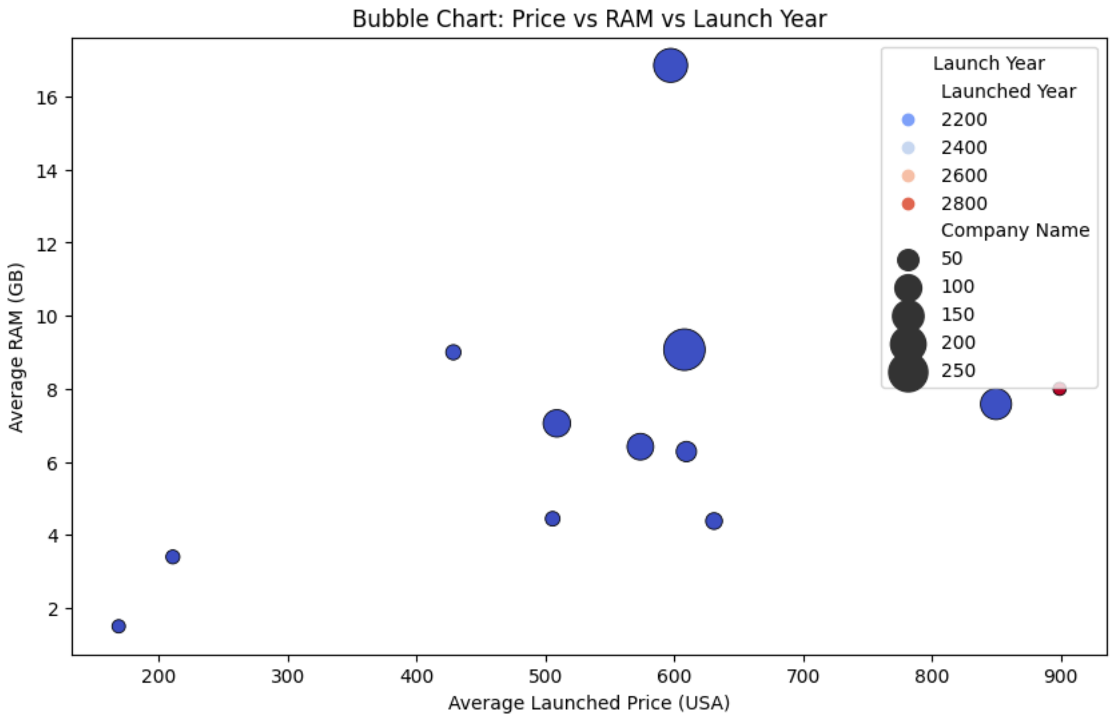


[27]:

```
from math import pi

launch_year_counts = df["Launched Year"].value_counts().sort_index()
categories = launch_year_counts.index
values = launch_year_counts.values

angles = [n / float(len(categories)) * 2 * pi for n in range(len(categories))]
values = list(values) + [values[0]]  # Loop back to start for a closed chart
angles += [angles[0]]

fig, ax = plt.subplots(figsize=(8, 8), subplot_kw={'projection': 'polar'})
ax.fill(angles, values, color='skyblue', alpha=0.6)
ax.plot(angles, values, color='darkblue', linewidth=2)
ax.set_xticks(angles[:-1])
ax.set_xticklabels(categories, fontsize=10)
ax.set_title("Radial Bar Chart: Models Launched Per Year")
plt.show()
```



[28]:
```
plt.figure(figsize=(10, 6))
df_grouped = df.groupby("Launched Year").agg({"Launched Price (USA)": "mean",␣
↪"RAM": "mean", "Company Name": "count"}).reset_index()
sns.scatterplot(x="Launched Price (USA)", y="RAM", size="Company Name",␣
↪hue="Launched Year", data=df_grouped, sizes=(50, 500), palette="coolwarm",␣
↪edgecolor="black")
plt.title("Bubble Chart: Price vs RAM vs Launch Year")
plt.xlabel("Average Launched Price (USA)")
plt.ylabel("Average RAM (GB)")
plt.legend(title="Launch Year")
plt.show()
```



[29]:
```
df.head()
```

[29]:
```
  Company Name            Model Name  Mobile Weight  RAM  Front Camera  \
0        Apple       iPhone 16 128GB          174.0  6.0          12.0
1        Apple       iPhone 16 256GB          174.0  6.0          12.0
2        Apple       iPhone 16 512GB          174.0  6.0          12.0
3        Apple  iPhone 16 Plus 128GB          203.0  6.0          12.0
4        Apple  iPhone 16 Plus 256GB          203.0  6.0          12.0

   Back Camera   Processor  Battery Capacity  Screen Size  \
0         48.0  A17 Bionic            3600.0          6.1
1         48.0  A17 Bionic            3600.0          6.1
2         48.0  A17 Bionic            3600.0          6.1
3         48.0  A17 Bionic            4200.0          6.7
4         48.0  A17 Bionic            4200.0          6.7

   Launched Price (Pakistan)  Launched Price (India)  Launched Price (China)  \
0                   224999.0                 79999.0                  5799.0
1                   234999.0                 84999.0                  6099.0
2                   244999.0                 89999.0                  6499.0
3                   249999.0                 89999.0                  6199.0
4                   259999.0                 94999.0                  6499.0

   Launched Price (USA)  Launched Price (Dubai)  Launched Year
```

0	799.0	2799.0	2024
1	849.0	2999.0	2024
2	899.0	3199.0	2024
3	899.0	3199.0	2024
4	949.0	3399.0	2024

[36]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

[37]:
```
label_encoder = LabelEncoder()
df["Company Name"] = label_encoder.fit_transform(df["Company Name"])
df["Processor"] = label_encoder.fit_transform(df["Processor"])

# Step 5: Select features and target variable
features = ["Mobile Weight", "RAM", "Front Camera", "Back Camera", "Battery␣
↪Capacity", "Screen Size"]
target = "Launched Price (India)"  # Choose the target column
```

[38]:
```
X = df[features]
y = df[target]

# Step 6: Split dataset into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[39]:
```
# Step 7: Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

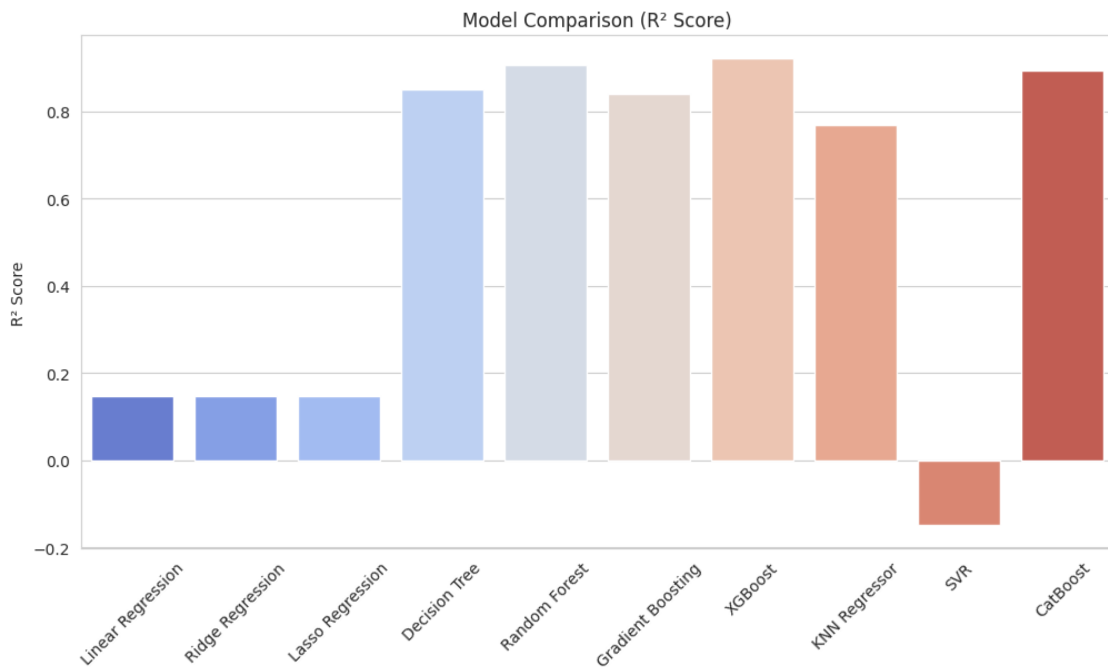
[40]:
```
# Step 8: Define regression models
models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(),
    "Lasso Regression": Lasso(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor(),
    "XGBoost": XGBRegressor(),
```

```
    "KNN Regressor": KNeighborsRegressor(),
    "SVR": SVR(),
    "CatBoost": CatBoostRegressor(verbose=0)  # Silent output
}
```

[41]:
```
# Step 9: Train and evaluate each model
results = {}

for name, model in models.items():
    model.fit(X_train, y_train)  # Train model
    y_pred = model.predict(X_test)  # Predict on test data

    # Step 10: Evaluate model performance
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)

    results[name] = [mae, rmse, r2]

# Step 11: Convert results into a DataFrame
results_df = pd.DataFrame(results, index=["MAE", "RMSE", "R2"]).T

# Step 12: Print performance metrics
print(results_df)
```

```
                            MAE          RMSE        R2
Linear Regression  28730.101752  36618.414259  0.147823
Ridge Regression   28754.311975  36639.884189  0.146823
Lasso Regression   28731.474366  36620.302136  0.147735
Decision Tree       9065.673835  15254.095510  0.852122
Random Forest       7766.220728  12124.772875  0.906572
Gradient Boosting  11169.730281  15873.801449  0.839863
XGBoost             7193.845530  11125.893031  0.921332
KNN Regressor      11988.235484  19042.603394  0.769546
SVR                29566.851392  42528.767618 -0.149467
CatBoost            8380.182603  12886.372915  0.894466
```

[42]:
```
# Step 13: Visualize performance
plt.figure(figsize=(12, 6))
sns.barplot(x=results_df.index, y=results_df["R2"], palette="coolwarm")
plt.xticks(rotation=45)
plt.title("Model Comparison (R² Score)")
plt.ylabel("R² Score")
plt.show()
```



[43]:
```
best_model = results_df["R2"].idxmax()
print(f"Best model: {best_model} with R² Score = {results_df.loc[best_model, 'R2']:.4f}")
```

```
Best model: XGBoost with R² Score = 0.9213
```

[44]:
```
X = df.drop(columns=["Launched Price (USA)", "Model Name"])  # Remove model name & target
y = df["Launched Price (USA)"]
```

[45]:
```
# Scale numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train-test split (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

[46]:
```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Predictions
y_pred_lr = lr_model.predict(X_test)

# Evaluate performance
```

```python
print("Linear Regression:")
print("MAE:", mean_absolute_error(y_test, y_pred_lr))
print("MSE:", mean_squared_error(y_test, y_pred_lr))
print("R2 Score:", r2_score(y_test, y_pred_lr))
```

```
Linear Regression:
MAE: 134.07979047831506
MSE: 32219.483081254857
R2 Score: 0.8099473083984648
```

[47]:
```python
# Train model
dt_model = DecisionTreeRegressor(max_depth=10, random_state=42)
dt_model.fit(X_train, y_train)

# Predictions
y_pred_dt = dt_model.predict(X_test)

# Evaluate performance
print("Decision Tree:")
print("MAE:", mean_absolute_error(y_test, y_pred_dt))
print("MSE:", mean_squared_error(y_test, y_pred_dt))
print("R2 Score:", r2_score(y_test, y_pred_dt))
```

```
Decision Tree:
MAE: 32.925156359918915
MSE: 5707.085263923878
R2 Score: 0.9663356822679992
```

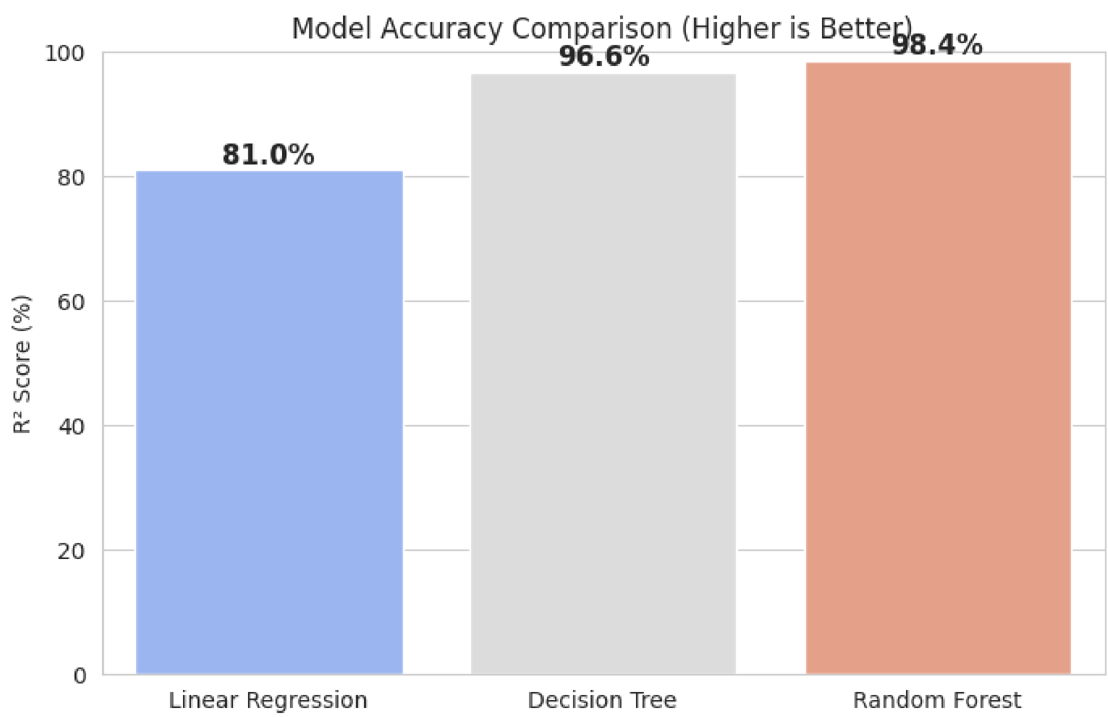
[48]:
```python
# Train model
rf_model = RandomForestRegressor(n_estimators=100, max_depth=10,
    random_state=42)
rf_model.fit(X_train, y_train)

# Predictions
y_pred_rf = rf_model.predict(X_test)

# Evaluate performance
print("Random Forest:")
print("MAE:", mean_absolute_error(y_test, y_pred_rf))
print("MSE:", mean_squared_error(y_test, y_pred_rf))
print("R2 Score:", r2_score(y_test, y_pred_rf))
```

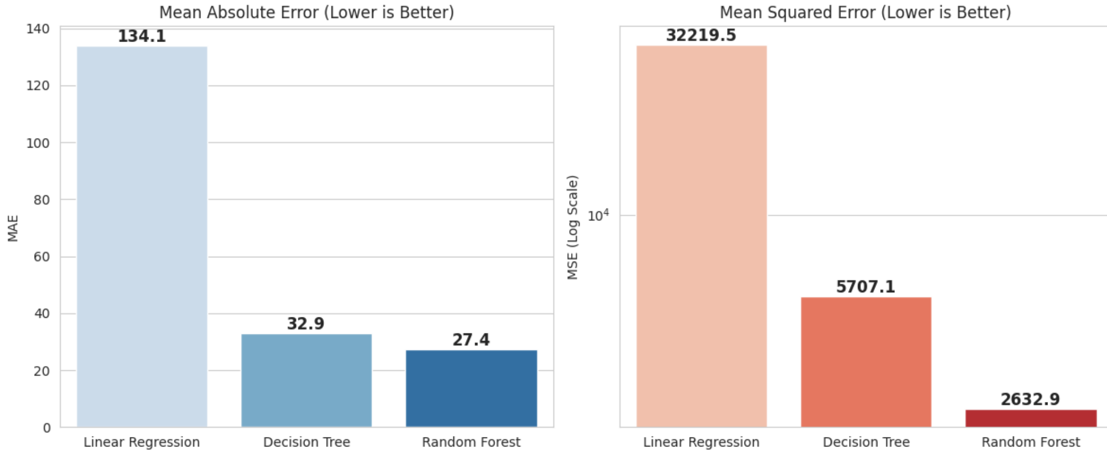
```
Random Forest:
MAE: 27.384281617887048
MSE: 2632.862803486459
R2 Score: 0.98446956268174
```

[49]:

```
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(max_depth=10, random_state=42),
    "Random Forest": RandomForestRegressor(n_estimators=100, max_depth=10,␣
 ↪random_state=42)
}

# Store results
results = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    r2 = r2_score(y_test, y_pred) * 100  # Convert R² score to percentage
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)

    results[name] = {"R2 Score (%)": r2, "MAE": mae, "MSE": mse}

df_results = pd.DataFrame(results).T

plt.figure(figsize=(8, 5))
ax = sns.barplot(x=df_results.index, y=df_results["R2 Score (%)"],␣
 ↪palette="coolwarm")
plt.ylim(0, 100)  # Set percentage range
plt.ylabel("R² Score (%)")
plt.title("Model Accuracy Comparison (Higher is Better)")

for p in ax.patches:
    ax.annotate(f'{p.get_height():.1f}%',
                (p.get_x() + p.get_width() / 2, p.get_height()),
                ha='center', va='bottom', fontsize=12, fontweight='bold')

plt.show()

fig, axes = plt.subplots(1, 2, figsize=(12, 5))

ax1 = sns.barplot(x=df_results.index, y=df_results["MAE"], ax=axes[0],␣
 ↪palette="Blues")
axes[0].set_title("Mean Absolute Error (Lower is Better)")
axes[0].set_ylabel("MAE")

# Add values on bars
for p in ax1.patches:
    ax1.annotate(f'{p.get_height():.1f}',
                 (p.get_x() + p.get_width() / 2, p.get_height()),
```

```
                 ha='center', va='bottom', fontsize=12, fontweight='bold')

# MSE (Log Scale)
ax2 = sns.barplot(x=df_results.index, y=df_results["MSE"], ax=axes[1],␣
↪palette="Reds")
axes[1].set_title("Mean Squared Error (Lower is Better)")
axes[1].set_ylabel("MSE (Log Scale)")
axes[1].set_yscale("log")  # Use log scale for better visibility

# Add values on bars
for p in ax2.patches:
    ax2.annotate(f'{p.get_height():.1f}',
                 (p.get_x() + p.get_width() / 2, p.get_height()),
                 ha='center', va='bottom', fontsize=12, fontweight='bold')

plt.tight_layout()
plt.show()
```




Mean Absolute Error (Lower is Better)
MAE
140
120
100
80
60
40
20
0
134.1
32.9
27.4
Linear Regression
Decision Tree
Random Forest
Mean Squared Error (Lower is Better)
MSE (Log Scale)
10^4
32219.5
5707.1
2632.9
Linear Regression
Decision Tree
Random Forest