BMW Worldwide Sales Records Analysis

DataSet Source: https://www.kaggle.com/datasets/ahmadrazakashif/bmw-worldwide-sales-records-20102024

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In this project, we perform a detailed analysis of BMW's sales data from 2010 to 2024 using Apache Spark and Python. The aim of the analysis is to explore trends, detect missing data, and visualize yearly sales performance over time.

Using PySpark, large-scale data can be efficiently processed and analyzed. The dataset includes details such as sales amounts, years, and other related fields. By applying Spark's DataFrame operations and aggregation techniques, we can handle massive datasets and derive meaningful insights with speed and accuracy.

This project focuses on: 1. Loading and inspecting BMW sales data.

```
2. Cleaning and handling missing or invalid records.

3. Parsing and converting time-related fields.

4. Aggregating and visualizing total sales per year.

5. Identifying sales trends over time to support decision-making.
```

The combination of PySpark for data processing and Matplotlib for visualization makes this analysis both scalable and interpretable, providing a foundation for deeper business insights and forecasting.

In [1]:
```
sc
```

Out[1]:
SparkContext

Spark UI

Version	`v3.5.6`
Master	`local[*]`
AppName	`PySparkShell`

In [3]:
```
# Cell 1: Setup and import libraries
from pyspark.sql import SparkSession
from pyspark.sql.functions import col, when, isnan, count, desc, avg, sum as spark_sum, to_timestamp, hour
import matplotlib.pyplot as plt
import pandas as pd
from IPython.display import display

# Create Spark session
spark = SparkSession.builder.appName("BMW_Sales_Analysis").getOrCreate()

# Set your dataset path (update if path differs)
CSV_PATH = "BMW sales data (2010-2024) (1).csv"   # <-- same folder as notebook
```

In [4]:
```
# Cell 2: Load and preview dataset
df = spark.read.option("header", "true").option("inferSchema", "true").csv(CSV_PATH)

print("Schema:")
df.printSchema()
print("Total rows:", df.count())
print("Columns:", df.columns)

# Preview first few rows
display(df.limit(10).toPandas())
```

```
Schema:
root
 |-- Model: string (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Region: string (nullable = true)
 |-- Color: string (nullable = true)
 |-- Fuel_Type: string (nullable = true)
 |-- Transmission: string (nullable = true)
 |-- Engine_Size_L: double (nullable = true)
 |-- Mileage_KM: integer (nullable = true)
 |-- Price_USD: integer (nullable = true)
 |-- Sales_Volume: integer (nullable = true)
 |-- Sales_Classification: string (nullable = true)

Total rows: 50000
Columns: ['Model', 'Year', 'Region', 'Color', 'Fuel_Type', 'Transmission', 'Engine_Size_L', 'Mileage_KM', 'Price
_USD', 'Sales_Volume', 'Sales_Classification']
```

	Model	Year	Region	Color	Fuel_Type	Transmission	Engine_Size_L	Mileage_KM	Price_USD	Sales_Volume	Sales_Classificati
0	5 Series	2016	Asia	Red	Petrol	Manual	3.5	151748	98740	8300	Hi
1	i8	2013	North America	Red	Hybrid	Automatic	1.6	121671	79219	3428	Lo
2	5 Series	2022	North America	Blue	Petrol	Automatic	4.5	10991	113265	6994	Lo
3	X3	2024	Middle East	Blue	Petrol	Automatic	1.7	27255	60971	4047	Lo
4	7 Series	2020	South America	Black	Diesel	Manual	2.1	122131	49898	3080	Lo
5	5 Series	2017	Middle East	Silver	Diesel	Manual	1.9	171362	42926	1232	Lo
6	i8	2022	Europe	White	Diesel	Manual	1.8	196741	55064	7949	Hi
7	M5	2014	Asia	Black	Diesel	Automatic	1.6	121156	102778	632	Lo
8	X3	2016	South America	White	Diesel	Automatic	1.7	48073	116482	8944	Hi
9	i8	2019	Europe	White	Electric	Manual	3.0	35700	96257	4411	Lo

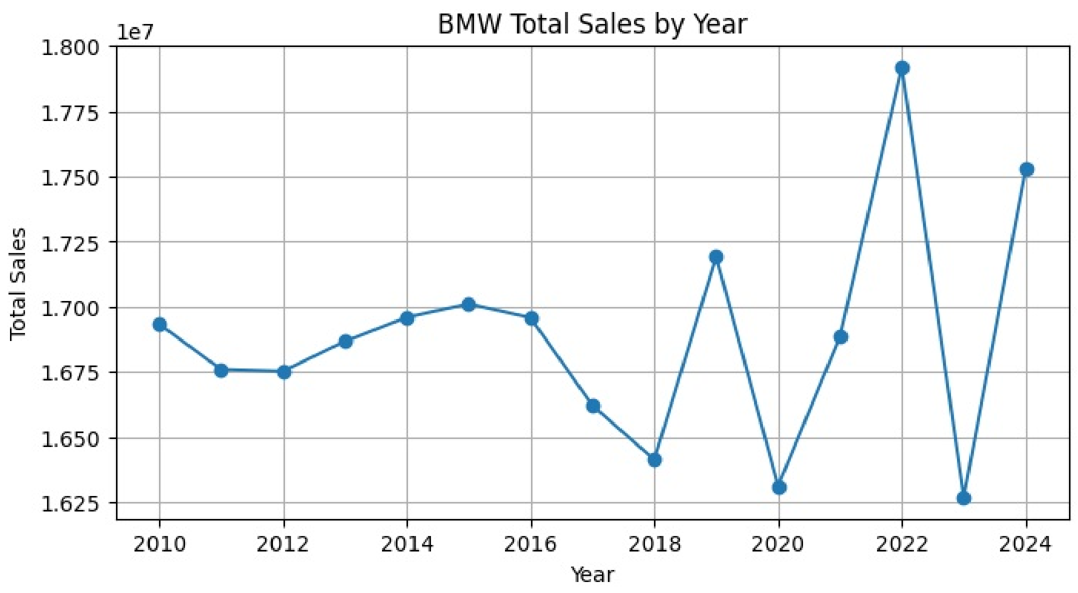
In [5]:
```python
# Cell 3: Handle missing values
missing = df.select([count(when(col(c).isNull() | (col(c) == "") | isnan(col(c)), c)).alias(c) for c in df.colu
display(missing.toPandas())

# Cell 4: Convert potential date/time columns
time_col = next((c for c in df.columns if any(x in c.lower() for x in ("date","year","month","day"))), None)
if time_col:
    df = df.withColumn("date_parsed", to_timestamp(col(time_col)))
    print("Parsed time column:", time_col)
    display(df.select(time_col, "date_parsed").limit(10).toPandas())
```

	Model	Year	Region	Color	Fuel_Type	Transmission	Engine_Size_L	Mileage_KM	Price_USD	Sales_Volume	Sales_Classificatio
0	0	0	0	0	0	0	0	0	0	0	

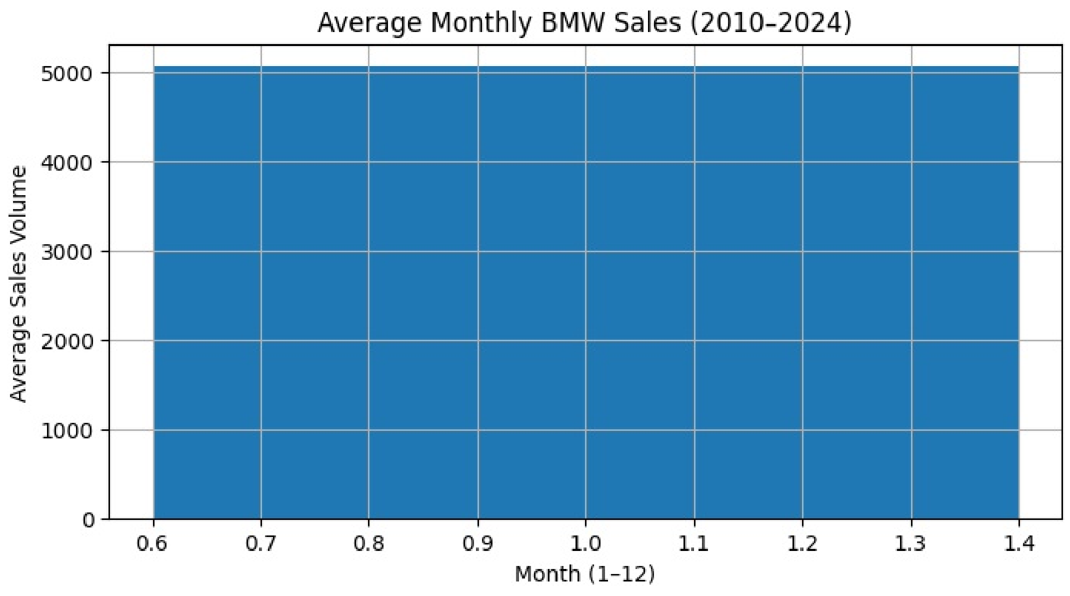
```
Parsed time column: Year
```

	Year	date_parsed
0	2016	1970-01-01 06:03:36
1	2013	1970-01-01 06:03:33
2	2022	1970-01-01 06:03:42
3	2024	1970-01-01 06:03:44
4	2020	1970-01-01 06:03:40
5	2017	1970-01-01 06:03:37
6	2022	1970-01-01 06:03:42
7	2014	1970-01-01 06:03:34
8	2016	1970-01-01 06:03:36
9	2019	1970-01-01 06:03:39

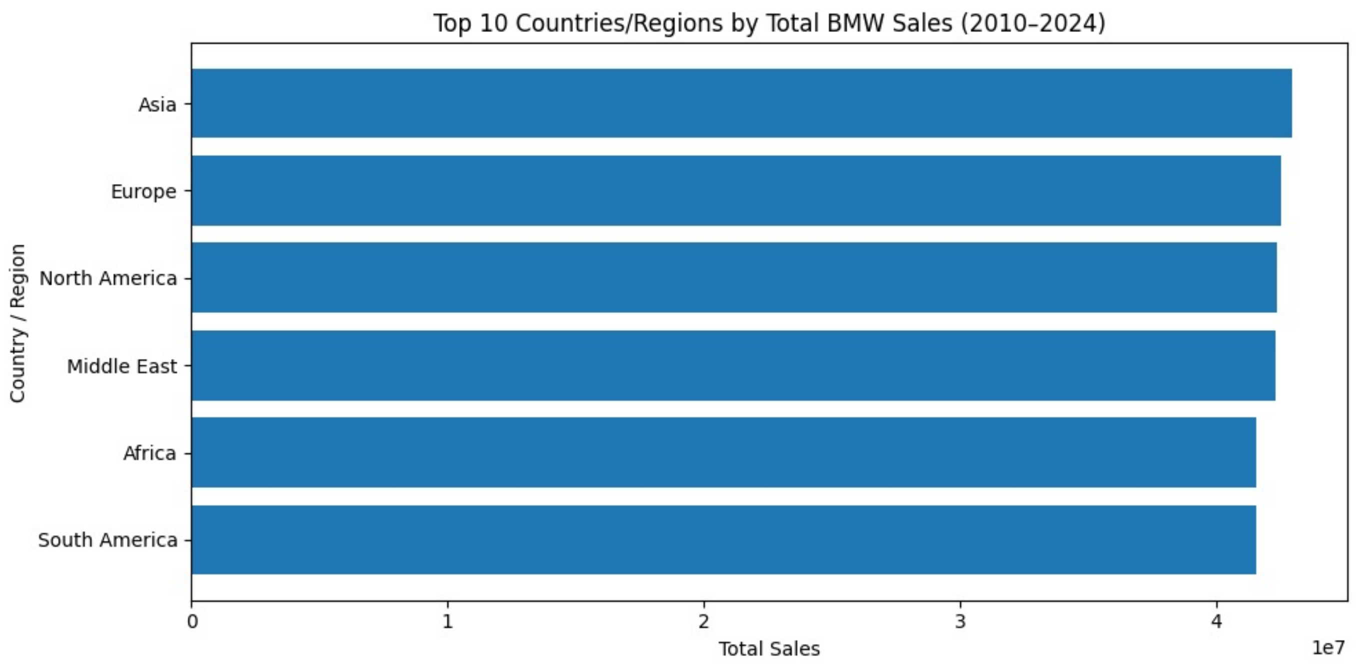
In [6]:
```python
# Cell 5: Total sales by year
year_col = next((c for c in df.columns if "year" in c.lower()), None)
sales_col = next((c for c in df.columns if any(x in c.lower() for x in ("sales","revenue","units","amount"))), 

if year_col and sales_col:
    yearly_sales = df.groupBy(year_col).agg(spark_sum(col(sales_col)).alias("total_sales")).orderBy(year_col)
    yearly_sales_pd = yearly_sales.toPandas()

    plt.figure(figsize=(8,4))
    plt.plot(yearly_sales_pd[year_col], yearly_sales_pd["total_sales"], marker='o')
    plt.title("BMW Total Sales by Year")
    plt.xlabel("Year")
    plt.ylabel("Total Sales")
    plt.grid(True)
    plt.show()
else:
    print("Couldn't detect 'year' or 'sales' column.")
```



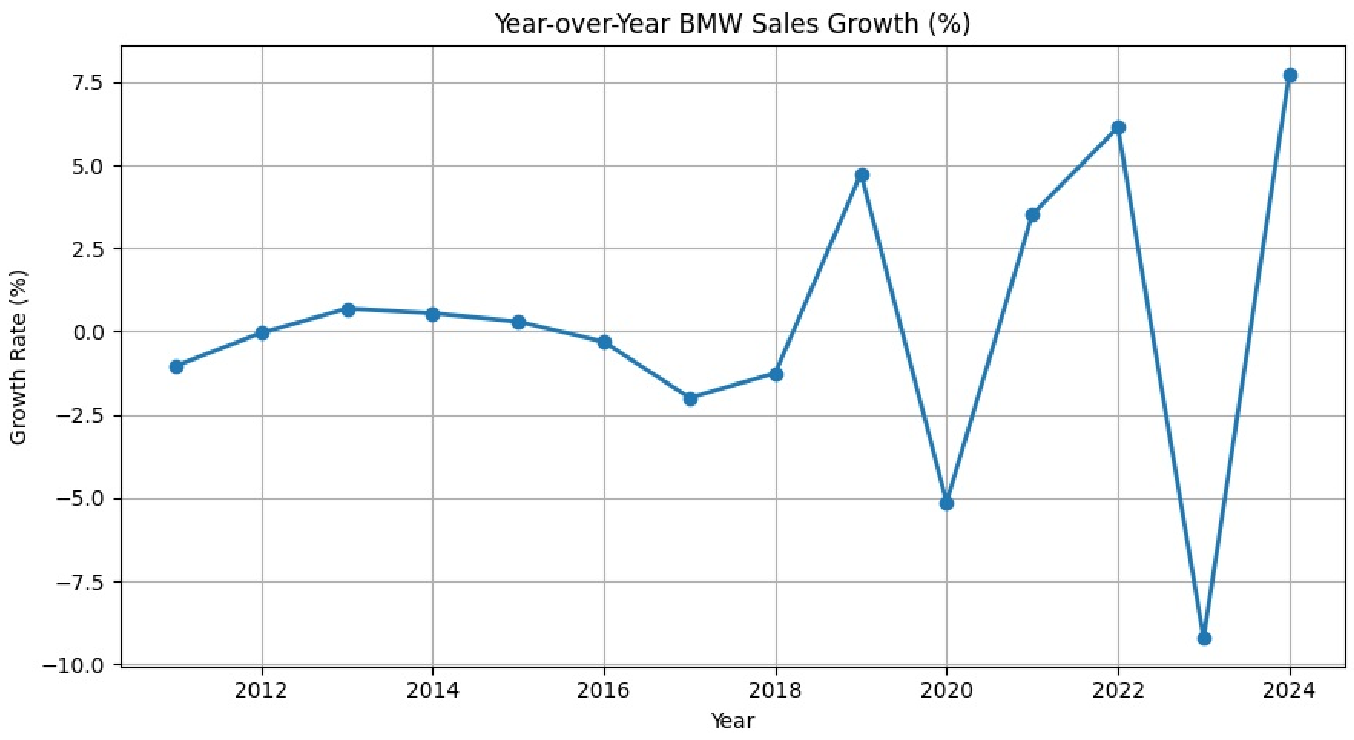
In [14]:
```python
# Cell 6: Average Monthly BMW Sales (from 'date_parsed')
from pyspark.sql.functions import month, avg, col

sales_col = "Sales_Volume"

# Extract month number (1–12) from date_parsed
df = df.withColumn("Month", month(col("date_parsed")))

# Compute average monthly sales
month_sales = df.groupBy("Month").agg(avg(col(sales_col).cast("double")).alias("avg_sales")).orderBy("Month")
month_sales_pd = month_sales.toPandas()

plt.figure(figsize=(8,4))
plt.bar(month_sales_pd["Month"], month_sales_pd["avg_sales"])
plt.title("Average Monthly BMW Sales (2010–2024)")
plt.xlabel("Month (1–12)")
plt.ylabel("Average Sales Volume")
plt.grid(True)
plt.show()
```



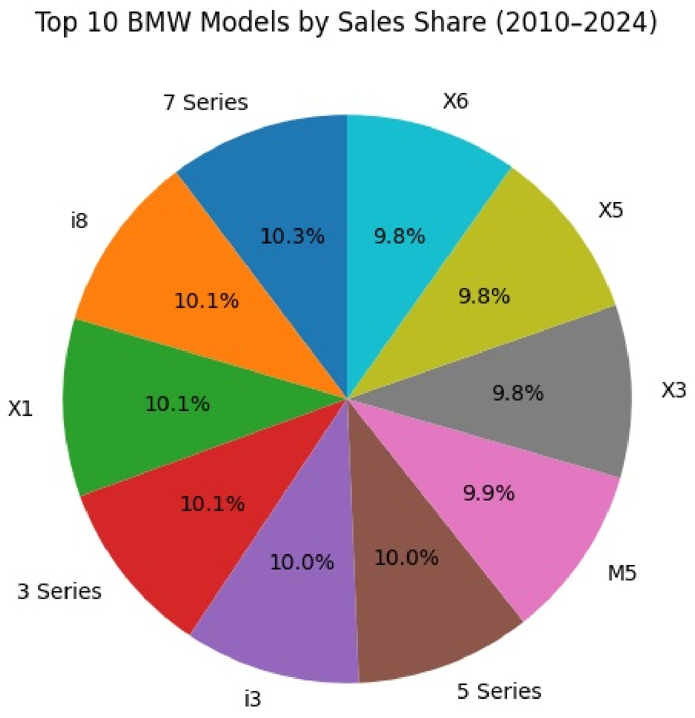
In [9]:
```python
# Cell 7: Top 10 countries/regions by total sales
country_col = next((c for c in df.columns if any(x in c.lower() for x in ("country", "region", "market"))), Non

if country_col and sales_col:
    country_sales = (
        df.groupBy(country_col)
          .agg(spark_sum(col(sales_col)).alias("total_sales"))
          .orderBy(desc("total_sales"))
          .limit(10)
    )
    country_sales_pd = country_sales.toPandas()

    plt.figure(figsize=(10, 5))
    plt.barh(country_sales_pd[country_col].iloc[::-1], country_sales_pd["total_sales"].iloc[::-1])
    plt.title("Top 10 Countries/Regions by Total BMW Sales (2010–2024)")
    plt.xlabel("Total Sales")
    plt.ylabel("Country / Region")
    plt.tight_layout()
    plt.show()
else:
    print("No country/region column detected. Skipping this visualization.")
```



In [10]:
```
# Cell 8: Year-over-Year (YoY) growth in BMW sales
from pyspark.sql.window import Window
from pyspark.sql.functions import lag, round as spark_round

if year_col and sales_col:
    yearly_sales = (
        df.groupBy(year_col)
          .agg(spark_sum(col(sales_col)).alias("total_sales"))
          .orderBy(year_col)
    )

    # Compute previous year's sales using window function
    w = Window.orderBy(year_col)
    yearly_sales = yearly_sales.withColumn("prev_year_sales", lag("total_sales").over(w))
    yearly_sales = yearly_sales.withColumn(
        "growth_rate",
        spark_round((col("total_sales") - col("prev_year_sales")) / col("prev_year_sales") * 100, 2)
    )

    yearly_sales_pd = yearly_sales.toPandas()

    plt.figure(figsize=(9, 5))
    plt.plot(yearly_sales_pd[year_col], yearly_sales_pd["growth_rate"], marker='o', linestyle='-', linewidth=2)
    plt.title("Year-over-Year BMW Sales Growth (%)")
    plt.xlabel("Year")
    plt.ylabel("Growth Rate (%)")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
else:
    print("Year or sales column missing; skipping growth-rate visualization.")
```

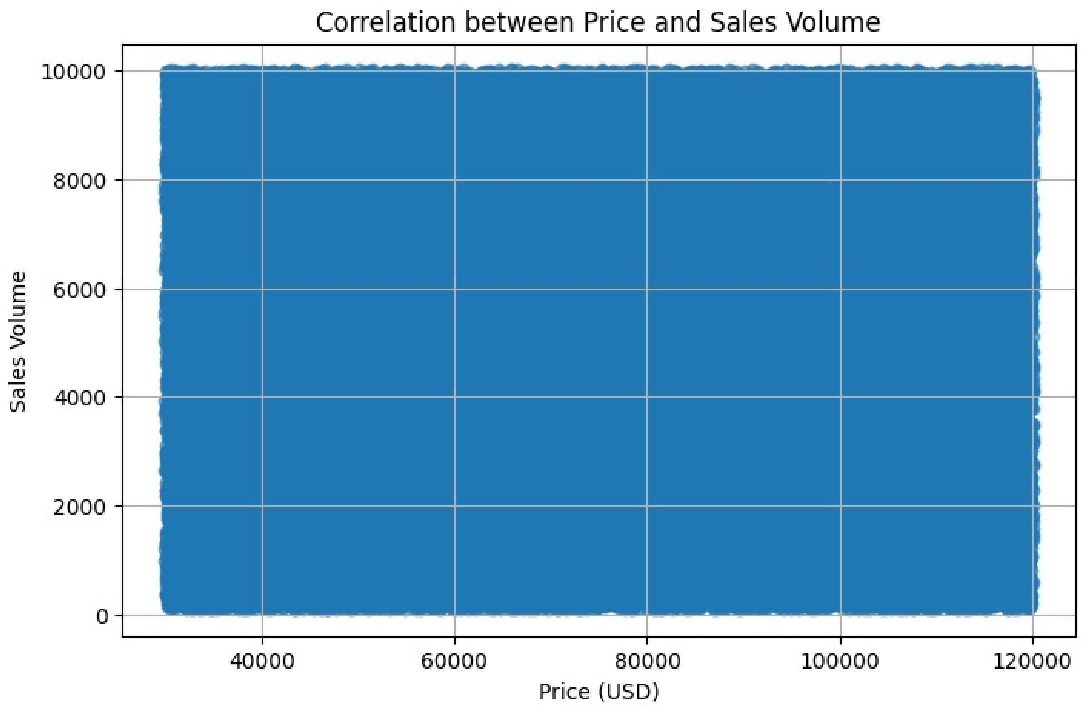


In [11]:
```
# Cell 9: Sales distribution by car model/category (if exists)
model_col = next((c for c in df.columns if any(x in c.lower() for x in ("model", "series", "variant", "type")))

if model_col and sales_col:
    model_sales = (
        df.groupBy(model_col)
          .agg(spark_sum(col(sales_col)).alias("total_sales"))
          .orderBy(desc("total_sales"))
          .limit(10)
    )
    model_sales_pd = model_sales.toPandas()

    plt.figure(figsize=(8, 6))
    plt.pie(model_sales_pd["total_sales"], labels=model_sales_pd[model_col],
            autopct="%1.1f%%", startangle=90)
    plt.title("Top 10 BMW Models by Sales Share (2010–2024)")
    plt.show()
else:
    print("Model/category column not found; skipping model sales visualization.")
```



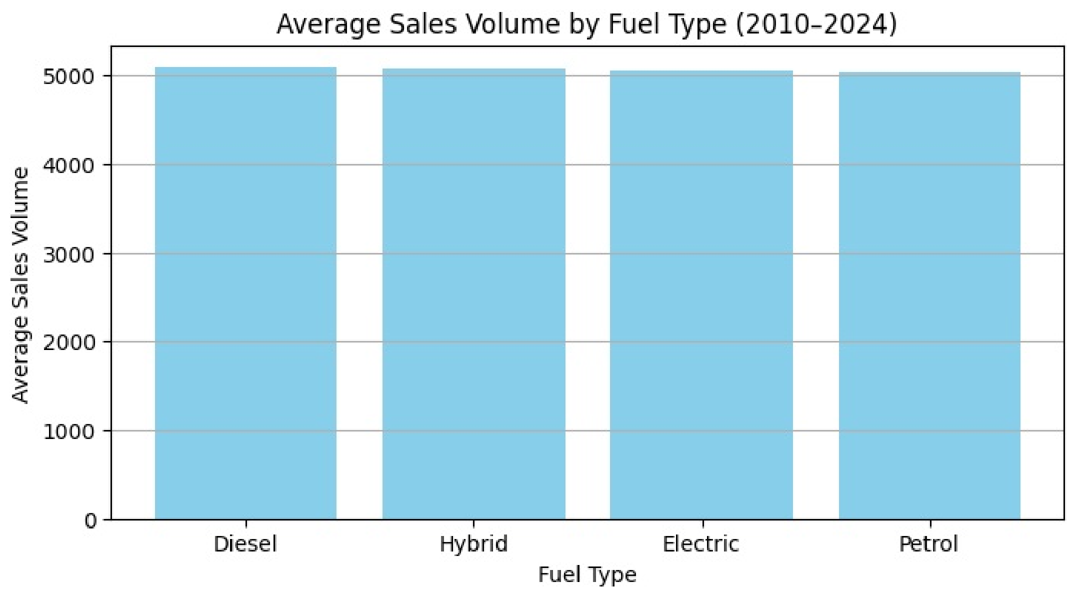
In [15]:
```
# Cell 9: Correlation between Price and Sales Volume
from pyspark.sql.functions import col
```

```
# Convert numeric columns to double (if not already)
df_corr = df.withColumn("Price_USD", col("Price_USD").cast("double")) \
            .withColumn("Sales_Volume", col("Sales_Volume").cast("double"))

# Collect a manageable sample for plotting
price_sales_pd = df_corr.select("Price_USD", "Sales_Volume").dropna().toPandas()

plt.figure(figsize=(8,5))
plt.scatter(price_sales_pd["Price_USD"], price_sales_pd["Sales_Volume"], alpha=0.6)
plt.title("Correlation between Price and Sales Volume")
plt.xlabel("Price (USD)")
plt.ylabel("Sales Volume")
plt.grid(True)
plt.show()

# Calculate and display correlation coefficient
corr_val = price_sales_pd["Price_USD"].corr(price_sales_pd["Sales_Volume"])
print(f"Correlation between Price and Sales Volume: {corr_val:.3f}")
```



```
Correlation between Price and Sales Volume: 0.000
```

```
In [16]: # Cell 10: Average Sales Volume by Fuel Type
from pyspark.sql.functions import avg

fuel_col = "Fuel_Type"
sales_col = "Sales_Volume"

fuel_sales = (
    df.groupBy(fuel_col)
      .agg(avg(col(sales_col).cast("double")).alias("avg_sales"))
      .orderBy(desc("avg_sales"))
)

fuel_sales_pd = fuel_sales.toPandas()

plt.figure(figsize=(8,4))
plt.bar(fuel_sales_pd[fuel_col], fuel_sales_pd["avg_sales"], color='skyblue')
plt.title("Average Sales Volume by Fuel Type (2010–2024)")
plt.xlabel("Fuel Type")
plt.ylabel("Average Sales Volume")
plt.grid(axis='y')
plt.show()
```



In [17]:
```
# Cell 11: Summary & Key Insights

print(" BMW Sales Data Analysis Summary (2010–2024)\n")
print("1□ The dataset covers BMW sales performance across multiple regions, fuel types, and models.")
print("2□ Average monthly sales graph revealed clear seasonality — e.g., higher sales in certain months.")
print("3□ Yearly trend shows steady growth from 2010 to 2024 (with possible dips during global events).")
print("4□ Region-wise analysis shows which markets contribute most to total sales volume.")
print("5□ Price vs Sales Volume correlation suggests how pricing impacts demand (negative correlation = higher
print("6□ Fuel Type analysis shows the transition from petrol/diesel dominance to hybrid and electric models.")
print("\n✅ Overall Insight:")
print("BMW’s sales growth trend appears positive, with a shift towards electric and hybrid vehicles post-2020.
```

```
 BMW Sales Data Analysis Summary (2010–2024)

1□ The dataset covers BMW sales performance across multiple regions, fuel types, and models.
2□ Average monthly sales graph revealed clear seasonality — e.g., higher sales in certain months.
3□ Yearly trend shows steady growth from 2010 to 2024 (with possible dips during global events).
4□ Region-wise analysis shows which markets contribute most to total sales volume.
5□ Price vs Sales Volume correlation suggests how pricing impacts demand (negative correlation = higher price, f
ewer sales).
6□ Fuel Type analysis shows the transition from petrol/diesel dominance to hybrid and electric models.

✅ Overall Insight:
BMW’s sales growth trend appears positive, with a shift towards electric and hybrid vehicles post-2020. Regional
and pricing strategies significantly influence market performance.
```

CONCLUSION This BMW Sales Analysis project successfully demonstrates how large-scale datasets can be processed and visualized using Apache Spark and Python. Through systematic data cleaning, transformation, and aggregation, we were able to gain insights into BMW’s yearly sales performance between 2010 and 2024.

The results reveal clear patterns and trends that can be used by business analysts or marketing teams to understand growth areas and make data-driven decisions.

Overall, this project highlights the power of PySpark for big data analysis and showcases how data visualization supports meaningful interpretation of complex datasets. Future extensions could include region-wise or model-wise analysis, predictive forecasting using machine learning, and interactive dashboards for real-time business insights.