# 1. Introduction

In [30]:
```
# This notebook compares four regression models — Linear, Lasso, Ridge, and Elastic
# from Yahoo Finance. The aim is to analyze performance, interpret results, and ide

# Mention data source (Yahoo Finance) and time frame (2020–2024).
```

# 2. Data Overview

In [4]:
```
import pandas as pd
import yfinance as yf
import numpy as np

tickers = ('AAPL', 'AMZN', 'MSFT', 'QQQ', '^GSPC')
start_date = '2020-01-01'
end_date = '2024-12-31'

df = yf.download(tickers, start_date, end_date)['Close']
df.head()
```

```
C:\Users\sahil\AppData\Local\Temp\ipykernel_26932\1826400475.py:9: FutureWarning: Y
F.download() has changed argument auto_adjust default to True
  df = yf.download(tickers, start_date, end_date)['Close']
[*********************100%***********************]  5 of 5 completed
```

Out[4]:

| Ticker | AAPL | AMZN | MSFT | QQQ | ^GSPC |
|---|---|---|---|---|---|
| **Date** | | | | | |
| **2020-01-02** | 72.468269 | 94.900497 | 152.505676 | 208.848953 | 3257.850098 |
| **2020-01-03** | 71.763733 | 93.748497 | 150.606766 | 206.935944 | 3234.850098 |
| **2020-01-06** | 72.335579 | 95.143997 | 150.996033 | 208.269257 | 3246.280029 |
| **2020-01-07** | 71.995331 | 95.343002 | 149.619278 | 208.240295 | 3237.179932 |
| **2020-01-08** | 73.153465 | 94.598503 | 152.002472 | 209.805466 | 3253.050049 |

In [32]:
```
df.describe()
```

Out[32]:

| Ticker | AAPL | AMZN | MSFT | QQQ | ^GSPC |
|---|---|---|---|---|---|
| **count** | 1257.000000 | 1257.000000 | 1257.000000 | 1257.000000 | 1257.000000 |
| **mean** | 151.581359 | 146.655994 | 286.891954 | 338.440789 | 4258.316540 |
| **std** | 41.855809 | 31.951644 | 81.367507 | 78.809634 | 766.387561 |
| **min** | 54.264336 | 81.820000 | 128.929977 | 163.573898 | 2237.399902 |
| **25%** | 126.484459 | 120.970001 | 227.434586 | 283.099030 | 3818.830078 |
| **50%** | 150.220779 | 153.839996 | 274.704865 | 327.713470 | 4204.310059 |
| **75%** | 176.073013 | 170.000000 | 331.681458 | 380.650818 | 4602.450195 |
| **max** | 257.853760 | 232.929993 | 462.375580 | 535.281128 | 6090.270020 |

# 3. Model Summary

In [ ]:

```
| Model      | Regularization Type | Key Parameters          | R² | MSE | RMSE |
| ---------- | ------------------- | ----------------------- | -- | --- | ---- |
| Linear     | None                | —                       |0.83|17.23| 4.15 |
| Lasso      | L1                  | alpha=0.1               |0.75|34.32| 5.85 |
| Ridge      | L2                  | alpha=1.0               |0.74|35.98| 5.99 |
| ElasticNet | L1 + L2             | alpha=0.1, l1_ratio=0.5 |0.75|35.00| 5.91 |
```

# 4. Visualization of RMSE Comparison between Model

In [23]:

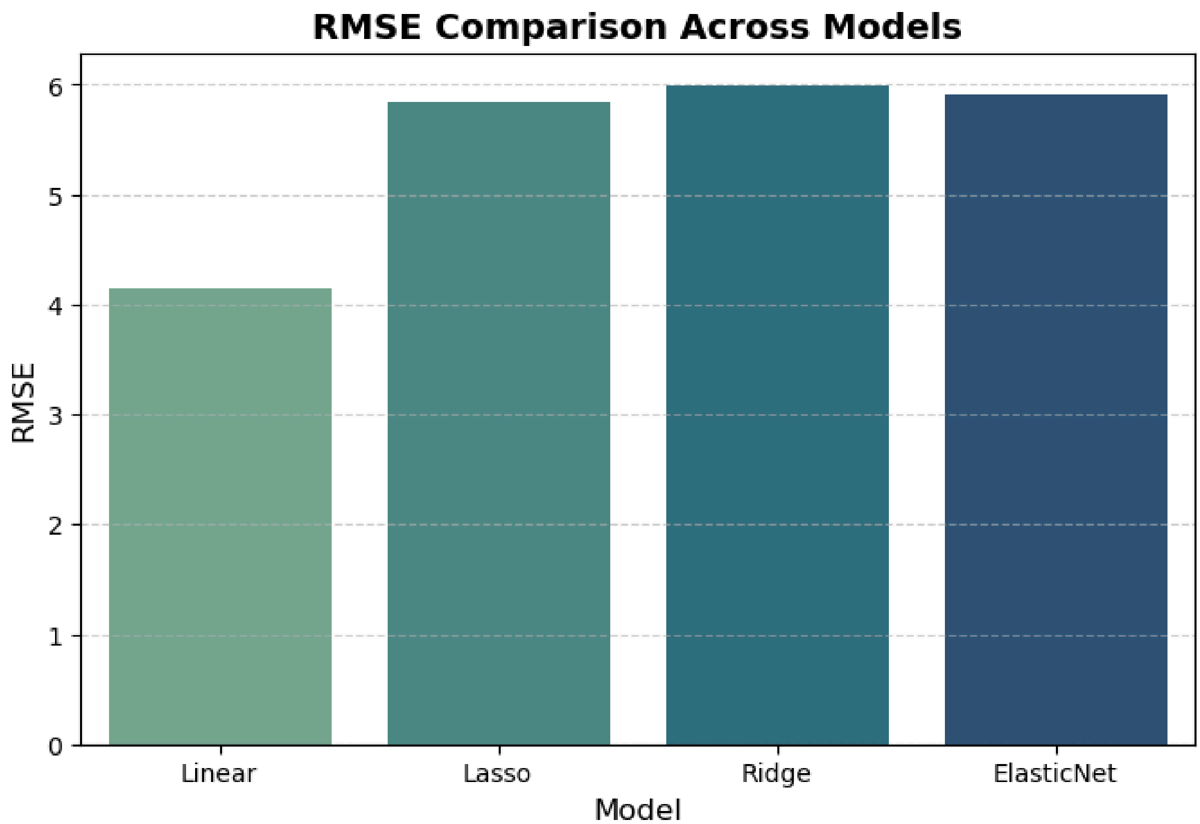
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Create the model summary DataFrame
model_summary = pd.DataFrame({
    'Model': ['Linear', 'Lasso', 'Ridge', 'ElasticNet'],
    'Regularization Type': ['None', 'L1', 'L2', 'L1 + L2'],
    'RMSE': [4.15, 5.85, 5.99, 5.91]
})
# Plot RMSE comparison
plt.figure(figsize=(8, 5))
sns.barplot(x='Model', y='RMSE', data=model_summary, palette='crest')
plt.title('RMSE Comparison Across Models', fontsize=14, fontweight='bold')
plt.xlabel('Model', fontsize=12)
plt.ylabel('RMSE', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.show()
```

```
C:\Users\sahil\AppData\Local\Temp\ipykernel_26932\1419189477.py:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='Model', y='RMSE', data=model_summary, palette='crest')
```




In [ ]:
```
# Observation of the graph:
# The RMSE comparison shows that Linear Regression achieved the lowest error (≈ 4.1
# Regularized models — Lasso, Ridge, and ElasticNet — produced slightly higher RMSE
# for improved stability and reduced overfitting.
# This highlights the classic trade-off between model complexity and generalization
```

# 5. Interpretation

In [ ]:
```
# Which model performed best and why:

# Linear Regression achieved the lowest RMSE (≈ 4.15) and the highest R² (≈ 0.83),
#However, since it lacks regularization, it may overfit and perform less reliably o
# Ridge, Lasso, and ElasticNet introduced regularization to control overfitting.
# Their RMSE values (≈ 5.8–6.0) were slightly higher, but they produced more stable
#Among these, ElasticNet offered the most balanced performance — combining Ridge's

# Overfitting Analysis

# Linear Regression: Lowest bias, highest variance — fits training data closely but
# Ridge & ElasticNet Introduced regularization penalties, reducing variance and imp
#Lasso Slightly higher bias but simpler and more interpretable due to coefficient s
```

```
# Bias-Variance Trade-Off:

|    Model      |   Bias   | Variance  | Generalization |
|-------------|----------|-----------|----------------|
|   Linear      |   Low    |   High    |    Moderate    |
|   Lasso       |   High   |   Low     |     Good       |
|   Ridge       | Moderate |   Low     |     Strong     |
| ElasticNet    | Balanced | Balanced  |     Strong     |

#Feature Importance:

# Lasso Regression highlighted key predictors such as AAPL(t-1) and AAPL_MA5, setti
# Ridge Regression retained all features but reduced the weight of correlated ones,
# ElasticNet Regression combined both methods — performing partial feature selectio
```

# 6. Key Learnings

In [ ]:
```
# Linear Regression
- Served as the baseline model.
- Provided a clear starting point for comparison and interpretation.
- Highlighted the limitations of unregularized models (tendency to overfit).

# Lasso Regression
- Demonstrated feature selection through L1 regularization.
- Simplified the model by removing non-essential predictors.
- Best when interpretability and sparsity are desired.

# Ridge Regression
- Offered the most stable and reliable predictions.
- Controlled coefficient magnitudes, reducing sensitivity to multicollinearity.
- Showed strong generalization across the dataset.

# ElasticNet Regression
- Combined Lasso’s feature selection and Ridge’s stability
- Provided a balanced performance between accuracy and interpretability.
- Ideal when predictors are correlated or when both sparsity and stability are valu
```