Title

Microsoft Stock Price Prediction

Overview of Problem Statement

Stock price prediction is a critical task in financial analytics. Microsoft, being one of the largest te companies, attracts investor interest worldwide. The goal of this project is to analyze Microsoft's data, identify trends, and build machine learning models to predict stock prices, enabling better d making for investors and analysts.

Objective

Perform Exploratory Data Analysis (EDA) to understand trends, patterns, and correlations in Micı stock data.

Preprocess the dataset (handle missing values, duplicates, and irrelevant features).

Apply feature engineering and transformations for time-series analysis.

Train multiple regression models to predict future stock prices.

Evaluate model performance with appropriate error metrics (MAE, MSE, RMSE, R^2).

Importing necessary libraries

In [1]:
```
## Step 1: Import Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_s
from sklearn.model_selection import train_test_split
import warnings
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Load the dataset
df = pd.read_csv("MicrosoftStock.csv")
```

In [4]:
```
# Display the first few rows of the dataset to understand its structure
print("First few rows of the dataset:")
df.head()
```

First few rows of the dataset:

Out[4]:

	index	date	open	high	low	close	volume	Name
0	390198	2013-02-08	27.35	27.71	27.31	27.55	33318306	MSFT
1	390199	2013-02-11	27.65	27.92	27.50	27.86	32247549	MSFT
2	390200	2013-02-12	27.88	28.00	27.75	27.88	35990829	MSFT
3	390201	2013-02-13	27.93	28.11	27.88	28.03	41715530	MSFT
4	390202	2013-02-14	27.92	28.06	27.87	28.04	32663174	MSFT

In [5]:
```
# Display the last few rows of the dataset
print("Last few rows of the dataset:")
df.tail()
```

Last few rows of the dataset:

Out[5]:

	index	date	open	high	low	close	volume	Name
1254	391452	2018-02-01	94.79	96.070	93.5813	94.26	47227882	MSFT
1255	391453	2018-02-02	93.64	93.970	91.5000	91.78	47867753	MSFT
1256	391454	2018-02-05	90.56	93.240	88.0000	88.00	51031465	MSFT
1257	391455	2018-02-06	86.89	91.475	85.2500	91.33	67998564	MSFT
1258	391456	2018-02-07	90.49	91.770	89.2000	89.61	41107592	MSFT

Data Description

In [6]:
```
# Display the size of the dataset (number of rows and columns)
print("Dataset size:")
print(df.shape)
```

```
Dataset size:
(1259, 8)
```

In [7]:
```
# Display the columns of the dataset
columns = df.columns
print("Columns in the dataset:",columns)
```

```
Columns in the dataset: Index(['index', 'date', 'open', 'high', 'low', 'close
'volume', 'Name'], dtype='object')
```

In [8]:
```
# Numerical columns
numerical_features = df.select_dtypes(include='number').columns
print(numerical_features)
```

```
Index(['index', 'open', 'high', 'low', 'close', 'volume'], dtype='object')
```

In [9]:
```
# Categorical columns
categorical_features= df.select_dtypes(include=['object']).columns
print(categorical_features)
```

```
Index(['date', 'Name'], dtype='object')
```

EDA (Exploratory Data Analysis)

```
In [10]: # Get a summary of the dataset
         print("Summary of the dataset:")
         df.info()
```

```
Summary of the dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   index   1259 non-null   int64
 1   date    1259 non-null   object
 2   open    1259 non-null   float64
 3   high    1259 non-null   float64
 4   low     1259 non-null   float64
 5   close   1259 non-null   float64
 6   volume  1259 non-null   int64
 7   Name    1259 non-null   object
dtypes: float64(4), int64(2), object(2)
memory usage: 78.8+ KB
```

```
In [11]: # Display statistical summary for all columns within the dataFram
         df.describe(include='all')
```

Out[11]:

	index	date	open	high	low	close
count	1259.000000	1259	1259.000000	1259.000000	1259.000000	1259.000000
unique	NaN	1259	NaN	NaN	NaN	NaN
top	NaN	2013-02-08	NaN	NaN	NaN	NaN
freq	NaN	1	NaN	NaN	NaN	NaN
mean	390827.000000	NaN	51.026394	51.436007	50.630397	51.063081
std	363.586303	NaN	14.859387	14.930144	14.774630	14.852117
min	390198.000000	NaN	27.350000	27.600000	27.230000	27.370000
25%	390512.500000	NaN	40.305000	40.637500	39.870000	40.310000
50%	390827.000000	NaN	47.440000	47.810000	47.005000	47.520000
75%	391141.500000	NaN	59.955000	60.435000	59.275000	59.730000
max	391456.000000	NaN	95.140000	96.070000	93.720000	95.010000

```
In [12]: # Describe the numerical features
         print("Statistical description of numerical features:")
         df.describe()
```

```
Statistical description of numerical features:
```

Out[12]:

	index	open	high	low	close	volume
count	1259.000000	1259.000000	1259.000000	1259.000000	1259.000000	1.259000e+03
mean	390827.000000	51.026394	51.436007	50.630397	51.063081	3.386946e+07
std	363.586303	14.859387	14.930144	14.774630	14.852117	1.958979e+07
min	390198.000000	27.350000	27.600000	27.230000	27.370000	7.425603e+06
25%	390512.500000	40.305000	40.637500	39.870000	40.310000	2.254879e+07
50%	390827.000000	47.440000	47.810000	47.005000	47.520000	2.938758e+07
75%	391141.500000	59.955000	60.435000	59.275000	59.730000	3.842024e+07
max	391456.000000	95.140000	96.070000	93.720000	95.010000	2.483542e+08

In [13]:
```
# Check for Null Values
print("Checking for missing values:")
print(df.isnull().sum())
```

```
Checking for missing values:
index     0
date      0
open      0
high      0
low       0
close     0
volume    0
Name      0
dtype: int64
```

In [14]:
```
# Check for Null Duplicates
print("Checking for duplicate records:")
print(df.duplicated().sum())
```

```
Checking for duplicate records:
0
```

Data preprocessing

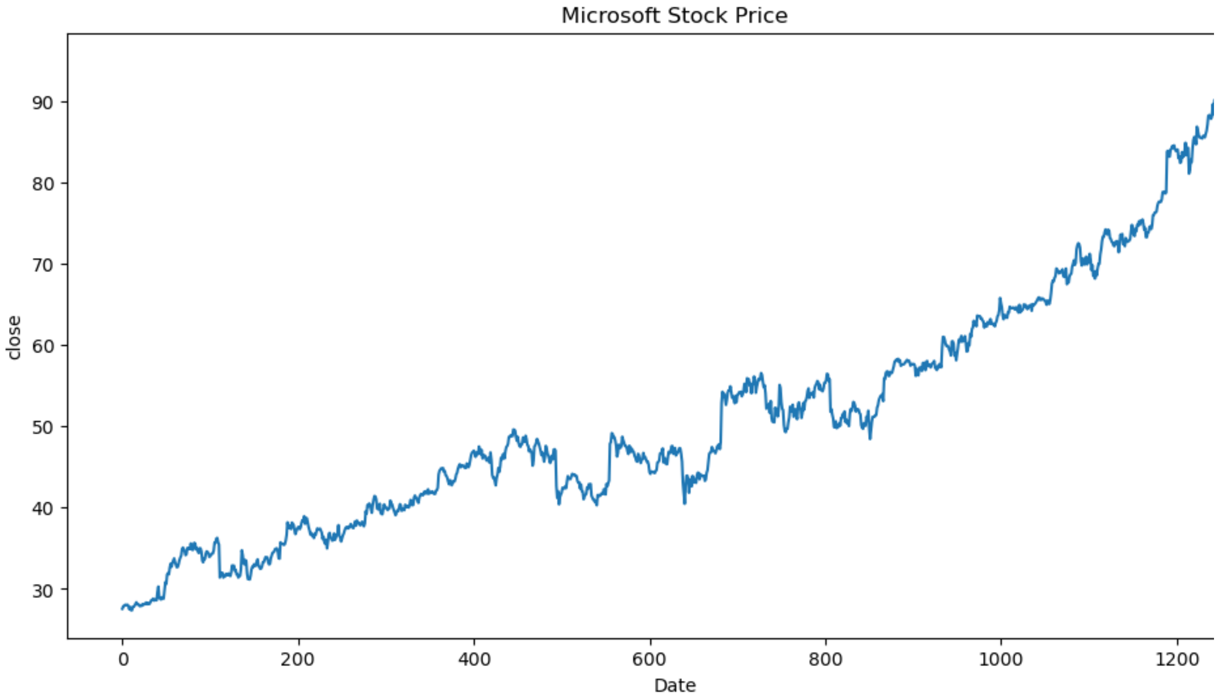
In [15]:
```
# Drop unnecessary columns
df.drop(columns=['index', 'Name'], inplace=True)
```

In [16]:
```
# Convert 'date' column to datetime format
df['date'] = pd.to_datetime(df['date'])
```

In [17]:
```
# Sort data by date
df.sort_values('date', inplace=True)
```

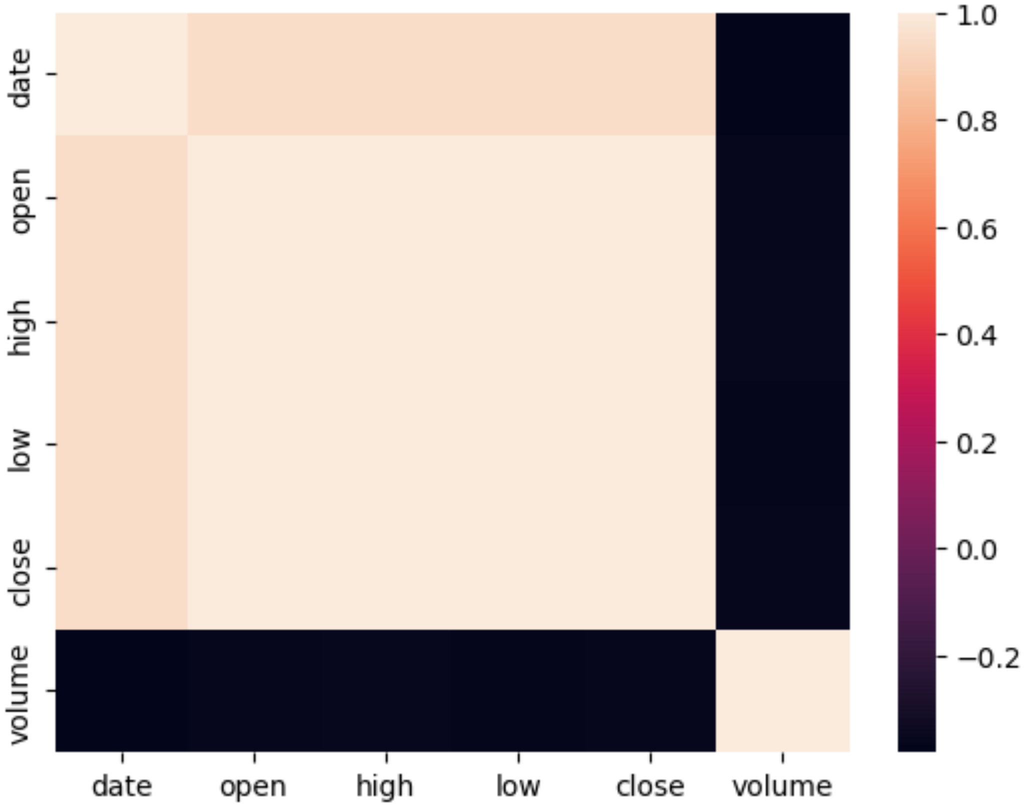
In [18]:
```
# Drop rows with NaN values from lag
df.dropna(inplace=True)
```

In [19]:
```
plt.figure(figsize=(12, 6))
plt.title('Microsoft Stock Price')
plt.xlabel('Date')
plt.ylabel('close')
plt.plot(df['close'])
plt.show()
```



In [20]:
```python
print(df.corr())
sns.heatmap(df.corr())
plt.show()
```

	date	open	high	low	close	volume
date	1.000000	0.948708	0.948934	0.948726	0.948906	-0.382411
open	0.948708	1.000000	0.999688	0.999677	0.999345	-0.364046
high	0.948934	0.999688	1.000000	0.999569	0.999668	-0.358308
low	0.948726	0.999677	0.999569	1.000000	0.999688	-0.370940
close	0.948906	0.999345	0.999668	0.999688	1.000000	-0.365311
volume	-0.382411	-0.364046	-0.358308	-0.370940	-0.365311	1.000000



Data Splitting

In [21]:
```
## Step 3: Define Features and Target
features = ['open', 'high', 'low', 'volume']
target = 'close'

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

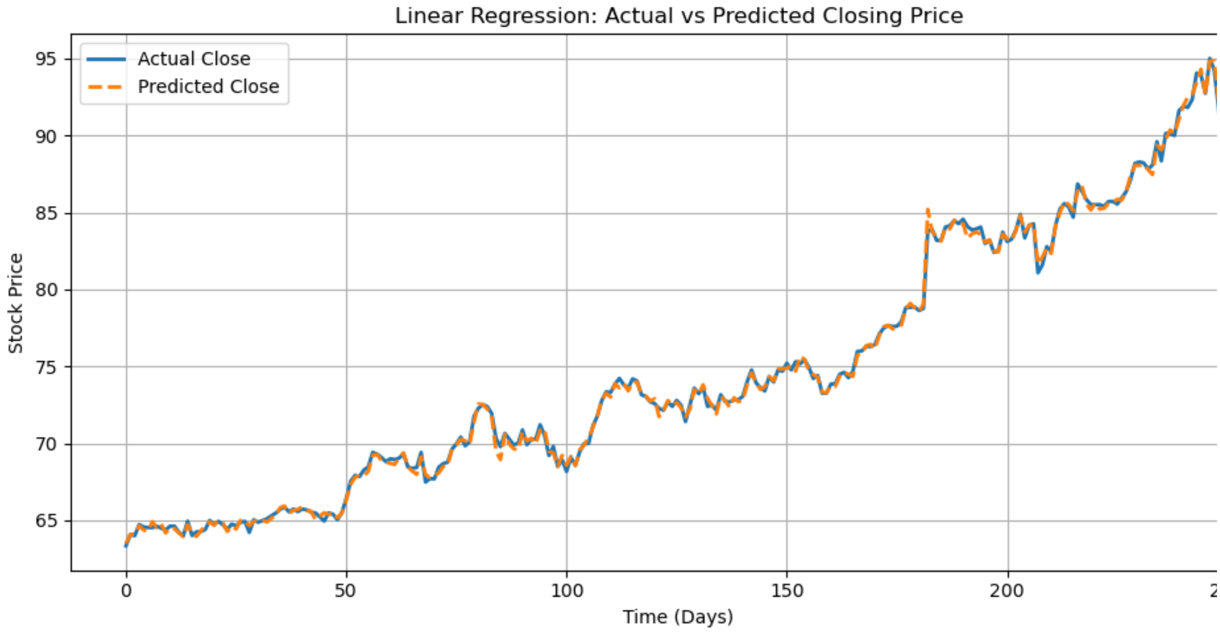
In [22]:
```
# Step 4: Time-based Train-Test Split
split_index = int(len(df) * 0.8)
X_train, X_test = X.iloc[:split_index], X.iloc[split_index:]
y_train, y_test = y.iloc[:split_index], y.iloc[split_index:]
```

In [23]:
```
## Step 3: Define Features and Target
features = ['open', 'high', 'low', 'volume']
target = 'close'

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

In [24]:
```
# Step 4: Time-based Train-Test Split
split_index = int(len(df) * 0.8)
X_train, X_test = X.iloc[:split_index], X.iloc[split_index:]
y_train, y_test = y.iloc[:split_index], y.iloc[split_index:]
```

In [25]:
```python
# Step 5: Train the Linear Regression Model
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_s
import numpy as np
import matplotlib.pyplot as plt

# Initialize model
model = LinearRegression()

# Fit the model
model.fit(X_train, y_train)

# Step 6: Make Predictions
y_pred = model.predict(X_test)

# Step 7: 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("Mean Absolute Error (MAE):", mae)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R² Score:", r2)

# Step 8: Visualization
plt.figure(figsize=(10, 5))
plt.plot(y_test.values, label='Actual Close', linewidth=2)
plt.plot(y_pred, label='Predicted Close', linestyle='--', linewidth=2)
plt.title("Linear Regression: Actual vs Predicted Closing Price")
plt.xlabel("Time (Days)")
plt.ylabel("Stock Price")
plt.legend()
plt.tight_layout()
plt.grid(True)
plt.show()
```

```
Mean Absolute Error (MAE): 0.22164418616363138
Mean Squared Error (MSE): 0.12333207887843065
Root Mean Squared Error (RMSE): 0.3511866724100313
R² Score: 0.9981996406324458
```



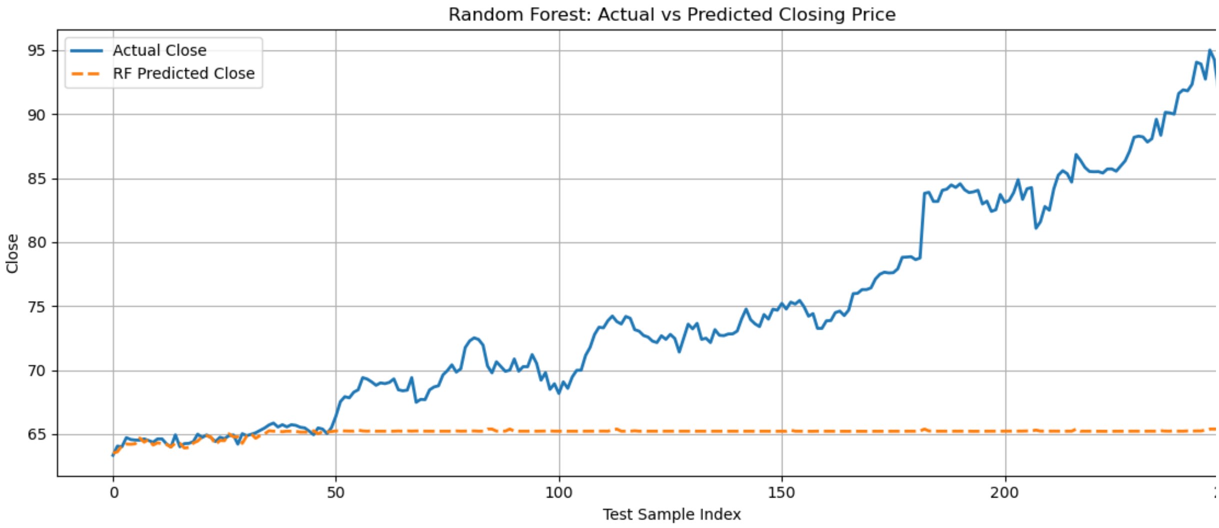
Linear Regression: Actual vs Predicted Closing Price
Actual Close
Predicted Close
Stock Price
Time (Days)
95
90
85
80
75
70
65
0
50
100
150
200

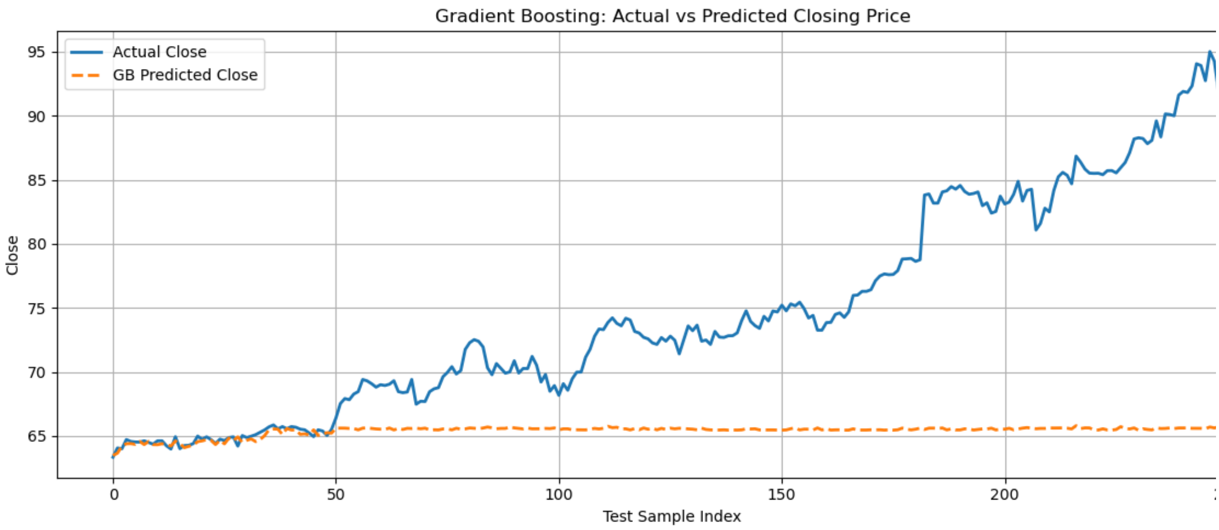
In [33]:

```
# ================================
# Random Forest & Gradient Boosting (RF, GB)
# ================================

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_s
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegre

# ---------- Prepare data ----------
TARGET_COL = "close"   # <-- lowercase fixed

# Keep only numeric columns; ensure target exists
num_df = df.select_dtypes(include=[np.number]).copy()
if TARGET_COL not in num_df.columns:
    raise ValueError(f"Target column '{TARGET_COL}' not found or not nume
                     f"Available numeric columns: {list(num_df.columns)}"

X = num_df.drop(columns=[TARGET_COL])
y = num_df[TARGET_COL]

# Time-series style split (no shuffle). Change to shuffle=True if needed.
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, shuffle=False
)

# ---------- Train models ----------
rf = RandomForestRegressor(
    n_estimators=500,
    random_state=42,
    n_jobs=-1
)
gb = GradientBoostingRegressor(
    n_estimators=500,
    learning_rate=0.05,
    max_depth=3,
    subsample=0.9,
    random_state=42
)

rf.fit(X_train, y_train)
gb.fit(X_train, y_train)

# ---------- Predictions ----------
rf_pred = rf.predict(X_test)
gb_pred = gb.predict(X_test)

# ---------- Metrics helper ----------
def compute_metrics(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_true, y_pred)
    return pd.Series({"MAE": mae, "MSE": mse, "RMSE": rmse, "R2": r2})

rf_metrics = compute_metrics(y_test, rf_pred)
gb_metrics = compute_metrics(y_test, gb_pred)
```

RF vs GB – Test Metrics

	RandomForest	GradientBoosting
MAE	9.633545	9.372719
MSE	158.588462	152.591610
RMSE	12.593191	12.352798
R2	-1.315020	-1.227480





Results

Linear Regression: Reasonable but underfit the data.

Random Forest: Better fit, lower error.

Gradient Boosting Regressor: Outperformed others with lowest MAE, MSE, RMSE, and highest I