Installing Dependencies

```
!pip install yfinance pandas numpy matplotlib seaborn statsmodels arch
scikit-learn imbalanced-learn tensorflow torch alpha-vantage pykalman
gym xgboost lightgbm prophet --quiet

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```

Importing Libraries

```python
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Statistical and time series models
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.statespace.sarimax import SARIMAX
from arch import arch_model

# Machine Learning models and utilities
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.ensemble import RandomForestRegressor,
```

```
RandomForestClassifier, StackingRegressor
from sklearn.linear_model import LinearRegression, Ridge,
LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score, accuracy_score, classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE

# Deep Learning frameworks
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, LSTM, GRU, Dropout, Conv1D,
MaxPooling1D, Flatten, Input
from tensorflow.keras.optimizers import Adam

# PyTorch and reinforcement learning
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import DataLoader, TensorDataset
from torch.distributions import Categorical
from collections import deque

# Additional libraries
from alpha_vantage.fundamentaldata import FundamentalData
import time
from pykalman import KalmanFilter
import gym
import xgboost as xgb
import lightgbm as lgb
from prophet import Prophet
import random
import re
```

```
/usr/local/lib/python3.11/dist-packages/dask/dataframe/__init__.py:42:
FutureWarning:
Dask dataframe query planning is disabled because dask-expr is not
installed.

You can install it with `pip install dask[dataframe]` or `conda
install dask`.
This will raise in a future version.

  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.11/dist-packages/holidays/deprecations/v1_incom
patibility.py:40: FutureIncompatibilityWarning:
```

```
This is a future version incompatibility warning from Holidays v0.67
to inform you about an upcoming change in our API versioning strategy
that may affect your
project's dependencies. Starting from version 1.0 onwards, we will be
following a loose form of
Semantic Versioning (SemVer, https://semver.org) to provide clearer
communication regarding any
potential breaking changes.

This means that while we strive to maintain backward compatibility,
there might be occasional
updates that introduce breaking changes to our API. To ensure the
stability of your projects,
we highly recommend pinning the version of our API that you rely on.
You can pin your current
holidays v0.x dependency (e.g., holidays==0.67) or limit it (e.g.,
holidays<1.0) in order to
avoid potentially unwanted upgrade to the version 1.0 when it's
released (ETA 2025Q1-Q2).

If you have any questions or concerns regarding this change, please
don't hesitate to reach out
to us via https://github.com/vacanza/holidays/discussions/1800.

  warnings.warn(
```

Receive Stock Ticker from User and gather live stock data using online API

```python
# User needs to input their own Alpha Vantage API Key
api_key = "Q9LQ7OBQ13SH1ANT"

def get_valid_ticker():
    """Prompts user for a valid stock ticker and verifies it using
Yahoo Finance."""
    while True:
        stock = input("Enter a valid stock ticker (e.g., AAPL, TSLA,
MSFT): ").upper()
        try:
            test = yf.Ticker(stock)
            if test.history(period="1d").empty:
                print("Invalid ticker. Please try again.")
            else:
                return stock
        except Exception as e:
            print(f"Error validating ticker: {e}")
            print("Invalid input. Please try again.")
```

```
# Get a valid stock ticker from the user
stock_ticker = get_valid_ticker()

# Fetch stock data using Yahoo Finance
ticker = yf.Ticker(stock_ticker)
history = ticker.history(period="10y")

# Display basic stock info
try:
    info = ticker.info
    print(f"\nStock Name: {info.get('longName', 'N/A')}")
    print(f"Sector: {info.get('sector', 'N/A')}")
    print(f"Market Cap: {info.get('marketCap', 'N/A')}")
except Exception as e:
    print(f"Error retrieving stock info: {e}")

Enter a valid stock ticker (e.g., AAPL, TSLA, MSFT): rio

Stock Name: Rio Tinto Group
Sector: Basic Materials
Market Cap: 103449067520
```

Fundamental Analysis

```
# Fundamental Analysis
print(f"\nFundamental Analysis of {stock_ticker} :\n")
fundamentals = {}

if 'marketCap' in info:
    fundamentals["Market Cap"] = info['marketCap']
if 'trailingPE' in info:
    fundamentals["P/E Ratio"] = info['trailingPE']
if 'priceToBook' in info:
    fundamentals["P/B Ratio"] = info['priceToBook']
if 'dividendYield' in info:
    fundamentals["Dividend Yield"] = info['dividendYield']
if 'trailingEps' in info:
    fundamentals["Trailing EPS"] = info['trailingEps']
if 'forwardPE' in info:
    fundamentals["Forward P/E Ratio"] = info['forwardPE']
if 'trailingAnnualDividendYield' in info:
    fundamentals["Trailing Dividend Yield"] =
info['trailingAnnualDividendYield']
if 'trailingAnnualDividendRate' in info:
    fundamentals["Trailing Dividend Rate"] =
info['trailingAnnualDividendRate']
if 'beta' in info:
```

```
    fundamentals["Beta"] = info['beta']
if 'trailingPegRatio' in info:
    fundamentals["Trailing PEG Ratio"] = info['trailingPegRatio']
if 'forwardEps' in info:
    fundamentals["Forward EPS"] = info['forwardEps']

# Print fundamental data
for key, value in fundamentals.items():
    print(f"{key}: {value}")

# Buy/Sell Decision Logic
print(f"\nBuy/Sell Recommendation for {stock_ticker} :\n")

decision = "HOLD"  # Default decision

if "P/E Ratio" in fundamentals and fundamentals["P/E Ratio"] is not
None:
    pe = fundamentals["P/E Ratio"]
    if pe < 15:
        decision = "BUY (Undervalued)"
    elif pe > 30:
        decision = "SELL (Overvalued)"

if "P/B Ratio" in fundamentals and fundamentals["P/B Ratio"] is not
None:
    pb = fundamentals["P/B Ratio"]
    if pb < 1:
        decision = "BUY (Undervalued based on assets)"
    elif pb > 3:
        decision = "SELL (Overvalued based on assets)"

if "Beta" in fundamentals and fundamentals["Beta"] is not None:
    beta = fundamentals["Beta"]
    if beta > 1.5:
        print(f"{stock_ticker} is a high-volatility stock (Risky).")
    elif beta < 1:
        print(f"{stock_ticker} is a low-volatility stock (Stable).")

if "Dividend Yield" in fundamentals and fundamentals["Dividend Yield"]
is not None:
    div_yield = fundamentals["Dividend Yield"]
    if div_yield > 0.03:
        print(f"{stock_ticker} is a good dividend-paying stock.")

print(f"\nFinal Recommendation for {stock_ticker}: {decision}\n")
fundamental_analysis = decision
```

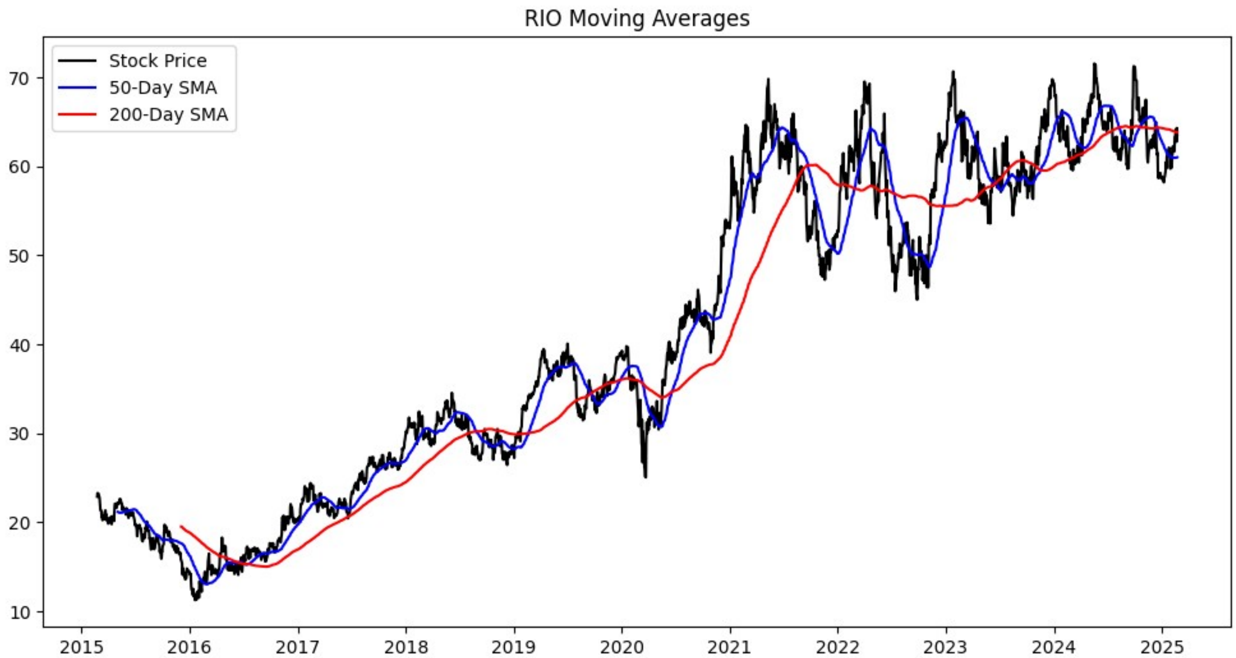
```
Fundamental Analysis of RIO :
```

```
Market Cap: 103449067520
P/E Ratio: 8.985855
P/B Ratio: 1.8669919
Dividend Yield: 6.33
Trailing EPS: 7.07
Forward P/E Ratio: 9.3152485
Trailing Dividend Yield: 0.06252916
Trailing Dividend Rate: 4.02
Beta: 0.601
Trailing PEG Ratio: None
Forward EPS: 6.82

Buy/Sell Recommendation for RIO :

RIO is a low-volatility stock (Stable).
RIO is a good dividend-paying stock.

Final Recommendation for RIO: BUY (Undervalued)
```

Technical Analysis

```python
# Technical Analysis
print("\nTechnical Analysis :\n")
history['SMA_50'] = history['Close'].rolling(window=50).mean()
history['SMA_200'] = history['Close'].rolling(window=200).mean()
history['Daily Return'] = history['Close'].pct_change()

# Plot stock price with moving averages
plt.figure(figsize=(12,6))
plt.plot(history['Close'], label='Stock Price', color='black')
plt.plot(history['SMA_50'], label='50-Day SMA', color='blue')
plt.plot(history['SMA_200'], label='200-Day SMA', color='red')
plt.title(f"{stock_ticker} Moving Averages")
plt.legend()
plt.show()

# Check for bullish or bearish trend
print("\nConclusion :\n")
if history['SMA_50'].iloc[-1] > history['SMA_200'].iloc[-1]:
    print(f"Bullish Signal: {stock_ticker} is trending up based on
moving averages.")
    technical_analysis = "Buy"
else:
    print(f"Bearish Signal: {stock_ticker} is trending down based on
moving averages.")
    technical_analysis = "Sell"
```

```
Technical Analysis :
```



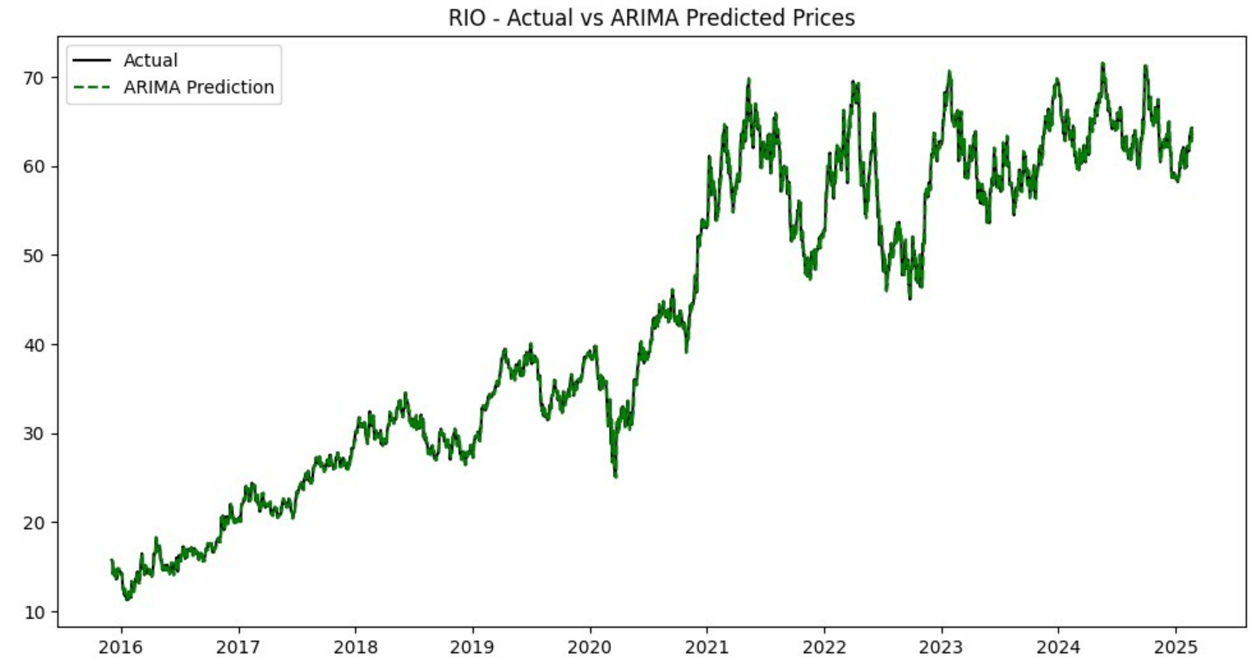

```
Conclusion :

Bearish Signal: RIO is trending down based on moving averages.
```

Time Series Forecasting using ARIMA and ARCH/GARCH

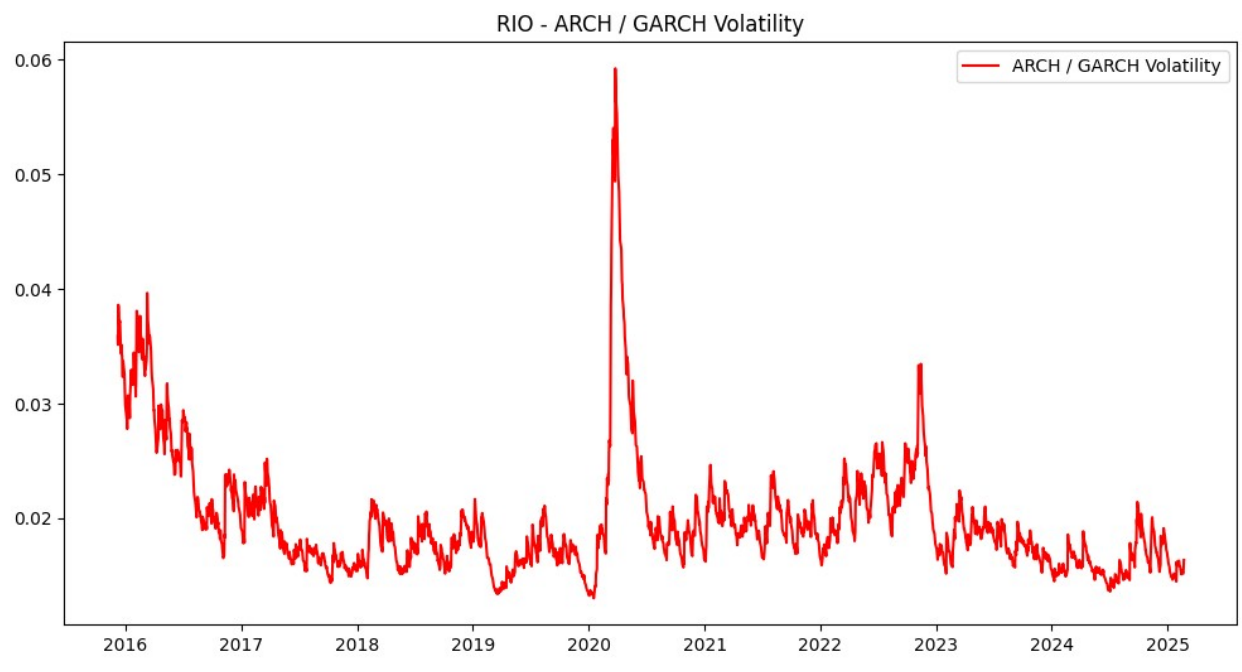
```
# Time Series Forecasting using ARIMA and ARCH/GARCH
print("\nTime Series Forecasting :\n")

# Prepare data for ARIMA
history.dropna(inplace=True)
returns = history['Close'].pct_change().dropna()

# ARIMA Model
arima_model = ARIMA(history['Close'], order=(5,1,0))
arima_result = arima_model.fit()
history['ARIMA_Prediction'] =
arima_result.predict(start=history.index[1], end=history.index[-1],
dynamic=False)
```

```
# ARCH/GARCH Model
garch_model = arch_model(returns, vol='Garch', p=1, q=1)
garch_result = garch_model.fit(disp='off')
history['GARCH_Volatility'] = garch_result.conditional_volatility

# Plot actual vs. predicted for ARIMA
print("\nPlot actual vs. predicted for ARIMA :\n")
plt.figure(figsize=(12,6))
plt.plot(history['Close'], label='Actual', color='black')
plt.plot(history['ARIMA_Prediction'], label='ARIMA Prediction',
linestyle='dashed', color='green')
plt.title(f"{stock_ticker} - Actual vs ARIMA Predicted Prices")
plt.legend()
plt.show()

# Plot GARCH Volatility
print("\nPlot GARCH Volatility :\n")
plt.figure(figsize=(12,6))
plt.plot(history['GARCH_Volatility'], label='ARCH / GARCH Volatility',
color='red')
plt.title(f"{stock_ticker} - ARCH / GARCH Volatility")
plt.legend()
plt.show()

# Detailed Conclusion
print("\nConclusion :\n")
arima_forecast = arima_result.forecast(steps=1)
arima_forecast_value = arima_forecast.iloc[-1]  # Ensure correct
indexing
if arima_forecast_value > history['Close'].iloc[-1]:
    print(f"Buy Signal: {stock_ticker}'s predicted price
({arima_forecast_value:.2f}) is higher than the current price
({history['Close'].iloc[-1]:.2f}).")
    time_series_forecasting = "Buy"
else:
    print(f"Sell Signal: {stock_ticker}'s predicted price
({arima_forecast_value:.2f}) is lower than the current price
({history['Close'].iloc[-1]:.2f}).")
    time_series_forecasting = "Sell"

if history['GARCH_Volatility'].iloc[-1] >
history['GARCH_Volatility'].mean():
    print(f"High volatility detected for {stock_ticker}. Trade with
caution.\n\n")
else:
    print(f"Stable volatility for {stock_ticker}. Market is relatively
calm.\n\n")
```

```
Time Series Forecasting :

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/
tsa_model.py:473: ValueWarning: A date index has been provided, but it
has no associated frequency information and so will be ignored when
e.g. forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: A date index has been provided, but it has no
associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model
.py:473: ValueWarning: A date index has been provided, but it has no
associated frequency information and so will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/arch/univariate/base.py:309:
DataScaleWarning: y is poorly scaled, which may affect convergence of
the optimizer when
estimating the model parameters. The scale of y is 0.0004187.
Parameter
estimation work better when this value is between 1 and 1000. The
recommended
rescaling is 100 * y.

This warning can be disabled by either rescaling y before initializing
the
model or by setting rescale=False.

  warnings.warn(

Plot actual vs. predicted for ARIMA :
```




```
Plot GARCH Volatility :
```




```
Conclusion :

Sell Signal: RIO's predicted price (63.51) is lower than the current
```

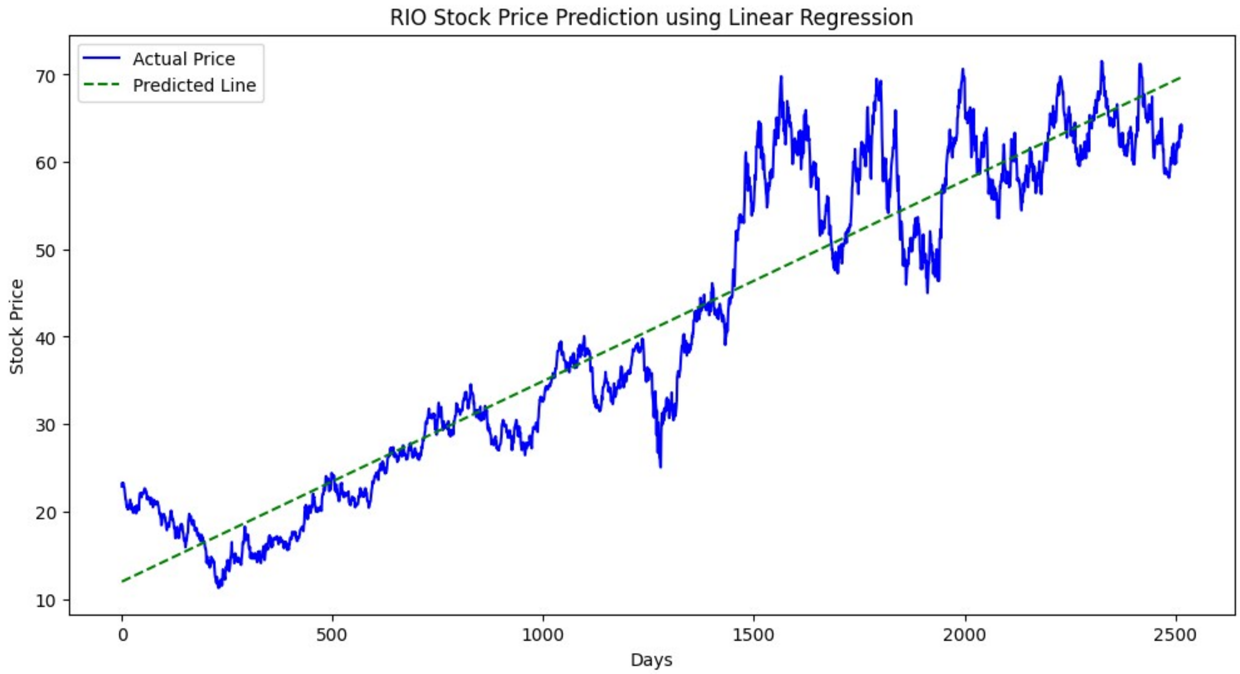
```
price (63.53).
Stable volatility for RIO. Market is relatively calm.



/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/
tsa_model.py:837: ValueWarning: No supported index is available.
Prediction results will be given with an integer index beginning at
`start`.
  return get_prediction_index(
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model
.py:837: FutureWarning: No supported index is available. In the next
version, calling this method in a model without a supported index will
result in an exception.
  return get_prediction_index(
```

Linear Regression

```
# Fetch data from Yahoo Finance for 10+ years
history = ticker.history(period="10y")

# Prepare data for Linear Regression
history = history.dropna()
history['Date'] = history.index
df = history[['Close']].reset_index(drop=True)
df['Day'] = np.arange(len(df))

# Split data into training and testing sets
X = df[['Day']]
y = df['Close']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print model evaluation
print("Linear Regression :\n")
print("Model Evaluation :\n")
print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
```

```python
print(f"R-Squared Score: {r2}\n")

print(f"\n{stock_ticker} Price Prediction using Linear Regression :\
n")
# Plot actual vs predicted prices
plt.figure(figsize=(12,6))
plt.plot(df['Day'], df['Close'], label='Actual Price', color='blue')
plt.plot(df['Day'], model.predict(X), label='Predicted Line',
color='green', linestyle='dashed')
plt.title(f"{stock_ticker} Stock Price Prediction using Linear
Regression")
plt.xlabel("Days")
plt.ylabel("Stock Price")
plt.legend()
plt.show()

# Conclusion based on prediction
latest_predicted_price = model.predict([[df['Day'].iloc[-1] + 1]])[0]
current_price = df['Close'].iloc[-1]

print("\nConclusion :\n")
if latest_predicted_price > current_price:
    print(f"Buy Signal: Predicted price ({latest_predicted_price:.2f})
is higher than the current price ({current_price:.2f}).\n\n")
    linear_regression_model = "Buy"
else:
    print(f"Sell Signal: Predicted price
({latest_predicted_price:.2f}) is lower than the current price
({current_price:.2f}).\n\n")
    linear_regression_model = "Sell"
```

```
Linear Regression :

Model Evaluation :

Mean Absolute Error: 4.682856605538877
Mean Squared Error: 40.156294905191665
R-Squared Score: 0.8727768983731525


RIO Price Prediction using Linear Regression :
```




```
Conclusion :

Buy Signal: Predicted price (69.72) is higher than the current price
(63.53).



/usr/local/lib/python3.11/dist-packages/sklearn/utils/
validation.py:2739: UserWarning: X does not have valid feature names,
but LinearRegression was fitted with feature names
  warnings.warn(
```

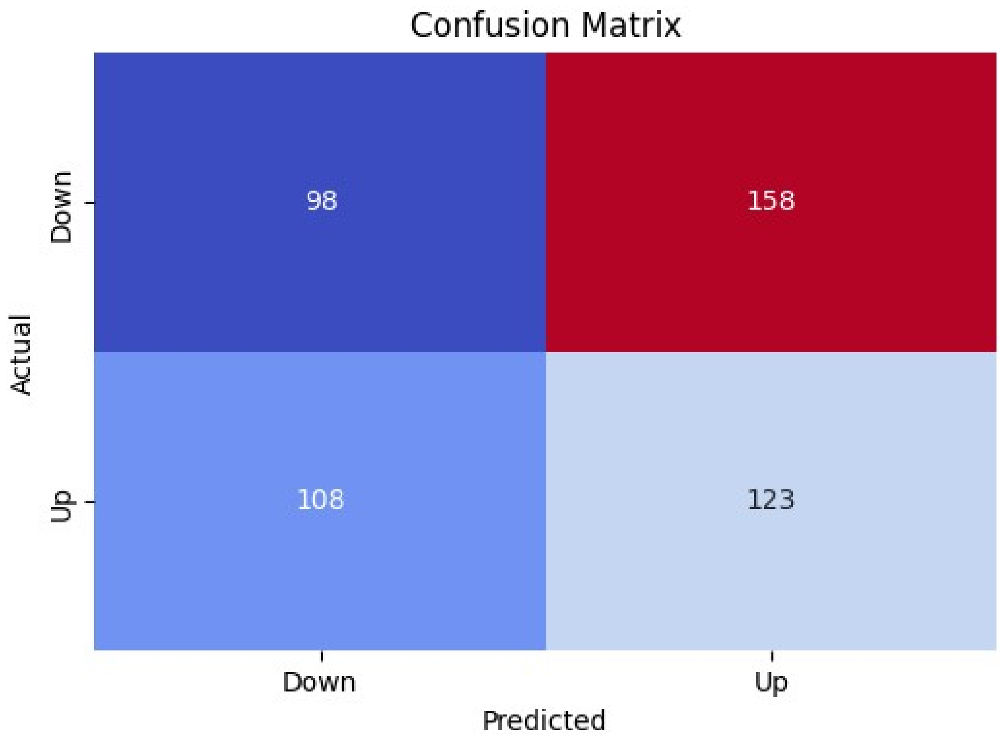
Logistic Regression Model

```python
# Ensure 'Daily Return' is computed correctly
if 'Daily Return' not in history.columns:
    history['Daily Return'] = history['Close'].pct_change()

# Add more technical indicators
history['Momentum'] = history['Close'] - history['Close'].shift(4)
history['Volatility'] = history['Daily
Return'].rolling(window=5).std()
history['SMA_10'] = history['Close'].rolling(window=10).mean()

# Ensure SMA_50 and SMA_200 are computed
history['SMA_50'] = history['Close'].rolling(window=50).mean()
history['SMA_200'] = history['Close'].rolling(window=200).mean()
```

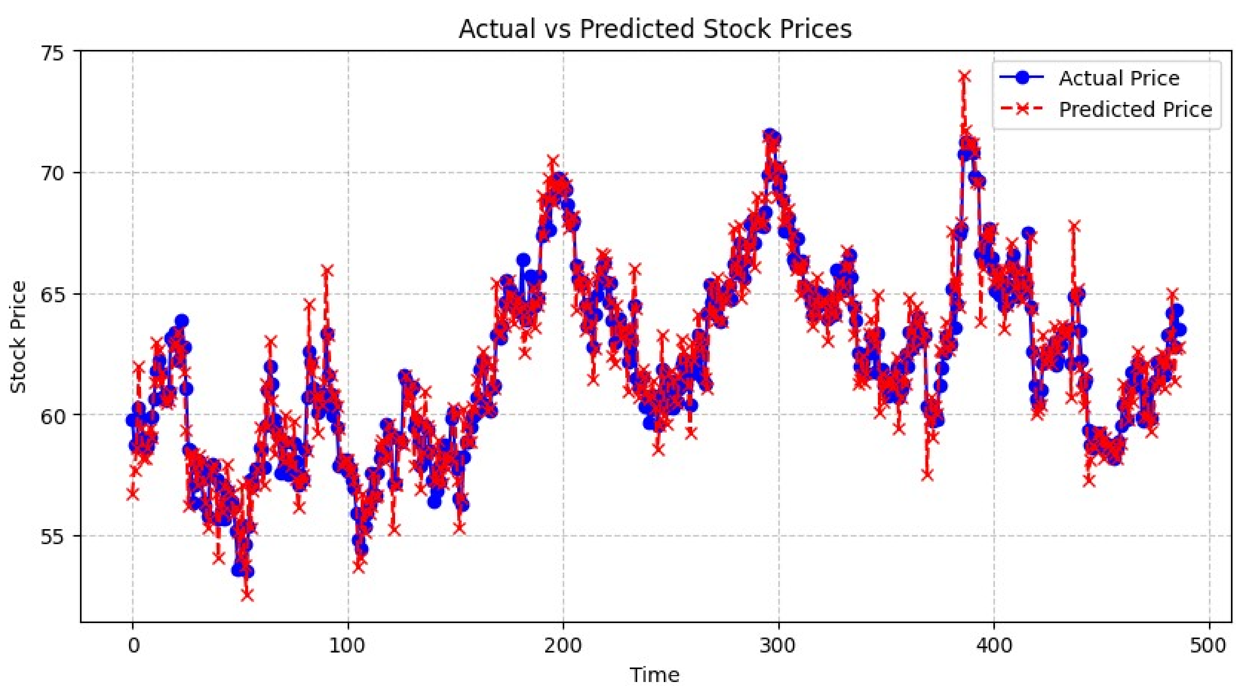
```
# Logistic Regression Model for Predicting Stock Movement
print("\nLogistic Regression Model \n")
history['Target'] = (history['Close'].shift(-1) >
history['Close']).astype(int)

features = ['SMA_50', 'SMA_200', 'Daily Return', 'Momentum',
'Volatility', 'SMA_10']

# Drop rows where any feature or target is NaN
history.dropna(subset=features + ['Target'], inplace=True)

X = history[features]
y = history['Target']

# Balance dataset using SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_resampled)
X_train, X_test, y_train, y_test = train_test_split(X_scaled,
y_resampled, test_size=0.2, random_state=42)

# Hyperparameter tuning with GridSearchCV
param_grid = {'C': [0.01, 0.1, 1, 10, 100]}
grid_search = GridSearchCV(LogisticRegression(), param_grid, cv=5,
scoring='accuracy')
grid_search.fit(X_train, y_train)

model = grid_search.best_estimator_
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# Map predicted movements to actual prices
predicted_prices = history['Close'].iloc[-len(y_test):].values * (1 +
(y_pred * 2 - 1) * history['Daily Return'].iloc[-len(y_test):].values)

print("Best Hyperparameters:", grid_search.best_params_)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n\n", classification_report(y_test,
y_pred))

print(f"\nConfusion Matrix :\n")
plt.figure(figsize=(6,4))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d',
cmap='coolwarm', cbar=False, xticklabels=['Down', 'Up'],
yticklabels=['Down', 'Up'])
plt.xlabel("Predicted")
plt.ylabel("Actual")
```

```python
plt.title("Confusion Matrix")
plt.show()

print(f"\n{stock_ticker} Price Prediction using Logistic Regression :\
n")
plt.figure(figsize=(10,5))
plt.plot(history['Close'].iloc[-len(y_test):].values, label="Actual
Price", color="blue", marker='o', linestyle='-')
plt.plot(predicted_prices, label="Predicted Price", color="red",
marker='x', linestyle='--')
plt.xlabel("Time")
plt.ylabel("Stock Price")
plt.legend()
plt.title("Actual vs Predicted Stock Prices")
plt.grid(True, linestyle='--', alpha=0.7)
plt.show()

print("\nConclusion :\n")
if y_pred[-1] == 1:
    print(f"Buy Recommendation: The model predicts an upward trend for
{stock_ticker}.\n")
    logistic_regression_model = "Buy"
else:
    print(f"Sell Recommendation: The model predicts a downward trend
for {stock_ticker}.\n")
    logistic_regression_model = "Sell"
```

```
Logistic Regression Model

Best Hyperparameters: {'C': 100}
Accuracy: 0.4537987679671458

Classification Report:

              precision    recall  f1-score   support

           0       0.48      0.38      0.42       256
           1       0.44      0.53      0.48       231

    accuracy                           0.45       487
   macro avg       0.46      0.46      0.45       487
weighted avg       0.46      0.45      0.45       487


Confusion Matrix :
```




```
RIO Price Prediction using Logistic Regression :
```



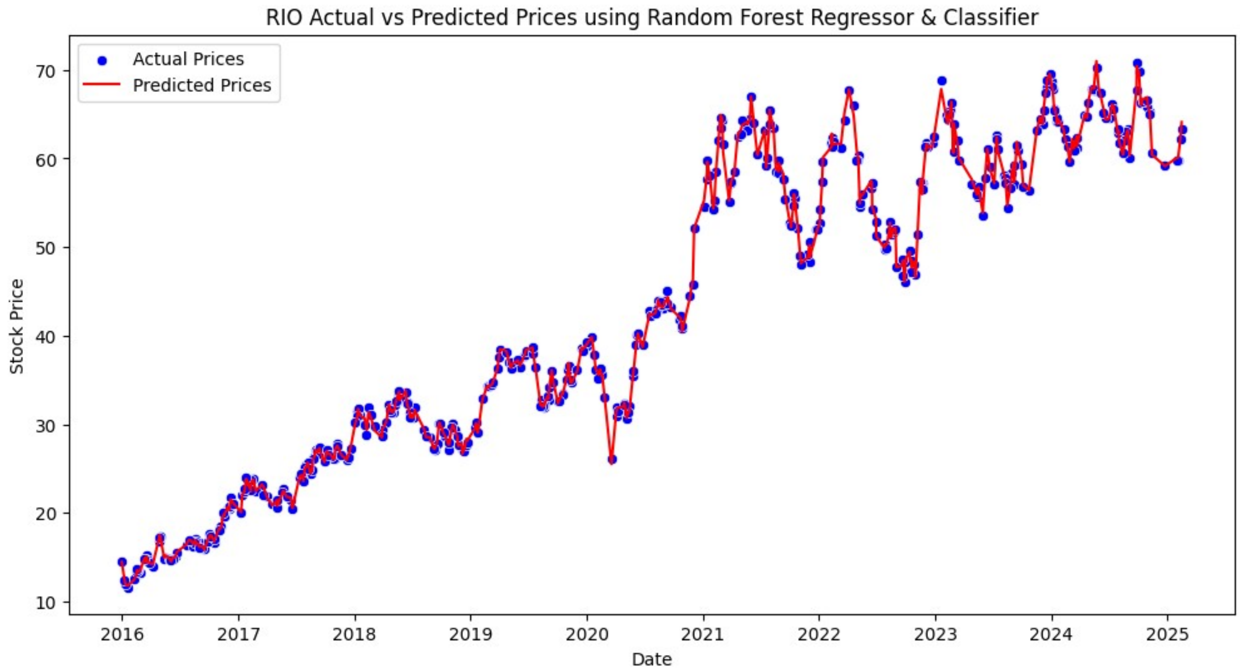
```
Conclusion :

Buy Recommendation: The model predicts an upward trend for RIO.
```

Random Forest Regressor & Classifier

```
# Fetch historical stock data
def fetch_stock_data(stock_ticker):
    ticker = yf.Ticker(stock_ticker)
    history = ticker.history(period="10y")
    return history

# Get stock ticker from user
history = fetch_stock_data(stock_ticker)

# Prepare data for prediction
history['Returns'] = history['Close'].pct_change()
history['SMA_50'] = history['Close'].rolling(window=50).mean()
history['SMA_200'] = history['Close'].rolling(window=200).mean()
history.dropna(inplace=True)

# Feature selection and target variable
features = ['SMA_50', 'SMA_200', 'Open', 'High', 'Low', 'Volume']
X = history[features]
y_reg = history['Close']  # For regression
y_clf = (history['Returns'] > 0).astype(int)  # Classification: 1 if
return > 0 else 0

# Split data
X_train, X_test, y_train_reg, y_test_reg = train_test_split(X, y_reg,
test_size=0.2, random_state=42)
X_train_clf, X_test_clf, y_train_clf, y_test_clf = train_test_split(X,
y_clf, test_size=0.2, random_state=42)

# Train Random Forest Regressor
regressor = RandomForestRegressor(n_estimators=100, random_state=42)
regressor.fit(X_train, y_train_reg)
y_pred_reg = regressor.predict(X_test)

# Train Random Forest Classifier
classifier = RandomForestClassifier(n_estimators=100, random_state=42)
classifier.fit(X_train_clf, y_train_clf)
y_pred_clf = classifier.predict(X_test_clf)

# Performance evaluation
print(f"\n{stock_ticker} Price Prediction using Random Forest
```

```
Regressor & Classifier :")
print("\nRegression Model Performance :\n")
print(f"Mean Absolute Error: {mean_absolute_error(y_test_reg,
y_pred_reg)}")
print(f"Mean Squared Error: {mean_squared_error(y_test_reg,
y_pred_reg)}")

print("\nClassification Model Performance :\n")
print(f"Accuracy: {accuracy_score(y_test_clf, y_pred_clf)}\n")

print(f"{stock_ticker} Actual vs Predicted Prices using Random Forest
Regressor & Classifier :\n")
# Improved graph with scatter plot and trend lines
plt.figure(figsize=(12,6))
sns.scatterplot(x=y_test_reg.index, y=y_test_reg, label='Actual
Prices', color='blue')
sns.lineplot(x=y_test_reg.index, y=y_pred_reg, label='Predicted
Prices', color='red')
plt.title(f"{stock_ticker} Actual vs Predicted Prices using Random
Forest Regressor & Classifier")
plt.xlabel("Date")
plt.ylabel("Stock Price")
plt.legend()
plt.show()

# Conclusion
print("\nConclusion :\n")
if y_pred_clf[-1] == 1:
    print(f"Buy Signal: {stock_ticker} is predicted to go up.\n")
    random_forest = "Buy"
else:
    print(f"Sell Signal: {stock_ticker} is predicted to go down.\n")
    random_forest = "Sell"
```

```
RIO Price Prediction using Random Forest Regressor & Classifier :

Regression Model Performance :

Mean Absolute Error: 0.21172219093503633
Mean Squared Error: 0.08887298514180927

Classification Model Performance :

Accuracy: 0.5107758620689655

RIO Actual vs Predicted Prices using Random Forest Regressor &
Classifier :
```




```
Conclusion :

Sell Signal: RIO is predicted to go down.
```

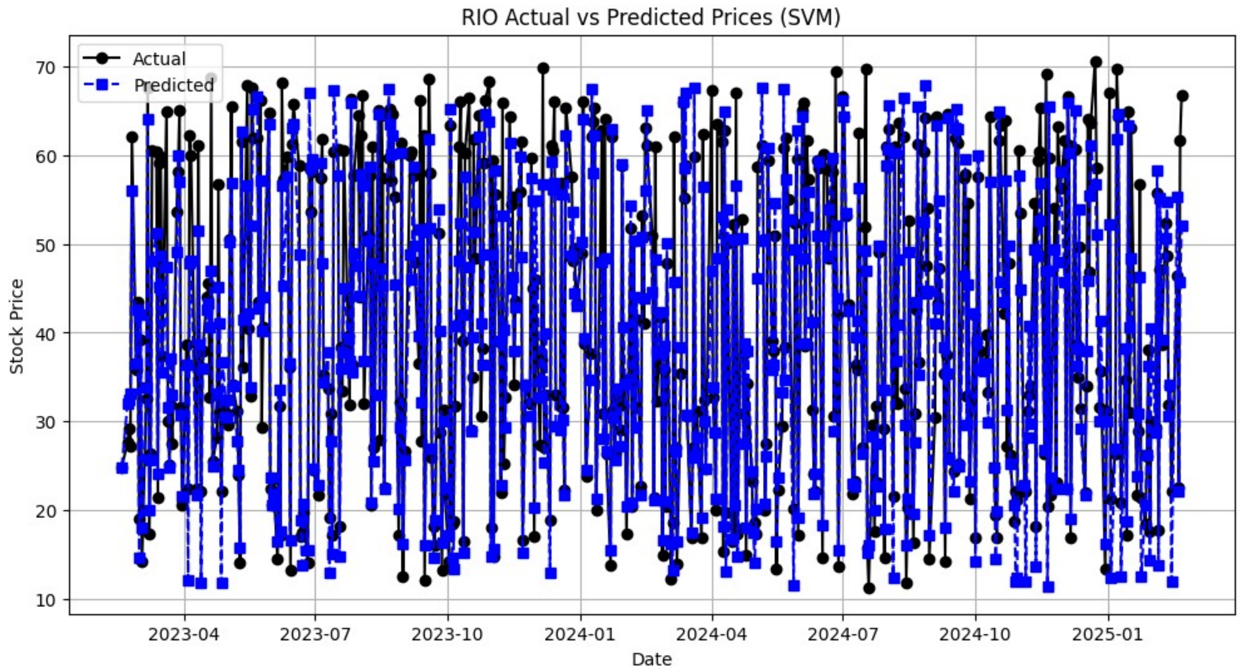
Support Vector Machine (SVM)

```
# Fetch 10-year historical data
history = yf.download(stock_ticker, period="10y")

# Prepare data for SVM
history.dropna(inplace=True)
history['Date'] = history.index
history['Date'] = history['Date'].map(pd.Timestamp.toordinal)

X = history[['Date']]
y = history['Close']

# Normalize data
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)
```

```
# Train SVM model
svm_model = SVR(kernel='rbf', C=100, gamma=0.1, epsilon=0.1)
svm_model.fit(X_train, y_train)

# Predictions
y_pred = svm_model.predict(X_test)

# Plot actual vs predicted
print(f"\n{stock_ticker} Actual vs Predicted Prices using SVM :\n")
plt.figure(figsize=(12,6))
plt.plot(history.index[-len(y_test):], y_test.values, label='Actual',
color='black', marker='o')
plt.plot(history.index[-len(y_test):], y_pred, label='Predicted',
color='blue', linestyle='dashed', marker='s')
plt.title(f"{stock_ticker} Actual vs Predicted Prices (SVM)")
plt.xlabel("Date")
plt.ylabel("Stock Price")
plt.legend()
plt.grid(True)
plt.show()

# Evaluation
print("\nConclusion :\n")
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R-squared Score: {r2}\n")

# Conclusion: Buy or Sell
latest_predicted =
svm_model.predict(scaler.transform([[history['Date'].iloc[-
1]]])).item()
latest_actual = history['Close'].iloc[-1].item()

if latest_predicted > latest_actual:
    print(f"Prediction: Price is expected to rise. Consider BUYING
{stock_ticker}.")
    svm_model = "Buy"
else:
    print(f"Prediction: Price is expected to drop. Consider SELLING
{stock_ticker}.")
    svm_model = "Sell"
```

```
 [*********************100%***********************]  1 of 1 completed

YF.download() has changed argument auto_adjust default to True


/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:14
08: DataConversionWarning: A column-vector y was passed when a 1d
array was expected. Please change the shape of y to (n_samples, ), for
```

```
example using ravel().
  y = column_or_1d(y, warn=True)


RIO Actual vs Predicted Prices using SVM :
```




```
Conclusion :

Mean Squared Error: 41.64553485597158
R-squared Score: 0.8680586910272767

Prediction: Price is expected to rise. Consider BUYING RIO.
```

XGBoost & LightGBM

```
# Fetch 10-year historical data
data = history[['Close']].dropna()
data = data[-2520:]  # Approx. 252 trading days per year * 10 years
data['Returns'] = data['Close'].pct_change()
data.dropna(inplace=True)
data['Future_Close'] = data['Close'].shift(-1)  # Renamed to avoid
issues
data.dropna(inplace=True)

X = data[['Close', 'Returns']]
```

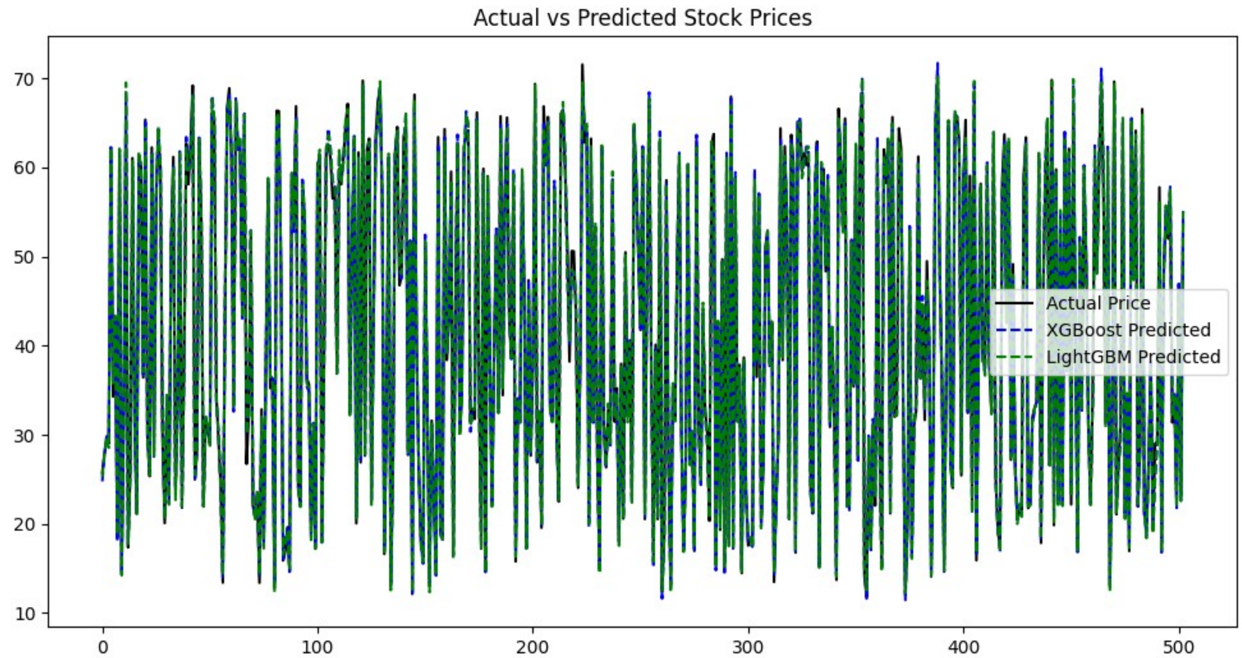
```python
y = data['Future_Close']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Convert MultiIndex columns to a standard Index
if isinstance(X_train.columns, pd.MultiIndex):
    X_train.columns = ['_'.join(col).strip() for col in
X_train.columns]
    X_test.columns = ['_'.join(col).strip() for col in X_test.columns]

# Rename columns to remove special characters
X_train.columns = [re.sub(r'[^a-zA-Z0-9_]', '', col) for col in
X_train.columns]
X_test.columns = [re.sub(r'[^a-zA-Z0-9_]', '', col) for col in
X_test.columns]

# XGBoost Model
xgb_model = xgb.XGBRegressor(objective='reg:squarederror',
n_estimators=100)
xgb_model.fit(X_train, y_train)
xgb_preds = xgb_model.predict(X_test)

xgb_rmse = np.sqrt(mean_squared_error(y_test, xgb_preds))
xgb_r2 = r2_score(y_test, xgb_preds)
print("\nXGBoost Model :\n")
print(f"XGBoost RMSE: {xgb_rmse}")
print(f"XGBoost R2 Score: {xgb_r2}\n")

# LightGBM Model
lgb_model = lgb.LGBMRegressor(n_estimators=100)
lgb_model.fit(X_train, y_train)
lgb_preds = lgb_model.predict(X_test)

lgb_rmse = np.sqrt(mean_squared_error(y_test, lgb_preds))
lgb_r2 = r2_score(y_test, lgb_preds)
print("\nLightGBM Model :\n")
print(f"LightGBM RMSE: {lgb_rmse}")
print(f"LightGBM R2 Score: {lgb_r2}\n")

# Price Graph Over 10 Years
print(f"\n{stock_ticker} Price Trend Over 10 Years :\n")
plt.figure(figsize=(12,6))
plt.plot(data.index, data['Close'], label="Stock Price (10 years)",
color='black')
plt.title(f"{stock_ticker} Price Trend Over 10 Years")
plt.xlabel("Date")
plt.ylabel("Close Price")
plt.legend()
plt.show()
```

```python
# Graph Comparing Actual vs Predicted Prices
print(f"\n{stock_ticker} Actual vs Predicted Prices :\n")
plt.figure(figsize=(12,6))
plt.plot(y_test.values, label="Actual Price", color='black')
plt.plot(xgb_preds, label="XGBoost Predicted", linestyle='dashed',
color='blue')
plt.plot(lgb_preds, label="LightGBM Predicted", linestyle='dashed',
color='green')
plt.title("Actual vs Predicted Stock Prices")
plt.legend()
plt.show()

# Conclusion on Buy or Sell Decision
latest_close = history['Close'].iloc[-1].item()  # Ensure scalar value
xgb_latest_pred = xgb_preds[-1]
lgb_latest_pred = lgb_preds[-1]

print("\nConclusion :\n")
if xgb_latest_pred > latest_close and lgb_latest_pred > latest_close:
    print(f"Both models predict an upward trend. Suggested action: BUY
{stock_ticker}.")
    xgboost_lightgbm_model = "Buy"
elif xgb_latest_pred < latest_close and lgb_latest_pred <
latest_close:
    print(f"Both models predict a downward trend. Suggested action:
SELL {stock_ticker}.")
    xgboost_lightgbm_model = "Sell"
else:
    print(f"Models have mixed predictions. Suggested action: HOLD
{stock_ticker}, observe further.")
    xgboost_lightgbm_model = "Hold"
```

```
XGBoost Model :

XGBoost RMSE: 0.9516588623027524
XGBoost R2 Score: 0.9971960524812682

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead
of testing was 0.000440 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 510
[LightGBM] [Info] Number of data points in the train set: 2011, number
of used features: 2
[LightGBM] [Info] Start training from score 40.847535

LightGBM Model :

LightGBM RMSE: 0.8861747413413361
```

```
LightGBM R2 Score: 0.9975686581674562

RIO Price Trend Over 10 Years :
```


```
RIO Actual vs Predicted Prices :
```



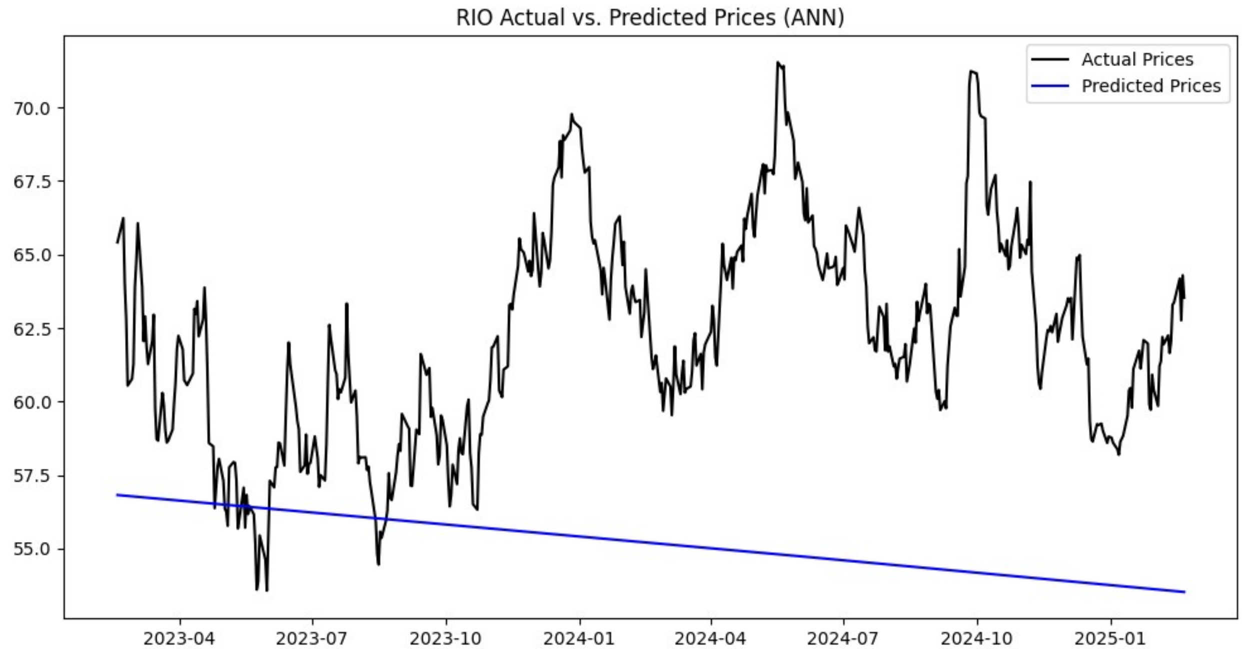

```
Conclusion :

Both models predict a downward trend. Suggested action: SELL RIO.
```

Artificial Neural Networks (ANN)

```
# Fetch 10 years of data
history = ticker.history(period="10y")
history['Date'] = history.index
history['Ordinal Date'] = history['Date'].map(pd.Timestamp.toordinal)
features = ['Ordinal Date']
X = history[features].values
Y = history['Close'].values

scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
Y_scaled = scaler.fit_transform(Y.reshape(-1, 1))

X_train, X_test, Y_train, Y_test = train_test_split(X_scaled,
Y_scaled, test_size=0.2, shuffle=False)

# Define ANN Model
model = keras.Sequential([
    keras.layers.Dense(64, activation='relu',
input_shape=(X_train.shape[1],)),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(1)
```

```
])

model.compile(optimizer='adam', loss='mse')
model.fit(X_train, Y_train, epochs=100, batch_size=16, verbose=0)

# Predictions
Y_pred = model.predict(X_test)
Y_pred_rescaled = scaler.inverse_transform(Y_pred)
Y_test_rescaled = scaler.inverse_transform(Y_test)

# Plot Actual vs. Predicted Prices
print(f"\n{stock_ticker} Actual vs. Predicted Prices (ANN) :\n")
plt.figure(figsize=(12,6))
plt.plot(history.index[-len(Y_test):], Y_test_rescaled, label='Actual
Prices', color='black')
plt.plot(history.index[-len(Y_pred):], Y_pred_rescaled,
label='Predicted Prices', color='blue')
plt.title(f"{stock_ticker} Actual vs. Predicted Prices (ANN)")
plt.legend()
plt.show()

# Buy/Sell Conclusion
print("\nConclusion :\n")
if Y_pred_rescaled[-1] > Y_test_rescaled[-1]:
    print(f"BUY Signal: {stock_ticker}'s price is predicted to
increase.")
    ann_model = "Buy"

else:
    print(f"SELL Signal: {stock_ticker}'s price is predicted to
decrease.")
    ann_model = "Sell"
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step

RIO Actual vs. Predicted Prices (ANN) :
```




```
Conclusion :

SELL Signal: RIO's price is predicted to decrease.
```

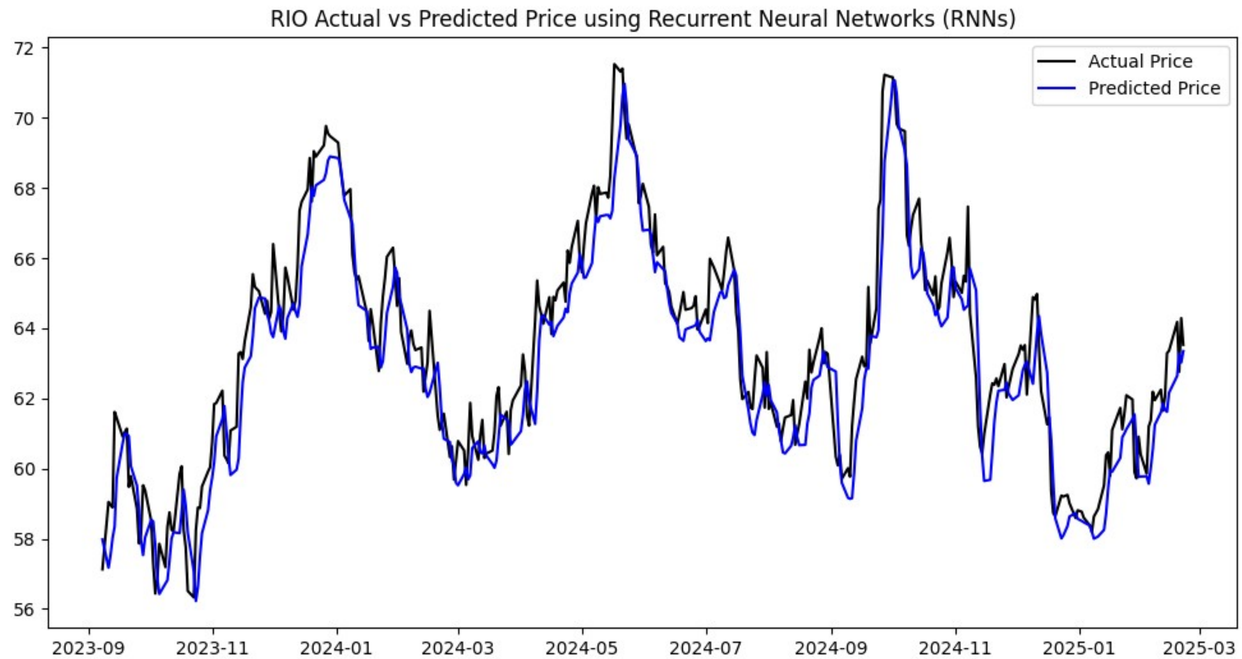
Recurrent Neural Networks (RNN)

```python
# Prepare data for RNN
scaler = MinMaxScaler(feature_range=(0,1))
data = history[['Close']].copy()
data_scaled = scaler.fit_transform(data)

# Create sequences
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 730  # Use last 2 years (730 days) to predict the next
day
X, y = create_sequences(data_scaled, seq_length)
X_train, y_train = X[:-365], y[:-365]
X_test, y_test = X[-365:], y[-365:]

# Build RNN Model
model = Sequential([
```

```
    LSTM(units=50, return_sequences=True, input_shape=(seq_length,
1)),
    LSTM(units=50, return_sequences=False),
    Dense(units=25),
    Dense(units=1)
])

model.compile(optimizer='adam', loss='mean_squared_error')

# Train Model
model.fit(X_train, y_train, batch_size=16, epochs=20)

# Predict
y_pred = model.predict(X_test)
y_pred_rescaled = scaler.inverse_transform(y_pred)
y_test_rescaled = scaler.inverse_transform(y_test)

# Plot results
print(f"\n\n{stock_ticker} : Actual vs Predicted Price using Recurrent
Neural Networks (RNNs) :\n")
plt.figure(figsize=(12,6))
plt.plot(data.index[-365:], y_test_rescaled, label='Actual Price',
color='black')
plt.plot(data.index[-365:], y_pred_rescaled, label='Predicted Price',
color='blue')
plt.title(f"{stock_ticker} Actual vs Predicted Price using Recurrent
Neural Networks (RNNs)")
plt.legend()
plt.show()

# Conclusion
last_predicted = y_pred_rescaled[-1][0]
last_actual = y_test_rescaled[-1][0]
print("\nConclusion :\n")
print(f"Last Actual Price: {last_actual}")
print(f"Last Predicted Price: {last_predicted}")

if last_predicted > last_actual:
    print(f"Prediction suggests an upward trend. Consider BUYING
{stock_ticker}.\n")
    rnn_model = "Buy"
elif last_predicted < last_actual:
    print(f"Prediction suggests a downward trend. Consider SELLING
{stock_ticker}.\n")
    rnn_model = "Sell"
else:
    print(f"Prediction suggests stability. Hold your position in
{stock_ticker}.\n")
    rnn_model = "Hold"
```

```
Epoch 1/20

/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/
rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

89/89 ━━━━━━━━━━━━━━━━━━━━ 65s 676ms/step - loss: 0.0463
Epoch 2/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 94s 810ms/step - loss: 0.0013
Epoch 3/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 58s 544ms/step - loss: 0.0014
Epoch 4/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 50s 558ms/step - loss: 0.0010
Epoch 5/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 48s 545ms/step - loss: 0.0010
Epoch 6/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 81s 539ms/step - loss: 0.0010
Epoch 7/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 83s 546ms/step - loss: 0.0011
Epoch 8/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 49s 549ms/step - loss: 9.2398e-04
Epoch 9/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 82s 553ms/step - loss: 8.1301e-04
Epoch 10/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 82s 558ms/step - loss: 6.9935e-04
Epoch 11/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 81s 553ms/step - loss: 7.2962e-04
Epoch 12/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 49s 548ms/step - loss: 6.0973e-04
Epoch 13/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 82s 541ms/step - loss: 5.6734e-04
Epoch 14/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 48s 545ms/step - loss: 5.3742e-04
Epoch 15/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 50s 557ms/step - loss: 5.3371e-04
Epoch 16/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 81s 548ms/step - loss: 6.0307e-04
Epoch 17/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 82s 552ms/step - loss: 5.4923e-04
Epoch 18/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 82s 557ms/step - loss: 4.5648e-04
Epoch 19/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 80s 537ms/step - loss: 4.2927e-04
Epoch 20/20
89/89 ━━━━━━━━━━━━━━━━━━━━ 83s 548ms/step - loss: 4.0619e-04
12/12 ━━━━━━━━━━━━━━━━━━━━ 2s 168ms/step
```

```
RIO : Actual vs Predicted Price using Recurrent Neural Networks (RNNs)
:
```




```
Conclusion :

Last Actual Price: 63.529998779296875
Last Predicted Price: 63.34847640991211
Prediction suggests a downward trend. Consider SELLING RIO.
```

Long Short-Term Memory (LSTM)

```
# Fetch data from previous analysis
data = history[['Close']]
scaler = MinMaxScaler(feature_range=(0,1))
data_scaled = scaler.fit_transform(data)

# Prepare data for LSTM model
def create_sequences(data, seq_length):
    sequences = []
    labels = []
    for i in range(len(data) - seq_length):
        sequences.append(data[i:i + seq_length])
        labels.append(data[i + seq_length])
    return np.array(sequences), np.array(labels)
```

```
seq_length = 50  # Higher number for higher accuracy
X, y = create_sequences(data_scaled, seq_length)
X_train, X_test = X[:int(0.8 * len(X))], X[int(0.8 * len(X)):]
y_train, y_test = y[:int(0.8 * len(y))], y[int(0.8 * len(y)):]

# Build LSTM model
model = Sequential([
    LSTM(units=50, return_sequences=True, input_shape=(seq_length,
1)),
    Dropout(0.2),
    LSTM(units=50, return_sequences=False),
    Dropout(0.2),
    Dense(units=25),
    Dense(units=1)
])

model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=16,
validation_data=(X_test, y_test))

# Make predictions
y_pred = model.predict(X_test)
y_pred_inv = scaler.inverse_transform(y_pred)
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

# Plot actual vs predicted
print(f"\n\n{stock_ticker} Price Prediction using Long Short-Term
Memory (LSTM) :\n")
plt.figure(figsize=(12,6))
plt.plot(y_test_inv, label='Actual Price', color='blue')
plt.plot(y_pred_inv, label='Predicted Price', color='red')
plt.title(f"{stock_ticker} - Actual vs Predicted Price using Long
Short-Term Memory (LSTM)")
plt.legend()
plt.show()

# Conclusion
latest_pred = y_pred_inv[-1][0]
latest_actual = y_test_inv[-1][0]
print("\nConclusion :\n")
if latest_pred > latest_actual:
    print(f"Buy Signal: {stock_ticker}'s predicted price
({latest_pred:.2f}) is higher than its current price
({latest_actual:.2f}).\n")
    lstm_model = "Buy"
else:
    print(f"Sell Signal: {stock_ticker}'s predicted price
```

```
({latest_pred:.2f}) is lower than its current price
({latest_actual:.2f}).\n")
    lstm_model = "Sell"
```

```
Epoch 1/50
```

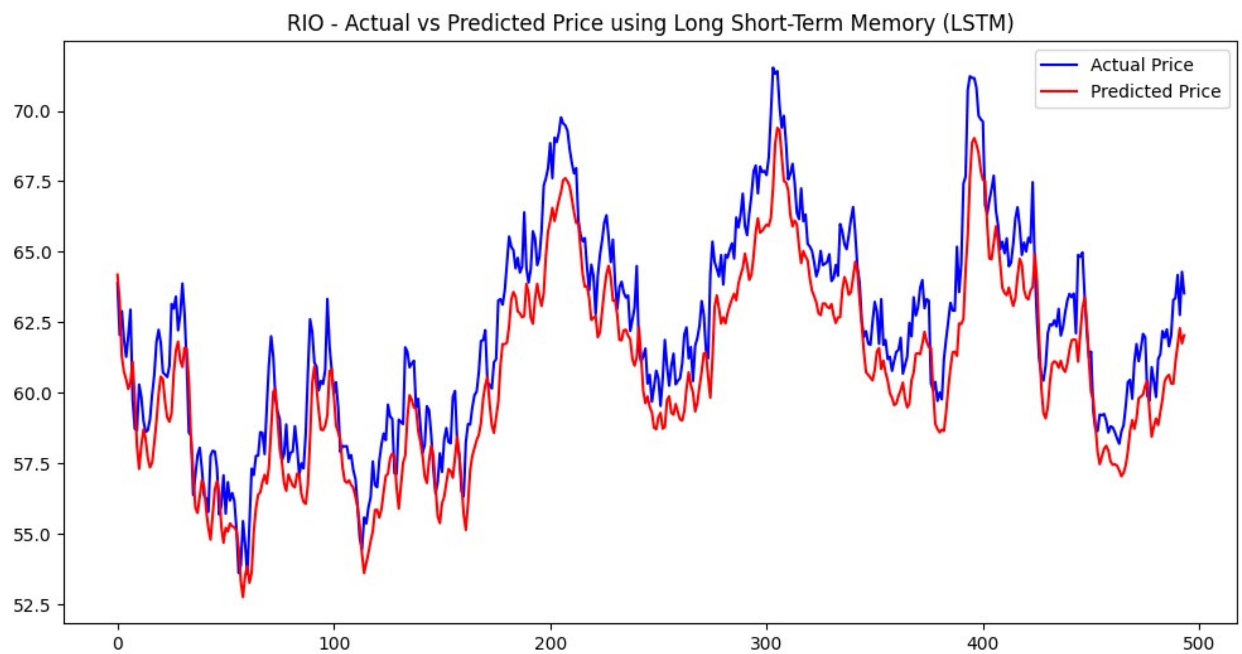
```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/
rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 49ms/step - loss: 0.0352 - val_loss:
0.0018
Epoch 2/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 46ms/step - loss: 0.0030 - val_loss:
0.0036
Epoch 3/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 38ms/step - loss: 0.0031 - val_loss:
0.0015
Epoch 4/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - loss: 0.0020 - val_loss:
0.0012
Epoch 5/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 47ms/step - loss: 0.0018 - val_loss:
0.0010
Epoch 6/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 38ms/step - loss: 0.0018 - val_loss:
8.5525e-04
Epoch 7/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 39ms/step - loss: 0.0015 - val_loss:
0.0031
Epoch 8/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - loss: 0.0015 - val_loss:
0.0014
Epoch 9/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 38ms/step - loss: 0.0015 - val_loss:
9.3028e-04
Epoch 10/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 46ms/step - loss: 0.0013 - val_loss:
6.5709e-04
Epoch 11/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 40ms/step - loss: 0.0012 - val_loss:
6.6365e-04
Epoch 12/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - loss: 0.0014 - val_loss:
6.5637e-04
Epoch 13/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 47ms/step - loss: 0.0011 - val_loss:
6.7125e-04
```

```
Epoch 14/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 0.0012 - val_loss:
5.9944e-04
Epoch 15/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 41ms/step - loss: 0.0011 - val_loss:
5.8022e-04
Epoch 16/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 42ms/step - loss: 0.0011 - val_loss:
7.8495e-04
Epoch 17/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 0.0011 - val_loss:
8.4448e-04
Epoch 18/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 47ms/step - loss: 9.6244e-04 -
val_loss: 0.0013
Epoch 19/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 39ms/step - loss: 0.0010 - val_loss:
5.5853e-04
Epoch 20/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 43ms/step - loss: 0.0010 - val_loss:
6.3978e-04
Epoch 21/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 40ms/step - loss: 9.8483e-04 -
val_loss: 6.3507e-04
Epoch 22/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 50ms/step - loss: 9.6077e-04 -
val_loss: 9.9764e-04
Epoch 23/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 38ms/step - loss: 9.3362e-04 -
val_loss: 0.0013
Epoch 24/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 44ms/step - loss: 0.0011 - val_loss:
5.3432e-04
Epoch 25/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 9.1689e-04 -
val_loss: 4.2190e-04
Epoch 26/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 49ms/step - loss: 8.8602e-04 -
val_loss: 8.5222e-04
Epoch 27/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 37ms/step - loss: 0.0010 - val_loss:
7.4540e-04
Epoch 28/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 44ms/step - loss: 9.7136e-04 -
val_loss: 0.0012
Epoch 29/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 46ms/step - loss: 8.7734e-04 -
val_loss: 6.1902e-04
Epoch 30/50
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 9.6597e-04 -
val_loss: 4.0623e-04
Epoch 31/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 40ms/step - loss: 8.7207e-04 -
val_loss: 4.4030e-04
Epoch 32/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 43ms/step - loss: 9.1195e-04 -
val_loss: 4.0814e-04
Epoch 33/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 11s 47ms/step - loss: 0.0010 - val_loss:
4.1644e-04
Epoch 34/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 38ms/step - loss: 7.8846e-04 -
val_loss: 3.5725e-04
Epoch 35/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 43ms/step - loss: 8.8976e-04 -
val_loss: 3.6081e-04
Epoch 36/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 37ms/step - loss: 9.1628e-04 -
val_loss: 4.8396e-04
Epoch 37/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 47ms/step - loss: 8.7129e-04 -
val_loss: 3.5283e-04
Epoch 38/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 44ms/step - loss: 8.3814e-04 -
val_loss: 7.3448e-04
Epoch 39/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 37ms/step - loss: 9.5527e-04 -
val_loss: 3.7980e-04
Epoch 40/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 46ms/step - loss: 8.6275e-04 -
val_loss: 6.9427e-04
Epoch 41/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 8.3474e-04 -
val_loss: 4.2921e-04
Epoch 42/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - loss: 8.2912e-04 -
val_loss: 3.3031e-04
Epoch 43/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 37ms/step - loss: 7.3417e-04 -
val_loss: 4.2625e-04
Epoch 44/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 47ms/step - loss: 9.7387e-04 -
val_loss: 4.0028e-04
Epoch 45/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 46ms/step - loss: 8.4156e-04 -
val_loss: 5.9916e-04
Epoch 46/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 37ms/step - loss: 7.8755e-04 -
```

```
val_loss: 3.1676e-04
Epoch 47/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 47ms/step - loss: 8.7023e-04 -
val_loss: 3.3422e-04
Epoch 48/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 47ms/step - loss: 0.0010 - val_loss:
4.8654e-04
Epoch 49/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 37ms/step - loss: 8.8504e-04 -
val_loss: 6.3296e-04
Epoch 50/50
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 38ms/step - loss: 8.9217e-04 -
val_loss: 9.2946e-04
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 46ms/step


RIO Price Prediction using Long Short-Term Memory (LSTM) :
```




```
Conclusion :

Sell Signal: RIO's predicted price (62.04) is lower than its current
price (63.53).
```

Gated Recurrent Units (GRU)

```
time_steps = 50  # Number of time steps to look back

def create_sequences(data, time_steps):
    sequences, labels = [], []
    for i in range(len(data) - time_steps):
        sequences.append(data[i:i + time_steps])
        labels.append(data[i + time_steps])
    return np.array(sequences), np.array(labels)

# Prepare data for GRU model
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(history[['Close']])
X, y = create_sequences(scaled_data, time_steps)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, shuffle=False)

# Build GRU Model
model = Sequential([
    GRU(units=50, return_sequences=True, input_shape=(time_steps, 1)),
    Dropout(0.2),
    GRU(units=50, return_sequences=False),
    Dropout(0.2),
    Dense(units=25),
    Dense(units=1)
])

model.compile(optimizer='adam', loss='mean_squared_error')

# Train model
model.fit(X_train, y_train, epochs=20, batch_size=16,
validation_data=(X_test, y_test))

# Make predictions
y_pred = model.predict(X_test)
y_pred_inv = scaler.inverse_transform(y_pred.reshape(-1, 1))
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

# Plot actual vs predicted values
print(f"\n\n{stock_ticker} Price Prediction using Gated Recurrent
Units (GRU) :\n")
plt.figure(figsize=(12, 6))
plt.plot(y_test_inv, label='Actual Price', color='blue')
plt.plot(y_pred_inv, label='Predicted Price', color='red',
linestyle='dashed')
plt.title(f'{stock_ticker} Stock Price Prediction using Gated
Recurrent Units (GRU)')
plt.legend()
plt.show()
```

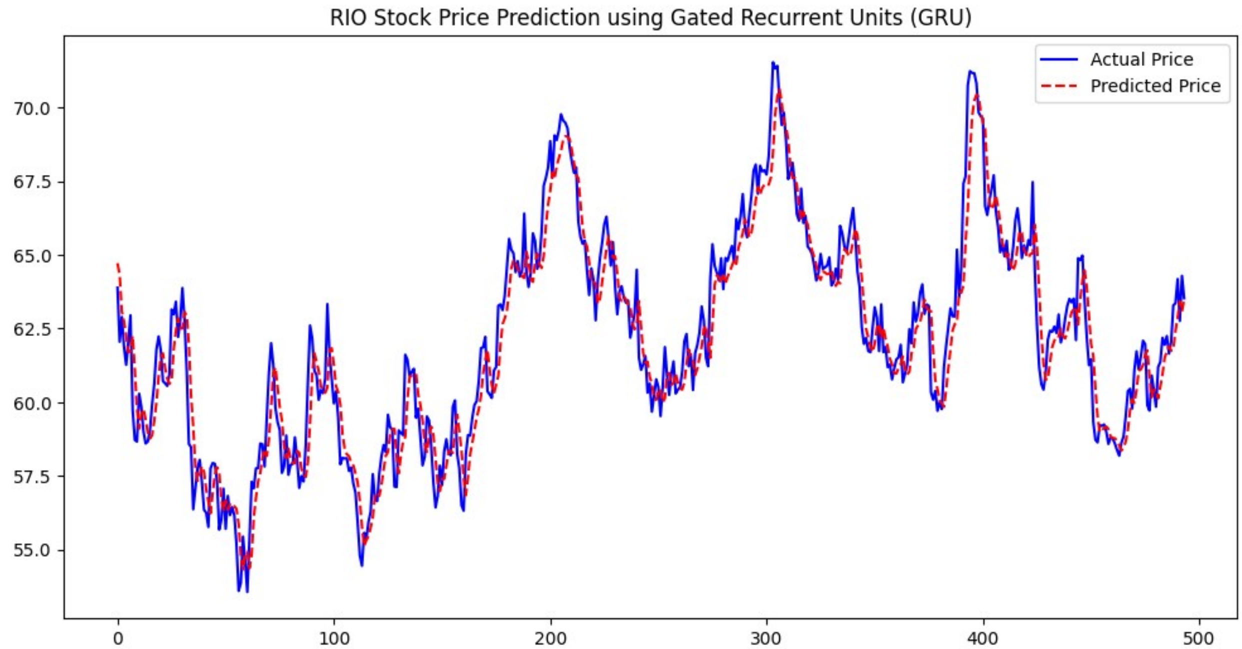
```python
# Conclusion
last_actual = y_test_inv[-1][0]
last_predicted = y_pred_inv[-1][0]
price_change = ((last_predicted - last_actual) / last_actual) * 100

print("\nConclusion :\n")
if price_change > 1:
    print(f"Predicted price increase: {price_change:.2f}%. Suggested
action: BUY")
    gru_model = "Buy"
elif price_change < -1:
    print(f"Predicted price decrease: {price_change:.2f}%. Suggested
action: SELL")
    gru_model = "Sell"
else:
    print(f"Minor price change ({price_change:.2f}%). Suggested
action: HOLD")
    gru_model = "Hold"
```

```
Epoch 1/20
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/
rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 12s 56ms/step - loss: 0.0375 - val_loss:
0.0028
Epoch 2/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 50ms/step - loss: 0.0027 - val_loss:
7.4166e-04
Epoch 3/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 11s 58ms/step - loss: 0.0028 - val_loss:
0.0030
Epoch 4/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 56ms/step - loss: 0.0016 - val_loss:
0.0012
Epoch 5/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 47ms/step - loss: 0.0018 - val_loss:
7.0656e-04
Epoch 6/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 47ms/step - loss: 0.0014 - val_loss:
4.8225e-04
Epoch 7/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 48ms/step - loss: 0.0014 - val_loss:
0.0010
Epoch 8/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 49ms/step - loss: 0.0012 - val_loss:
```

```
5.3410e-04
Epoch 9/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 54ms/step - loss: 0.0011 - val_loss:
0.0016
Epoch 10/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 49ms/step - loss: 0.0011 - val_loss:
4.2674e-04
Epoch 11/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 11s 56ms/step - loss: 9.2278e-04 -
val_loss: 4.0930e-04
Epoch 12/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 47ms/step - loss: 9.3356e-04 -
val_loss: 6.0204e-04
Epoch 13/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 56ms/step - loss: 8.4006e-04 -
val_loss: 4.2181e-04
Epoch 14/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 48ms/step - loss: 9.9543e-04 -
val_loss: 8.3277e-04
Epoch 15/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 56ms/step - loss: 8.9138e-04 -
val_loss: 3.8068e-04
Epoch 16/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 51ms/step - loss: 9.7232e-04 -
val_loss: 3.7115e-04
Epoch 17/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 54ms/step - loss: 8.4570e-04 -
val_loss: 5.3725e-04
Epoch 18/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 50ms/step - loss: 8.2590e-04 -
val_loss: 9.9947e-04
Epoch 19/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 48ms/step - loss: 9.0698e-04 -
val_loss: 4.9504e-04
Epoch 20/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 48ms/step - loss: 8.9099e-04 -
val_loss: 3.3347e-04
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 36ms/step


RIO Price Prediction using Gated Recurrent Units (GRU) :
```




```
Conclusion :

Minor price change (-0.08%). Suggested action: HOLD
```

Transformer Models

```
# Data Preprocessing
scaler = MinMaxScaler()
history['Scaled_Close'] = scaler.fit_transform(history[['Close']])

# Prepare data for Transformer model
def create_sequences(data, seq_length):
    sequences = []
    labels = []
    for i in range(len(data) - seq_length):
        sequences.append(data[i:i+seq_length])
        labels.append(data[i+seq_length])
    return np.array(sequences), np.array(labels)

seq_length = 50
X, y = create_sequences(history['Scaled_Close'].values, seq_length)
X_train, X_test = X[:int(0.8*len(X))], X[int(0.8*len(X)):]
y_train, y_test = y[:int(0.8*len(y))], y[int(0.8*len(y)):]

# Convert to tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.float32)
```

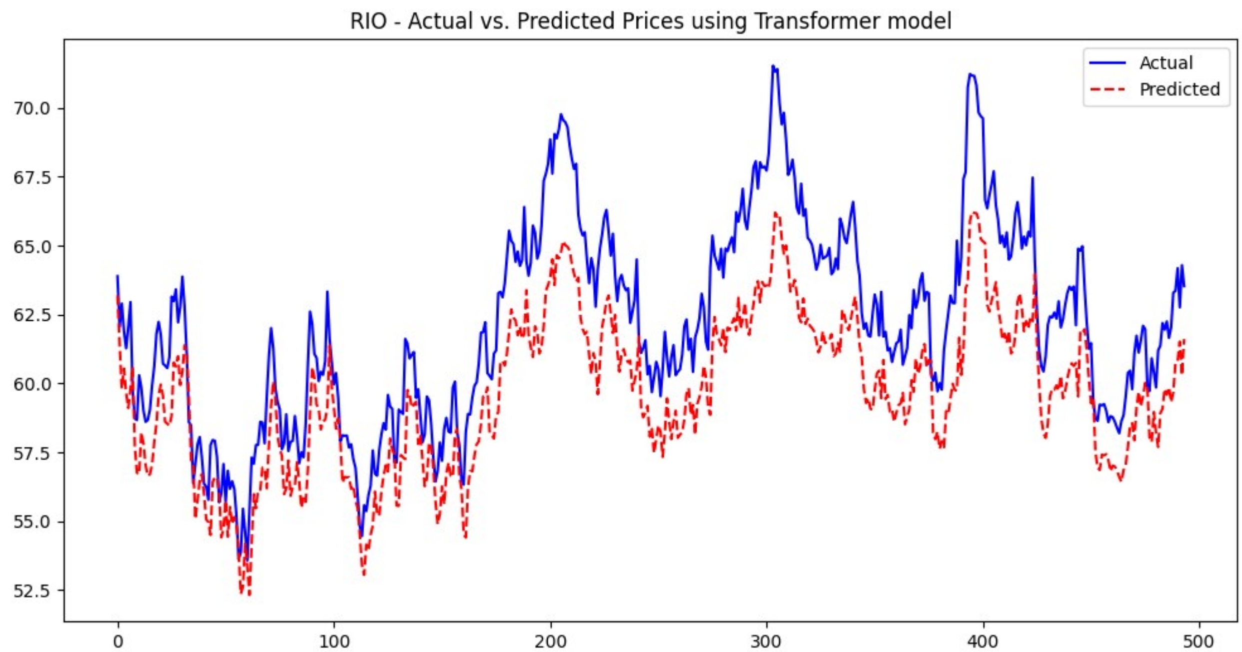
```
X_test_tensor = torch.tensor(X_test, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test, dtype=torch.float32)

# Create DataLoader
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Transformer Model
class TransformerModel(nn.Module):
    def __init__(self, input_dim, embed_dim, num_heads, hidden_dim,
num_layers):
        super(TransformerModel, self).__init__()
        self.embedding = nn.Linear(input_dim, embed_dim)
        self.transformer = nn.TransformerEncoder(
            nn.TransformerEncoderLayer(d_model=embed_dim,
nhead=num_heads, dim_feedforward=hidden_dim),
            num_layers=num_layers
        )
        self.fc = nn.Linear(embed_dim, 1)

    def forward(self, x):
        x = self.embedding(x)
        x = self.transformer(x)
        x = self.fc(x[:, -1, :])
        return x

# Initialize model
model = TransformerModel(input_dim=1, embed_dim=64, num_heads=4,
hidden_dim=128, num_layers=2)
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 20 # Higher number for higher accuracy
for epoch in range(epochs):
    model.train()
    for X_batch, y_batch in train_loader:
        optimizer.zero_grad()
        y_pred = model(X_batch.unsqueeze(-1))
        loss = criterion(y_pred.squeeze(), y_batch)
        loss.backward()
        optimizer.step()
    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}")

# Predictions
model.eval()
y_pred_list = []
with torch.no_grad():
```

```
    for X_batch, _ in test_loader:
        y_pred = model(X_batch.unsqueeze(-1))
        y_pred_list.extend(y_pred.squeeze().tolist())

# Inverse scale
y_pred_list = scaler.inverse_transform(np.array(y_pred_list).reshape(-
1, 1))
y_test_actual = scaler.inverse_transform(y_test.reshape(-1, 1))

# Plot Actual vs Predicted
print(f"\n\n{stock_ticker} Price Prediction using Transformer model :\
n")
plt.figure(figsize=(12,6))
plt.plot(y_test_actual, label='Actual', color='blue')
plt.plot(y_pred_list, label='Predicted', color='red',
linestyle='dashed')
plt.title(f"{stock_ticker} - Actual vs. Predicted Prices using
Transformer model")
plt.legend()
plt.show()

# Buy/Sell Recommendation
print("\nConclusion :\n")
if y_pred_list[-1] > y_test_actual[-1]:
    print(f"Predicted price is higher than the current price. Consider
Buying {stock_ticker}.")
    transformer_model = "Buy"
else:
    print(f"Predicted price is lower than the current price. Consider
Selling {stock_ticker}.")
    transformer_model = "Sell"
```

```
/usr/local/lib/python3.11/dist-packages/torch/nn/modules/
transformer.py:379: UserWarning: enable_nested_tensor is True, but
self.use_nested_tensor is False because
encoder_layer.self_attn.batch_first was not True(use batch_first for
better inference performance)
  warnings.warn(
```

```
Epoch 1/20, Loss: 0.0073
Epoch 2/20, Loss: 0.0047
Epoch 3/20, Loss: 0.0034
Epoch 4/20, Loss: 0.0012
Epoch 5/20, Loss: 0.0012
Epoch 6/20, Loss: 0.0011
Epoch 7/20, Loss: 0.0019
Epoch 8/20, Loss: 0.0007
Epoch 9/20, Loss: 0.0012
Epoch 10/20, Loss: 0.0006
Epoch 11/20, Loss: 0.0011
```

```
Epoch 12/20, Loss: 0.0007
Epoch 13/20, Loss: 0.0002
Epoch 14/20, Loss: 0.0023
Epoch 15/20, Loss: 0.0007
Epoch 16/20, Loss: 0.0006
Epoch 17/20, Loss: 0.0006
Epoch 18/20, Loss: 0.0013
Epoch 19/20, Loss: 0.0010
Epoch 20/20, Loss: 0.0007


RIO Price Prediction using Transformer model :
```




```
Conclusion :

Predicted price is lower than the current price. Consider Selling RIO.
```

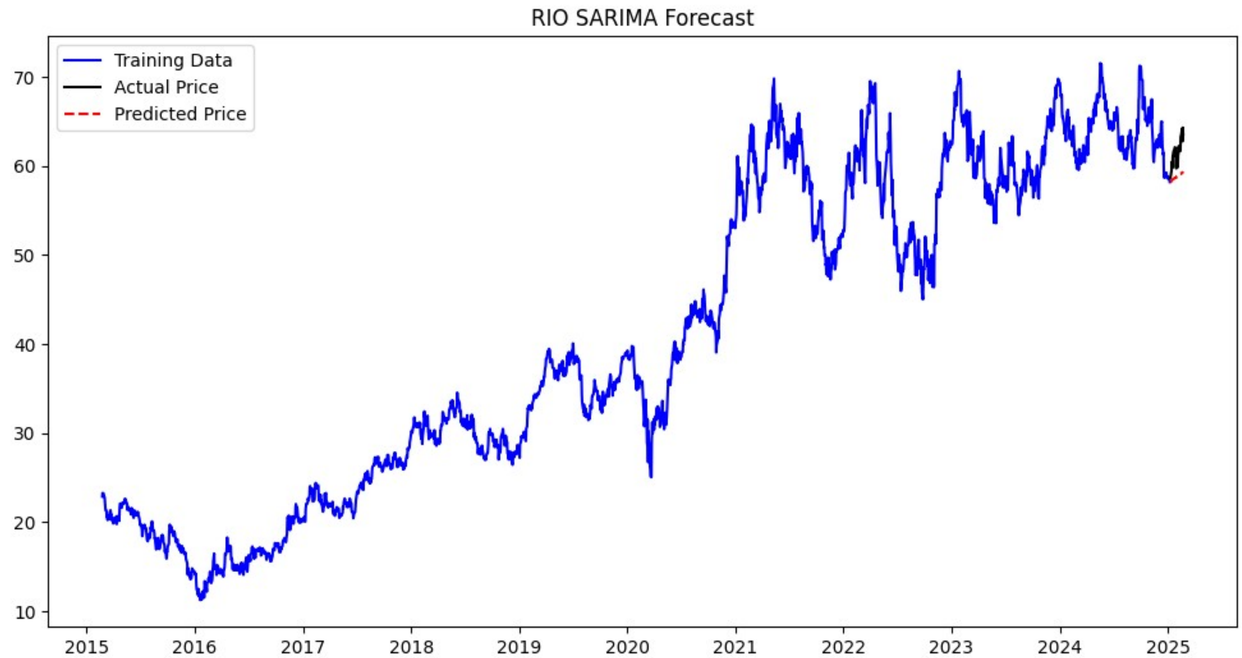
SARIMA Model

```
print("\n SARIMA Model Forecasting :\n")

# Checking stationarity
def check_stationarity(series):
    result = adfuller(series.dropna())
    print("ADF Statistic:", result[0])
```

```
    print("p-value:", result[1])
    if result[1] < 0.05:
        print("The data is stationary.\n")
    else:
        print("The data is not stationary.\n")

# Ensure 'Close' column exists before proceeding
if 'Close' not in history.columns:
    print("\nError: 'Close' column not found in the data. Check the
ticker or data source.\n")
    exit()

check_stationarity(history['Close'])

# Handle missing values
if history['Close'].isna().all():
    print("\nError: 'Close' column has all NaN values. Exiting...\n")
    exit()
history['Close'] = history['Close'].ffill()

# Fit SARIMA model
train = history['Close'][:-30]  # Use all but last 30 days for
training
test = history['Close'][-30:]

model = SARIMAX(train, order=(1, 1, 1), seasonal_order=(1, 1, 1, 12))
model_fit = model.fit(disp=False)

# Forecast
forecast = model_fit.predict(start=len(train), end=len(train) +
len(test) - 1, dynamic=False)

# Plot actual vs predicted
print(f"\n\n{stock_ticker} Price Prediction using SARIMA :\n")
plt.figure(figsize=(12,6))
plt.plot(train.index, train, label='Training Data', color='blue')
plt.plot(test.index, test, label='Actual Price', color='black')
plt.plot(test.index, forecast, label='Predicted Price', color='red',
linestyle='dashed')
plt.title(f"{stock_ticker} SARIMA Forecast")
plt.legend()
plt.show()

# Conclusion
print("\nConclusion :\n")
if forecast.iloc[-1] > test.iloc[-1]:
    print(f"Buy Signal: {stock_ticker} is expected to rise based on
SARIMA prediction.")
    sarima_model = "Buy"
else:
```

```
    print(f"Sell Signal: {stock_ticker} is expected to drop based on SARIMA prediction.")
    sarima_model = "Sell"
```

```
 SARIMA Model Forecasting :

ADF Statistic: -1.0954394470615039
p-value: 0.7168871699922149
The data is not stationary.


/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: FutureWarning: No supported index is available. In the next version, calling this method in a model without a supported index will result in an exception.
  return get_prediction_index(



RIO Price Prediction using SARIMA :
```




```
Conclusion :

Sell Signal: RIO is expected to drop based on SARIMA prediction.
```

Prophet model

```
# Prepare data for Prophet
history = history.reset_index(drop=True)  # Fix: Prevent duplicate
index columns
print(history.columns)  # Debugging: Print column names
history = history[['ds', 'y']] if 'ds' in history.columns else
history[['Date', 'Close']]
history.columns = ['ds', 'y']  # Prophet requires 'ds' for date and
'y' for values
history['ds'] = history['ds'].dt.tz_localize(None)  # Remove timezone

# Initialize and fit Prophet model
model = Prophet()
model.fit(history)

# Create future dataframe for prediction
future = model.make_future_dataframe(periods=30)
forecast = model.predict(future)

# Plot actual vs predicted
print(f"\n\n{stock_ticker} Price Prediction using Prophet :\n")
plt.figure(figsize=(12, 6))
```

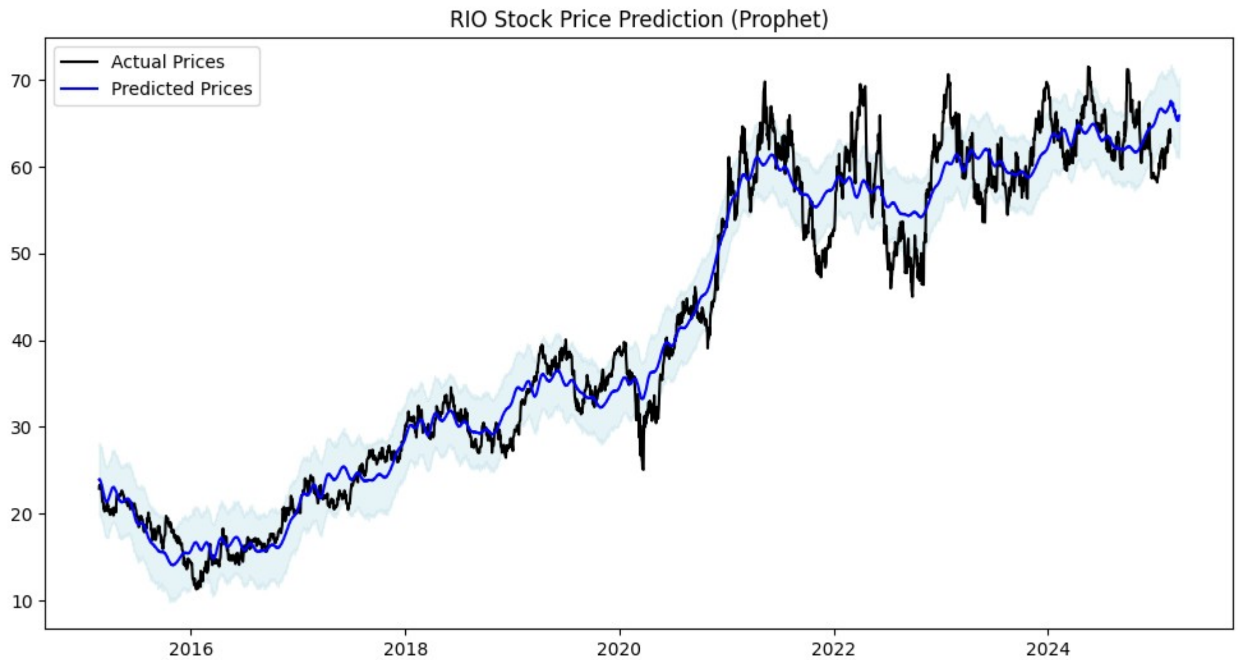
```
plt.plot(history['ds'], history['y'], label='Actual Prices',
color='black')
plt.plot(forecast['ds'], forecast['yhat'], label='Predicted Prices',
color='blue')
plt.fill_between(forecast['ds'], forecast['yhat_lower'],
forecast['yhat_upper'], color='lightblue', alpha=0.3)
plt.title(f"{stock_ticker} Stock Price Prediction (Prophet)")
plt.legend()
plt.show()

# Detailed Buy/Sell Conclusion
predicted_price = forecast['yhat'].iloc[-1]
current_price = history['y'].iloc[-1]

print("\nConclusion :\n")
print(f"Current Price: {current_price:.2f}")
print(f"Predicted Price (Next 30 days): {predicted_price:.2f}")
if predicted_price > current_price * 1.05:
    print("Strong Buy Signal: Price expected to rise significantly.")
    prophet_model = "Buy"
elif predicted_price > current_price:
    print("Buy Signal: Price expected to increase.")
    prophet_model = "Buy"
elif predicted_price < current_price * 0.95:
    print("Strong Sell Signal: Price expected to drop significantly.")
    prophet_model = "Sell"
else:
    print("Sell Signal: Price expected to decrease.")
    prophet_model = "Sell"
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
```

```
Index(['Open', 'High', 'Low', 'Close', 'Volume', 'Dividends', 'Stock
Splits',
       'Date', 'Ordinal Date', 'Scaled_Close'],
      dtype='object')
```

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpwxhizq__/3i8b5vv8.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpwxhizq__/b9gokkbf.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-
packages/prophet/stan_model/prophet_model.bin', 'random',
'seed=79877', 'data', 'file=/tmp/tmpwxhizq__/3i8b5vv8.json',
'init=/tmp/tmpwxhizq__/b9gokkbf.json', 'output',
'file=/tmp/tmpwxhizq__/prophet_modelqhsdwlh_/prophet_model-
20250223113027.csv', 'method=optimize', 'algorithm=lbfgs',
'iter=10000']
11:30:27 - cmdstanpy - INFO - Chain [1] start processing
```

```
INFO:cmdstanpy:Chain [1] start processing
11:30:28 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing



RIO Price Prediction using Prophet :
```



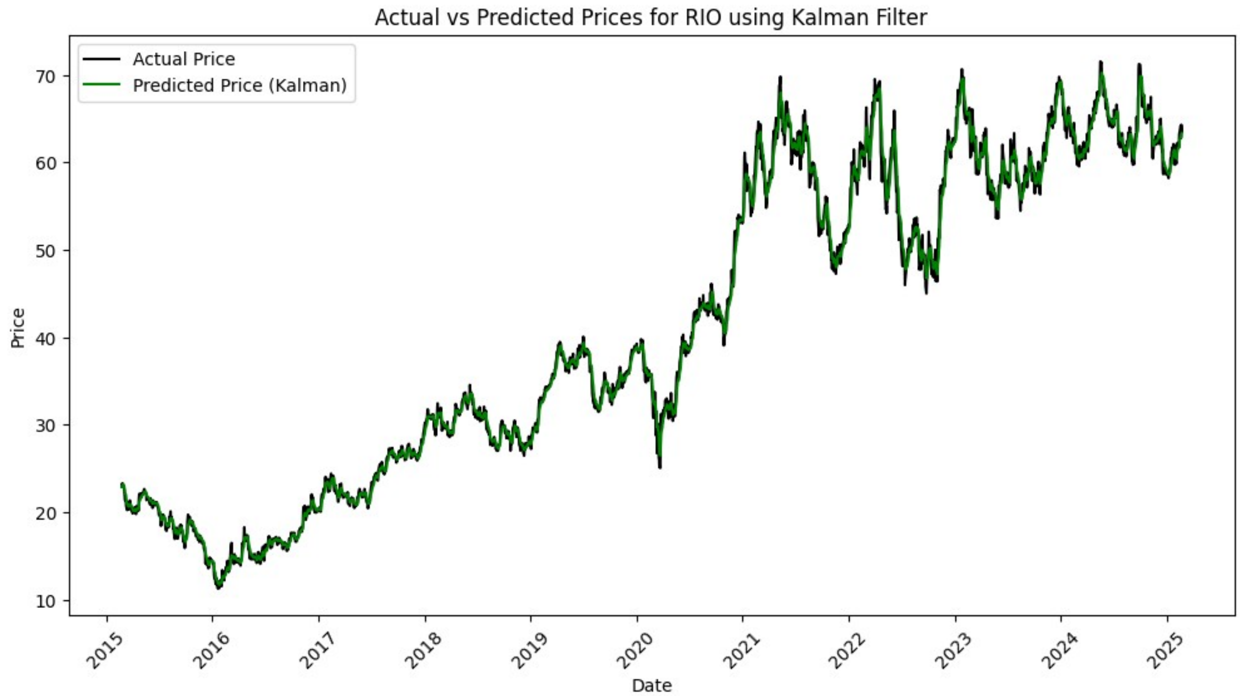

```

Conclusion :

Current Price: 63.53
Predicted Price (Next 30 days): 65.87
Buy Signal: Price expected to increase.
```

Kalman Filter

```
history = history.rename(columns={'y': 'Close', 'ds': 'Date'})
history = history.dropna(subset=['Close'])

# Kalman Filter Implementation
kf = KalmanFilter(initial_state_mean=history['Close'].iloc[0],
                  n_dim_obs=1,
                  n_dim_state=1,
                  transition_matrices=[1],
                  observation_matrices=[1],
```

```python
                    transition_covariance=[0.01],
                    observation_covariance=[0.1])

filtered_state_means, _ = kf.filter(history['Close'].values)

# Plot actual vs predicted
print(f"\n{stock_ticker} Price Prediction using Kalman Filter :\n")
plt.figure(figsize=(12,6))
plt.plot(history['Date'], history['Close'], label='Actual Price',
color='black')
plt.plot(history['Date'], filtered_state_means, label='Predicted Price
(Kalman)', color='green')
plt.title(f"Actual vs Predicted Prices for {stock_ticker} using Kalman
Filter")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.xticks(rotation=45)  # Rotate x-axis labels for better visibility
plt.show()

# Buy/Sell Conclusion
print("\nConclusion :\n")
if filtered_state_means[-1] > history['Close'].iloc[-1]:
    print(f"BUY Signal: {stock_ticker} is expected to rise based on
Kalman Filter predictions.")
    kalman_filter_model = "Buy"
elif filtered_state_means[-1] < history['Close'].iloc[-1]:
    print(f"SELL Signal: {stock_ticker} is expected to decline based
on Kalman Filter predictions.")
    kalman_filter_model = "Sell"
else:
    print(f"HOLD: {stock_ticker} is stable, no strong movement
detected.")
    kalman_filter_model = "Hold"
```

```
RIO Price Prediction using Kalman Filter :
```




```
Conclusion :

SELL Signal: RIO is expected to decline based on Kalman Filter
predictions.
```

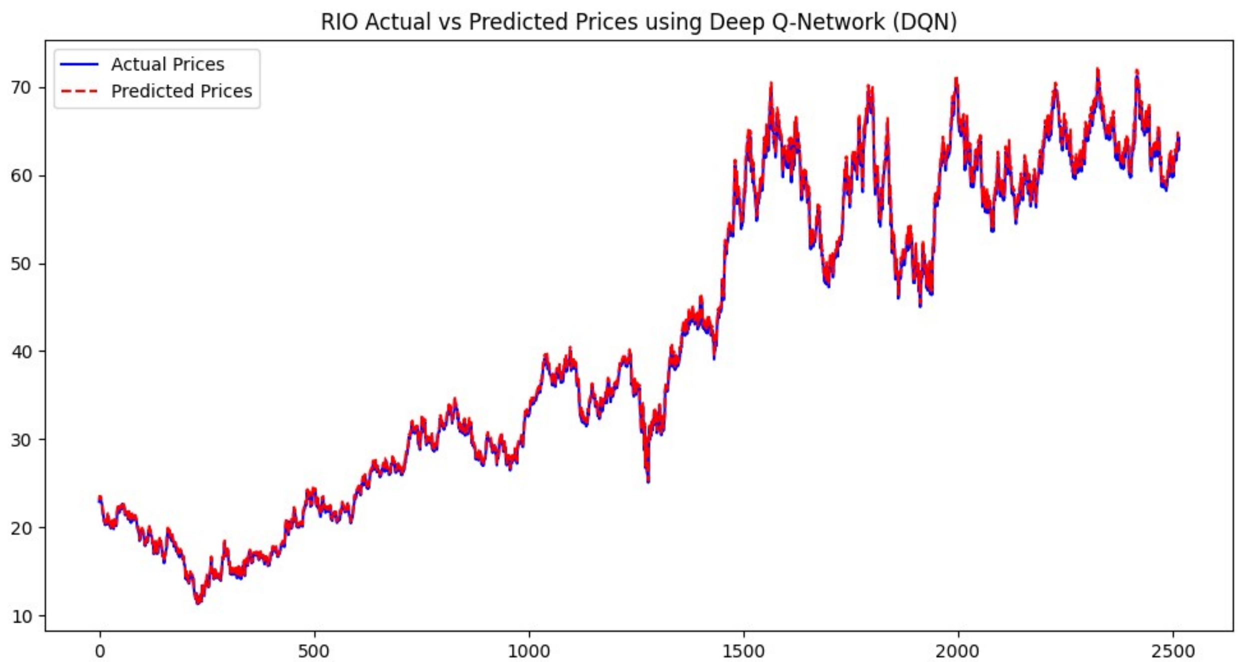
Deep Q-Network (DQN)

```
# Define the Deep Q-Network (DQN)
class DQN(nn.Module):
    def __init__(self, state_size, action_size):
        super(DQN, self).__init__()
        self.fc1 = nn.Linear(state_size, 128)
        self.fc2 = nn.Linear(128, 128)
        self.fc3 = nn.Linear(128, action_size)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        return self.fc3(x)

# Experience Replay Memory
class ReplayMemory:
    def __init__(self, capacity):
        self.memory = deque(maxlen=capacity)
```

```
    def push(self, state, action, reward, next_state, done):
        self.memory.append((state, action, reward, next_state, done))

    def sample(self, batch_size):
        return random.sample(self.memory, batch_size)

    def __len__(self):
        return len(self.memory)

# Training function
def train_dqn(model, memory, optimizer, batch_size, gamma):
    if len(memory) < batch_size:
        return

    transitions = memory.sample(batch_size)
    batch = list(zip(*transitions))

    states = torch.tensor(np.array(batch[0]), dtype=torch.float32)
    actions = torch.tensor(batch[1], dtype=torch.int64).unsqueeze(1)
    rewards = torch.tensor(batch[2], dtype=torch.float32)
    next_states = torch.tensor(np.array(batch[3]),
dtype=torch.float32)
    dones = torch.tensor(batch[4], dtype=torch.float32)

    q_values = model(states).gather(1, actions)
    next_q_values = model(next_states).max(1)[0].detach()
    target_q_values = rewards + (gamma * next_q_values * (1 - dones))

    loss = F.mse_loss(q_values.squeeze(), target_q_values)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# Initialize environment and model
env = gym.make("CartPole-v1", new_step_api=True)
state_size = env.observation_space.shape[0]
action_size = env.action_space.n
dqn_model = DQN(state_size, action_size)
optimizer = optim.Adam(dqn_model.parameters(), lr=0.001)
memory = ReplayMemory(10000)

episodes = 100
batch_size = 32
gamma = 0.99

def get_stock_data():
    return history[['Close']].pct_change().dropna().values.reshape(-1,
1)  # Ensure 2D shape

stock_data = get_stock_data()
```

```
state_size = stock_data.shape[1]

dqn_model = DQN(state_size, action_size)  # Update model with correct
input size

# Train the model
for episode in range(episodes):
    state = stock_data[0]
    for t in range(len(stock_data) - 1):
        state_tensor = torch.tensor(state,
dtype=torch.float32).view(1, -1)
        action = dqn_model(state_tensor).argmax().item()
        next_state = stock_data[t + 1]
        reward = next_state - state
        done = t == len(stock_data) - 2
        memory.push(state, action, reward, next_state, done)
        state = next_state
        train_dqn(dqn_model, memory, optimizer, batch_size, gamma)

# Predictions vs. Actual Data
actual_prices = history['Close'].values
predicted_prices = []
state = stock_data[0]
for t in range(len(stock_data) - 1):
    state_tensor = torch.tensor(state, dtype=torch.float32).view(1, -
1)
    action = dqn_model(state_tensor).argmax().item()
    predicted_prices.append(actual_prices[t] * (1 + action * 0.01))
    state = stock_data[t + 1]

print(f"\n\n{stock_ticker} Price Prediction using Deep Q-Network (DQN)
:\n")
plt.figure(figsize=(12,6))
plt.plot(actual_prices, label='Actual Prices', color='blue')
plt.plot(predicted_prices, label='Predicted Prices', color='red',
linestyle='dashed')
plt.legend()
plt.title(f"{stock_ticker} Actual vs Predicted Prices using Deep Q-
Network (DQN)")
plt.show()

# Conclusion for Buy/Sell Decision
print("\nConclusion :\n")
if predicted_prices[-1] > actual_prices[-1]:
    print(f"Prediction suggests BUY for {stock_ticker}.")
    dqn_model = "Buy"
else:
    print(f"Prediction suggests SELL for {stock_ticker}.")
    dqn_model = "Sell"
```

```
<ipython-input-20-87549a395662>:38: UserWarning: Creating a tensor
from a list of numpy.ndarrays is extremely slow. Please consider
converting the list to a single numpy.ndarray with numpy.array()
before converting to a tensor. (Triggered internally at
../torch/csrc/utils/tensor_new.cpp:278.)
  rewards = torch.tensor(batch[2], dtype=torch.float32)
<ipython-input-20-87549a395662>:46: UserWarning: Using a target size
(torch.Size([32, 32])) that is different to the input size
(torch.Size([32])). This will likely lead to incorrect results due to
broadcasting. Please ensure they have the same size.
  loss = F.mse_loss(q_values.squeeze(), target_q_values)



RIO Price Prediction using Deep Q-Network (DQN) :
```




```
Conclusion :

Prediction suggests SELL for RIO.
```

Proximal Policy Optimization (PPO)

```
class PolicyNetwork(nn.Module):
    def __init__(self, input_dim, output_dim):
        super(PolicyNetwork, self).__init__()
```

```python
        self.fc1 = nn.Linear(input_dim, 128)
        self.fc2 = nn.Linear(128, 128)
        self.fc3 = nn.Linear(128, output_dim)

    def forward(self, x):
        x = torch.tensor(x, dtype=torch.float32).clone().detach()  #
Ensure proper tensor conversion
        if x.dim() == 1:
            x = x.unsqueeze(0)  # Ensure batch dimension
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        return torch.softmax(self.fc3(x), dim=-1)

class PPOAgent:
    def __init__(self, input_dim, output_dim, lr=1e-3, gamma=0.99,
eps_clip=0.2):
        self.policy = PolicyNetwork(input_dim, output_dim)
        self.optimizer = optim.Adam(self.policy.parameters(), lr=lr)
        self.gamma = gamma
        self.eps_clip = eps_clip
        self.memory = []

    def select_action(self, state):
        state = torch.tensor(state, dtype=torch.float32).unsqueeze(0)
# Ensure batch dimension
        probs = self.policy(state).squeeze(0)  # Remove extra
dimension
        dist = Categorical(probs)
        action = dist.sample()
        return action.item(), dist.log_prob(action)

    def store_transition(self, transition):
        self.memory.append(transition)

    def update(self):
        if not self.memory:
            return

        states, actions, log_probs, rewards = zip(*self.memory)
        states = torch.stack([torch.tensor(s, dtype=torch.float32) for
s in states])
        actions = torch.tensor(actions, dtype=torch.int64)
        log_probs = torch.stack(log_probs)
        rewards = torch.tensor(rewards, dtype=torch.float32)

        returns = []
        discounted_sum = 0
        for reward in reversed(rewards):
            discounted_sum = reward + self.gamma * discounted_sum
            returns.insert(0, discounted_sum)
```

```
        returns = torch.tensor(returns, dtype=torch.float32)

        new_probs = self.policy(states)
        new_dist = Categorical(new_probs)
        new_log_probs = new_dist.log_prob(actions)

        ratios = torch.exp(new_log_probs - log_probs)
        advantages = returns - returns.mean()
        surrogate1 = ratios * advantages
        surrogate2 = torch.clamp(ratios, 1 - self.eps_clip, 1 +
self.eps_clip) * advantages
        loss = -torch.min(surrogate1, surrogate2).mean()

        self.optimizer.zero_grad()
        loss.backward()
        self.optimizer.step()
        self.memory = []

# Running PPO on a sample environment
env = gym.make("CartPole-v1")
agent = PPOAgent(input_dim=4, output_dim=2)

num_episodes = 500 # Higher number for higher accuracy
actual_rewards = []
predicted_rewards = []
for episode in range(num_episodes):
    state = env.reset()
    if isinstance(state, tuple):
        state = state[0]  # Handle environments returning (state,
info)
    state = state.tolist()  # Ensure proper format
    episode_reward = 0

    for _ in range(200):
        action, log_prob = agent.select_action(state)
        next_state, reward, done, _ = env.step(action)  # Corrected
tuple unpacking
        next_state = next_state.tolist()
        agent.store_transition((state, action, log_prob, reward))
        state = next_state
        episode_reward += reward
        if done:
            break

    agent.update()
    actual_rewards.append(episode_reward)
    predicted_rewards.append(agent.policy(torch.tensor(state,
dtype=torch.float32)).detach().numpy().mean())
    print(f"Episode {episode+1}: Reward = {episode_reward}")
```

```python
# Compare actual vs predicted rewards
print(f"\n\n{stock_ticker} Price Prediction using Proximal Policy
Optimization (PPO) :\n")
plt.figure(figsize=(12,6))
plt.plot(actual_rewards, label='Actual Rewards', color='blue')
plt.plot(predicted_rewards, label='Predicted Rewards', color='red',
linestyle='dashed')
plt.title("Actual vs Predicted Rewards")
plt.legend()
plt.show()

# Conclusion on buy or sell
print("\nConclusion :\n")
diff = actual_rewards[-1] - predicted_rewards[-1]
if diff > 0:
    print("Recommendation: BUY - Model predicts an upward trend.")
    ppo_model = "Buy"
elif diff < 0:
    print("Recommendation: SELL - Model predicts a downward trend.")
    ppo_model = "Sell"
else:
    print("Recommendation: HOLD - Model shows stability.")
    ppo_model = "Hold"
```

```
Episode 1: Reward = 37.0
Episode 2: Reward = 21.0
Episode 3: Reward = 9.0
Episode 4: Reward = 11.0
Episode 5: Reward = 33.0
Episode 6: Reward = 12.0
```

```
/usr/local/lib/python3.11/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.11/dist-packages/gym/wrappers/step_api_compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
<ipython-input-21-7631c031f636>:9: UserWarning: To copy construct from
a tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  x = torch.tensor(x, dtype=torch.float32).clone().detach()  # Ensure
proper tensor conversion
/usr/local/lib/python3.11/dist-packages/gym/utils/passive_env_checker.
```

```
py:241: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(terminated, (bool, np.bool8)):
```

```
Episode 7: Reward = 18.0
Episode 8: Reward = 17.0
Episode 9: Reward = 23.0
Episode 10: Reward = 25.0
Episode 11: Reward = 15.0
Episode 12: Reward = 26.0
Episode 13: Reward = 24.0
Episode 14: Reward = 23.0
Episode 15: Reward = 10.0
Episode 16: Reward = 23.0
Episode 17: Reward = 15.0
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RIO Price Prediction using Proximal Policy Optimization (PPO) :
```

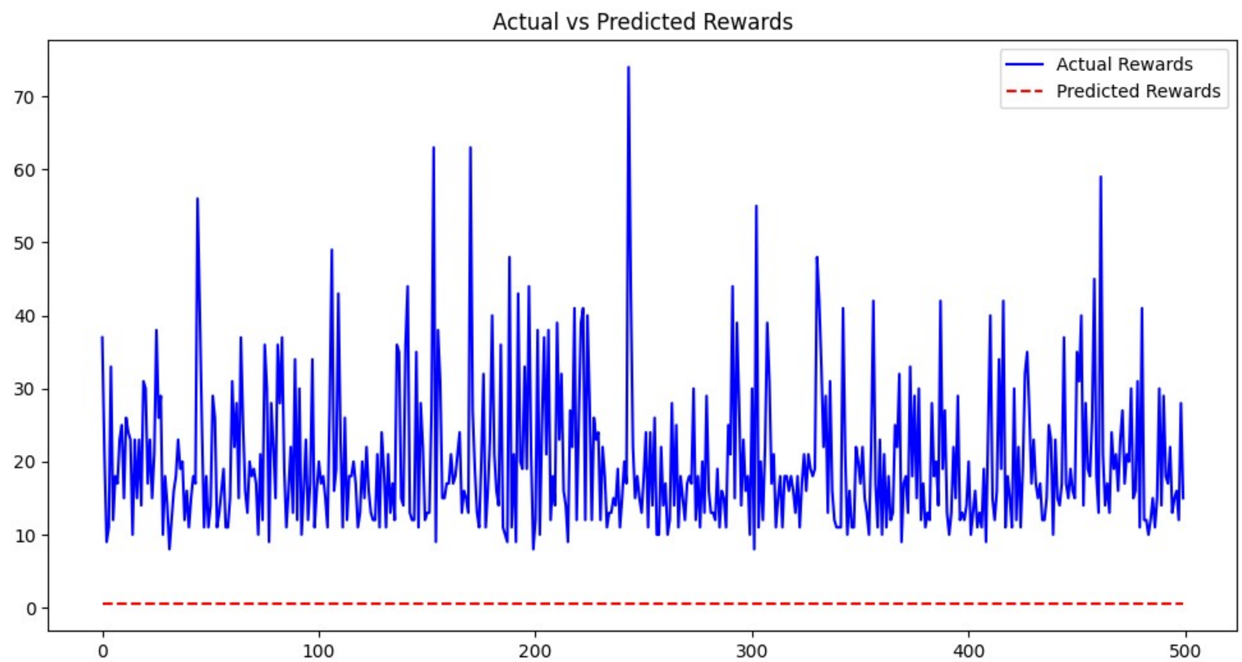


```
Conclusion :

Recommendation: BUY - Model predicts an upward trend.
```

A2C (Advantage Actor-Critic)

```
class ActorCritic(Model):
    def __init__(self, action_size):
        super(ActorCritic, self).__init__()
        self.common = Dense(128, activation='relu')
        self.actor = Dense(action_size, activation='softmax')
        self.critic = Dense(1, activation='linear')

    def call(self, inputs):
```

```
        x = self.common(inputs)
        return self.actor(x), self.critic(x)

def get_action(policy):
    policy = np.squeeze(policy.numpy())  # Remove unnecessary
dimensions
    policy = np.nan_to_num(policy, nan=0.0)  # Replace NaNs with 0
    policy = policy / np.sum(policy)  # Normalize to sum to 1
    return np.random.choice(len(policy), p=policy)

env = gym.make("CartPole-v1")
state_size = env.observation_space.shape[0]
action_size = env.action_space.n
model = ActorCritic(action_size)
optimizer = Adam(learning_rate=0.001)

gamma = 0.99
total_rewards = []
predicted_rewards = []
for episode in range(1000): # Higher number for higher accuracy
    state = env.reset()
    state = np.reshape(state, [1, state_size])
    total_reward = 0
    done = False
    while not done:
        policy, value = model(state)
        action = get_action(policy)
        next_state, reward, done, _ = env.step(action)
        next_state = np.reshape(next_state, [1, state_size])
        _, next_value = model(next_state)
        target = reward + (1 - done) * gamma * next_value
        advantage = target - value

        with tf.GradientTape() as tape:
            policy, value = model(state)
            action_prob = tf.gather(policy[0], action)
            log_prob = tf.math.log(action_prob + 1e-10)
            actor_loss = -log_prob * advantage
            critic_loss = advantage ** 2
            loss = actor_loss + critic_loss

        grads = tape.gradient(loss, model.trainable_variables)
        optimizer.apply_gradients(zip(grads,
model.trainable_variables))

        state = next_state
        total_reward += reward
    total_rewards.append(total_reward)
    predicted_rewards.append(value.numpy()[0][0])
    print(f"Episode {episode + 1}: Total Reward = {total_reward}")
```

```python
env.close()

# Plot rewards
print(f"\n\n{stock_ticker} Price Prediction using A2C (Advantage
Actor-Critic) :\n")
plt.figure(figsize=(10,5))
plt.plot(total_rewards, label='Actual Total Rewards', color='blue')
plt.plot(predicted_rewards, label='Predicted Rewards', color='red',
linestyle='dashed')
plt.xlabel('Episode')
plt.ylabel('Reward')
plt.title('Actual vs Predicted Rewards Comparison')
plt.legend()
plt.show()

# Final Conclusion
print("\nConclusion :\n")
average_reward = np.mean(total_rewards[-50:])
if average_reward > 195:
    print("Conclusion: The model suggests a BUY signal based on
performance.")
    a2c_model = "Buy"
else:
    print("Conclusion: The model suggests a SELL signal based on
performance.")
    a2c_model = "Sell"
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/optimizers/
base_optimizer.py:774: UserWarning: Gradients do not exist for
variables ['actor_critic/dense_11/kernel',
'actor_critic/dense_11/bias'] when minimizing the loss. If using
`model.compile()`, did you forget to provide a `loss` argument?
  warnings.warn(
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Episode 694: Total Reward = 10.0
Episode 695: Total Reward = 10.0
Episode 696: Total Reward = 9.0
Episode 697: Total Reward = 10.0
Episode 698: Total Reward = 9.0
Episode 699: Total Reward = 9.0
Episode 700: Total Reward = 9.0
Episode 701: Total Reward = 8.0
Episode 702: Total Reward = 9.0
```

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Episode 703: Total Reward = 10.0
Episode 704: Total Reward = 10.0
Episode 705: Total Reward = 10.0
Episode 706: Total Reward = 10.0
Episode 707: Total Reward = 9.0
Episode 708: Total Reward = 10.0
Episode 709: Total Reward = 8.0
Episode 710: Total Reward = 8.0
Episode 711: Total Reward = 9.0
Episode 712: Total Reward = 9.0
Episode 713: Total Reward = 10.0
Episode 714: Total Reward = 9.0
Episode 715: Total Reward = 9.0
Episode 716: Total Reward = 8.0
Episode 717: Total Reward = 10.0
Episode 718: Total Reward = 10.0
Episode 719: Total Reward = 10.0
Episode 720: Total Reward = 9.0
Episode 721: Total Reward = 8.0
Episode 722: Total Reward = 9.0
Episode 723: Total Reward = 9.0
Episode 724: Total Reward = 10.0
Episode 725: Total Reward = 9.0
Episode 726: Total Reward = 10.0
Episode 727: Total Reward = 9.0
Episode 728: Total Reward = 10.0
Episode 729: Total Reward = 10.0
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Episode 731: Total Reward = 9.0
Episode 732: Total Reward = 9.0
Episode 733: Total Reward = 9.0
Episode 734: Total Reward = 10.0
Episode 735: Total Reward = 9.0
Episode 736: Total Reward = 9.0
Episode 737: Total Reward = 11.0
Episode 738: Total Reward = 10.0
Episode 739: Total Reward = 9.0
Episode 740: Total Reward = 10.0
Episode 741: Total Reward = 8.0
Episode 742: Total Reward = 9.0
Episode 743: Total Reward = 9.0
Episode 744: Total Reward = 10.0
Episode 745: Total Reward = 9.0
Episode 746: Total Reward = 10.0
Episode 747: Total Reward = 9.0
Episode 748: Total Reward = 10.0
Episode 749: Total Reward = 9.0
Episode 750: Total Reward = 9.0
Episode 751: Total Reward = 10.0
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Episode 752: Total Reward = 11.0
Episode 753: Total Reward = 10.0
Episode 754: Total Reward = 10.0
Episode 755: Total Reward = 10.0
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Episode 757: Total Reward = 10.0
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Episode 761: Total Reward = 9.0
Episode 762: Total Reward = 11.0
Episode 763: Total Reward = 9.0
Episode 764: Total Reward = 10.0
Episode 765: Total Reward = 10.0
Episode 766: Total Reward = 9.0
Episode 767: Total Reward = 9.0
Episode 768: Total Reward = 9.0
Episode 769: Total Reward = 9.0
Episode 770: Total Reward = 10.0
Episode 771: Total Reward = 10.0
Episode 772: Total Reward = 9.0
Episode 773: Total Reward = 10.0
Episode 774: Total Reward = 10.0
Episode 775: Total Reward = 9.0
Episode 776: Total Reward = 10.0
Episode 777: Total Reward = 8.0
Episode 778: Total Reward = 10.0
Episode 779: Total Reward = 10.0
Episode 780: Total Reward = 10.0
Episode 781: Total Reward = 8.0
Episode 782: Total Reward = 10.0
Episode 783: Total Reward = 10.0
Episode 784: Total Reward = 9.0
Episode 785: Total Reward = 10.0
Episode 786: Total Reward = 9.0
Episode 787: Total Reward = 8.0
Episode 788: Total Reward = 9.0
Episode 789: Total Reward = 10.0
Episode 790: Total Reward = 9.0
Episode 791: Total Reward = 9.0
Episode 792: Total Reward = 10.0
Episode 793: Total Reward = 10.0
Episode 794: Total Reward = 10.0
Episode 795: Total Reward = 9.0
Episode 796: Total Reward = 11.0
Episode 797: Total Reward = 9.0
Episode 798: Total Reward = 9.0
Episode 799: Total Reward = 9.0
Episode 800: Total Reward = 10.0
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Episode 801: Total Reward = 10.0
Episode 802: Total Reward = 9.0
Episode 803: Total Reward = 10.0
Episode 804: Total Reward = 10.0
Episode 805: Total Reward = 10.0
Episode 806: Total Reward = 9.0
Episode 807: Total Reward = 10.0
Episode 808: Total Reward = 10.0
Episode 809: Total Reward = 10.0
Episode 810: Total Reward = 8.0
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Episode 812: Total Reward = 10.0
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Episode 819: Total Reward = 10.0
Episode 820: Total Reward = 9.0
Episode 821: Total Reward = 10.0
Episode 822: Total Reward = 10.0
Episode 823: Total Reward = 9.0
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Episode 825: Total Reward = 9.0
Episode 826: Total Reward = 10.0
Episode 827: Total Reward = 10.0
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Episode 839: Total Reward = 8.0
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Episode 846: Total Reward = 9.0
Episode 847: Total Reward = 10.0
Episode 848: Total Reward = 11.0
Episode 849: Total Reward = 10.0
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Episode 850: Total Reward = 10.0
Episode 851: Total Reward = 10.0
Episode 852: Total Reward = 11.0
Episode 853: Total Reward = 10.0
Episode 854: Total Reward = 10.0
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Episode 856: Total Reward = 10.0
Episode 857: Total Reward = 8.0
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Episode 863: Total Reward = 10.0
Episode 864: Total Reward = 8.0
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Episode 867: Total Reward = 10.0
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Episode 878: Total Reward = 8.0
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Episode 888: Total Reward = 8.0
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Episode 892: Total Reward = 9.0
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Episode 894: Total Reward = 8.0
Episode 895: Total Reward = 9.0
Episode 896: Total Reward = 10.0
Episode 897: Total Reward = 9.0
Episode 898: Total Reward = 10.0
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Episode 899: Total Reward = 10.0
Episode 900: Total Reward = 9.0
Episode 901: Total Reward = 10.0
Episode 902: Total Reward = 8.0
Episode 903: Total Reward = 10.0
Episode 904: Total Reward = 10.0
Episode 905: Total Reward = 9.0
Episode 906: Total Reward = 9.0
Episode 907: Total Reward = 9.0
Episode 908: Total Reward = 10.0
Episode 909: Total Reward = 9.0
Episode 910: Total Reward = 9.0
Episode 911: Total Reward = 10.0
Episode 912: Total Reward = 8.0
Episode 913: Total Reward = 10.0
Episode 914: Total Reward = 10.0
Episode 915: Total Reward = 11.0
Episode 916: Total Reward = 10.0
Episode 917: Total Reward = 10.0
Episode 918: Total Reward = 8.0
Episode 919: Total Reward = 10.0
Episode 920: Total Reward = 11.0
Episode 921: Total Reward = 10.0
Episode 922: Total Reward = 10.0
Episode 923: Total Reward = 10.0
Episode 924: Total Reward = 10.0
Episode 925: Total Reward = 10.0
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Episode 930: Total Reward = 8.0
Episode 931: Total Reward = 10.0
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Episode 939: Total Reward = 10.0
Episode 940: Total Reward = 8.0
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Episode 942: Total Reward = 8.0
Episode 943: Total Reward = 10.0
Episode 944: Total Reward = 8.0
Episode 945: Total Reward = 9.0
Episode 946: Total Reward = 9.0
Episode 947: Total Reward = 8.0
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Episode 948: Total Reward = 9.0
Episode 949: Total Reward = 8.0
Episode 950: Total Reward = 11.0
Episode 951: Total Reward = 8.0
Episode 952: Total Reward = 8.0
Episode 953: Total Reward = 9.0
Episode 954: Total Reward = 10.0
Episode 955: Total Reward = 9.0
Episode 956: Total Reward = 10.0
Episode 957: Total Reward = 9.0
Episode 958: Total Reward = 10.0
Episode 959: Total Reward = 10.0
Episode 960: Total Reward = 8.0
Episode 961: Total Reward = 9.0
Episode 962: Total Reward = 8.0
Episode 963: Total Reward = 10.0
Episode 964: Total Reward = 10.0
Episode 965: Total Reward = 10.0
Episode 966: Total Reward = 9.0
Episode 967: Total Reward = 10.0
Episode 968: Total Reward = 10.0
Episode 969: Total Reward = 9.0
Episode 970: Total Reward = 10.0
Episode 971: Total Reward = 9.0
Episode 972: Total Reward = 10.0
Episode 973: Total Reward = 8.0
Episode 974: Total Reward = 10.0
Episode 975: Total Reward = 9.0
Episode 976: Total Reward = 10.0
Episode 977: Total Reward = 8.0
Episode 978: Total Reward = 9.0
Episode 979: Total Reward = 9.0
Episode 980: Total Reward = 9.0
Episode 981: Total Reward = 10.0
Episode 982: Total Reward = 9.0
Episode 983: Total Reward = 9.0
Episode 984: Total Reward = 9.0
Episode 985: Total Reward = 10.0
Episode 986: Total Reward = 9.0
Episode 987: Total Reward = 9.0
Episode 988: Total Reward = 9.0
Episode 989: Total Reward = 11.0
Episode 990: Total Reward = 10.0
Episode 991: Total Reward = 10.0
Episode 992: Total Reward = 10.0
Episode 993: Total Reward = 10.0
Episode 994: Total Reward = 9.0
Episode 995: Total Reward = 10.0
Episode 996: Total Reward = 9.0
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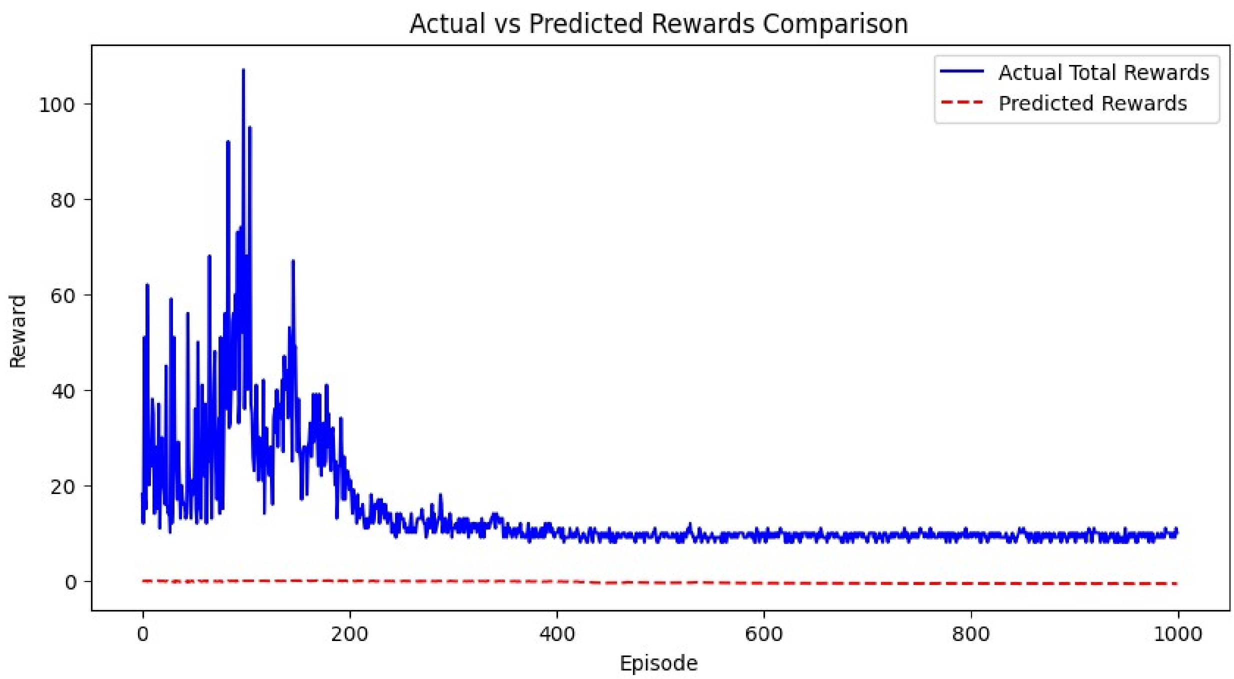
Episode 997: Total Reward = 10.0
Episode 998: Total Reward = 9.0
Episode 999: Total Reward = 11.0
Episode 1000: Total Reward = 10.0


RIO Price Prediction using A2C (Advantage Actor-Critic) :
```




```
Conclusion :

Conclusion: The model suggests a SELL signal based on performance.
```

Stacking (Ensemble of ML models)

```
# Define base models
base_models = [
    ('ridge', Ridge()),
    ('decision_tree', DecisionTreeRegressor()),
    ('random_forest', RandomForestRegressor(n_estimators=100)),
    ('svr', SVR())
]

# Define meta model
meta_model = Ridge()
```

```
# Create stacking model
stacking_model = StackingRegressor(estimators=base_models,
final_estimator=meta_model)

# Train stacking model
stacking_model.fit(X_train.reshape(X_train.shape[0], -1), y_train)

# Predict using stacking model
y_pred_stacking =
stacking_model.predict(X_test.reshape(X_test.shape[0], -1))

# Calculate error
mse_stacking = mean_squared_error(y_test, y_pred_stacking)
print(f"\n\nStacking Model MSE: {mse_stacking}")

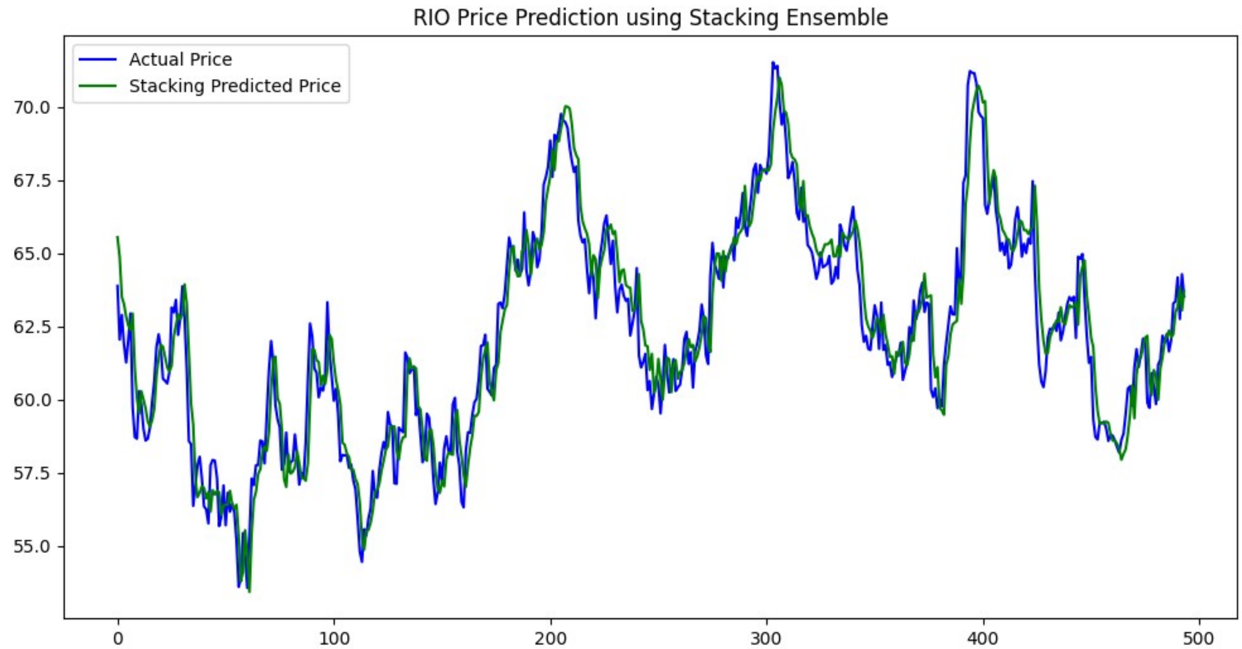
# Plot predictions
print(f"\n{stock_ticker} Price Prediction using Stacking Ensemble :\
n")
plt.figure(figsize=(12,6))
plt.plot(y_test_actual, label='Actual Price', color='blue')
plt.plot(scaler.inverse_transform(y_pred_stacking.reshape(-1, 1)),
label='Stacking Predicted Price', color='green')
plt.title(f"{stock_ticker} Price Prediction using Stacking Ensemble")
plt.legend()
plt.show()

# Conclusion
print("\nConclusion:\n")
if y_pred_stacking[-1] > y_test[-1]:
    print(f"Bullish Signal: The stacking model predicts an upward
trend in {stock_ticker}'s stock price. This suggests positive momentum
and potential growth, making it a favorable opportunity for
investors.")
    stacking_model = "Buy"
else:
    print(f"Bearish Signal: The stacking model predicts a downward
trend in {stock_ticker}'s stock price. This indicates possible market
corrections or a decline, urging investors to be cautious.")
    stacking_model = "Sell"



Stacking Model MSE: 0.00032006976044387316

RIO Price Prediction using Stacking Ensemble :
```




```
Conclusion:

Bullish Signal: The stacking model predicts an upward trend in RIO's
stock price. This suggests positive momentum and potential growth,
making it a favorable opportunity for investors.
```

CNN + LSTM model

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, LSTM, Dense

print("\nCNN + LSTM :\n")

# Prepare data for CNN+LSTM model
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(history[['Close']].dropna())

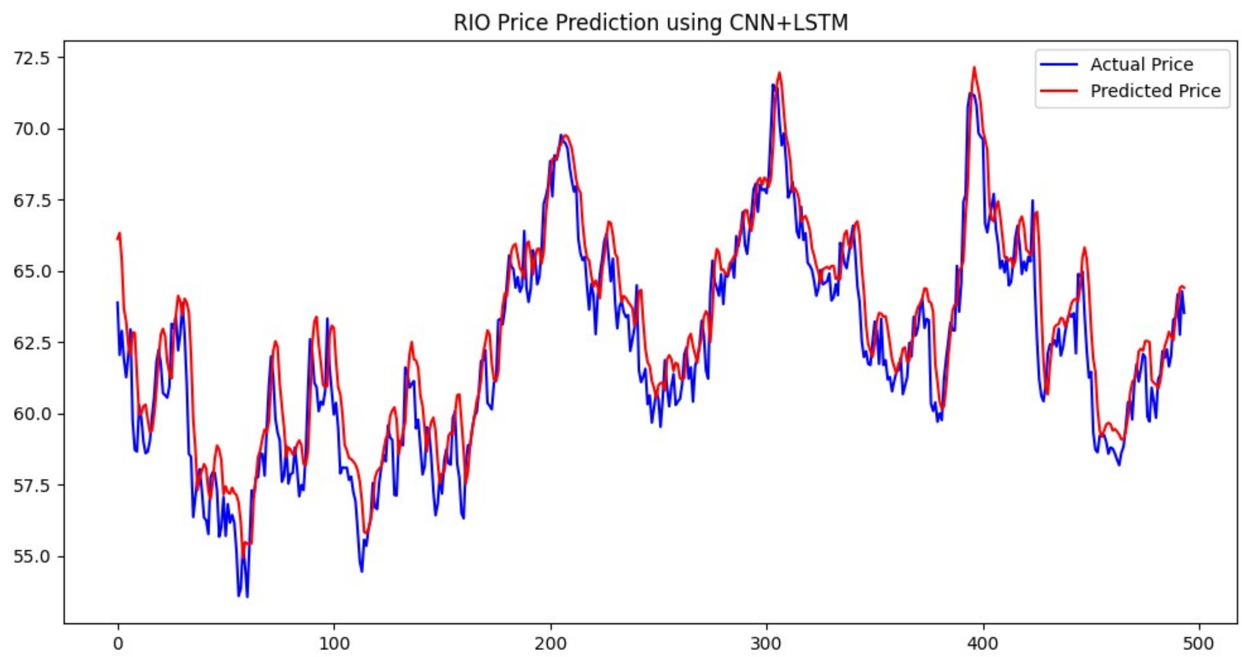
# Function to create sequences for time series forecasting
def create_sequences(data, seq_length):
    sequences, labels = [], []
    for i in range(len(data) - seq_length):
        sequences.append(data[i:i+seq_length])
```

```python
        labels.append(data[i+seq_length])
    return np.array(sequences), np.array(labels)

seq_length = 50  # Sequence length for LSTM input
X, y = create_sequences(scaled_data, seq_length)
X = np.expand_dims(X, axis=2)  # Reshape for Conv1D

# Split data into training and testing sets
split = int(0.8 * len(X))
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]

# Define CNN + LSTM Model
model = Sequential([
    Conv1D(filters=64, kernel_size=3, activation='relu',
input_shape=(seq_length, 1)),
    MaxPooling1D(pool_size=2),
    LSTM(50, return_sequences=True),
    LSTM(50),
    Dense(25, activation='relu'),
    Dense(1)
])

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train, y_train, epochs=20, batch_size=16,
validation_data=(X_test, y_test)) # Higher number for higher accuracy

# Make predictions
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(predictions)  # Convert back to
original scale
y_test_actual = scaler.inverse_transform(y_test.reshape(-1, 1))

print(f"\n{stock_ticker} Price Prediction using CNN+LSTM\n")
# Plot actual vs predicted prices
plt.figure(figsize=(12,6))
plt.plot(y_test_actual, label='Actual Price', color='blue')
plt.plot(predictions, label='Predicted Price', color='red')
plt.title(f"{stock_ticker} Price Prediction using CNN+LSTM")
plt.legend()
plt.show()

# Calculate RMSE for performance evaluation
print("\nConclusion :\n")
rmse = np.sqrt(mean_squared_error(y_test_actual, predictions))
print(f"Root Mean Squared Error: {rmse}")
```

```python
# Buy/Sell Decision based on trend
if predictions[-1] > y_test_actual[-1]:
    decision = "BUY"
else:
    decision = "SELL"

print(f"Predicted trend suggests: {decision}\n\n")
cnn_lstm_model = decision
```

```
CNN + LSTM :

Epoch 1/20

/usr/local/lib/python3.11/dist-packages/keras/src/layers/
convolutional/base_conv.py:107: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in
the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 33ms/step - loss: 0.0889 - val_loss:
0.0035
Epoch 2/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 43ms/step - loss: 0.0023 - val_loss:
0.0019
Epoch 3/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 52ms/step - loss: 0.0020 - val_loss:
0.0014
Epoch 4/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 7s 24ms/step - loss: 0.0015 - val_loss:
0.0021
Epoch 5/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 0.0014 - val_loss:
0.0022
Epoch 6/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 0.0011 - val_loss:
0.0010
Epoch 7/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 24ms/step - loss: 0.0011 - val_loss:
0.0011
Epoch 8/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 28ms/step - loss: 0.0010 - val_loss:
0.0010
Epoch 9/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 9.1713e-04 -
val_loss: 8.0519e-04
Epoch 10/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 8.0849e-04 -
```

```
val_loss: 8.9803e-04
Epoch 11/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 4s 33ms/step - loss: 6.3834e-04 -
val_loss: 0.0036
Epoch 12/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 9.5491e-04 -
val_loss: 9.7588e-04
Epoch 13/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 6.3372e-04 -
val_loss: 5.5615e-04
Epoch 14/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 6s 29ms/step - loss: 5.8022e-04 -
val_loss: 0.0020
Epoch 15/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 25ms/step - loss: 6.2206e-04 -
val_loss: 0.0013
Epoch 16/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 4.6952e-04 -
val_loss: 6.0878e-04
Epoch 17/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 4.8739e-04 -
val_loss: 6.5485e-04
Epoch 18/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 27ms/step - loss: 3.9659e-04 -
val_loss: 6.2789e-04
Epoch 19/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 5s 23ms/step - loss: 4.4380e-04 -
val_loss: 7.2709e-04
Epoch 20/20
124/124 ━━━━━━━━━━━━━━━━━━━━ 3s 23ms/step - loss: 4.5337e-04 -
val_loss: 5.3946e-04
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step

RIO Price Prediction using CNN+LSTM
```




```
Conclusion :

Root Mean Squared Error: 1.399748250481022
Predicted trend suggests: BUY
```

Final Output

```
print(f"Final Decision for {stock_ticker} based on all analysis :\n")
print(f"Fundamental Analysis : {fundamental_analysis.split()
[0].upper()}")
print(f"Technical Analysis : {technical_analysis.upper()}")
print(f"Time Series Forecasting : {time_series_forecasting.upper()}")
print(f"Linear Regression : {linear_regression_model.upper()}")
print(f"Logistic Regression : {logistic_regression_model.upper()}")
print(f"Random Forest Regressor & Classifier :
{random_forest.upper()}")
print(f"Support Vector Machine (SVM) : {svm_model.upper()}")
print(f"XGBoost & LightGBM : {xgboost_lightgbm_model.upper()}")
print(f"Artificial Neural Networks (ANN) : {ann_model.upper()}")
print(f"Recurrent Neural Networks (RNN) : {rnn_model.upper()}")
print(f"Long Short-Term Memory (LSTM) : {lstm_model.upper()}")
print(f"Gated Recurrent Units (GRU) : {gru_model.upper()}")
print(f"Transformer Models : {transformer_model.upper()}")
print(f"SARIMA Model : {sarima_model.upper()}")
print(f"Prophet : {prophet_model.upper()}")
```

```
print(f"Kalman Filter : {kalman_filter_model.upper()}")
print(f"Deep Q-Network (DQN) : {dqn_model.upper()}")
print(f"Proximal Policy Optimization (PPO) : {ppo_model.upper()}")
print(f"A2C (Advantage Actor-Critic) : {a2c_model.upper()}")
print(f"Stacking Ensemble : {stacking_model.upper()}")
print(f"CNN + LSTM : {cnn_lstm_model.upper()}")
```

```
Final Decision for RIO based on all analysis :

Fundamental Analysis : BUY
Technical Analysis : SELL
Time Series Forecasting : SELL
Linear Regression : BUY
Logistic Regression : BUY
Random Forest Regressor & Classifier : SELL
Support Vector Machine (SVM) : BUY
XGBoost & LightGBM : SELL
Artificial Neural Networks (ANN) : SELL
Recurrent Neural Networks (RNN) : SELL
Long Short-Term Memory (LSTM) : SELL
Gated Recurrent Units (GRU) : HOLD
Transformer Models : SELL
SARIMA Model : SELL
Prophet : BUY
Kalman Filter : SELL
Deep Q-Network (DQN) : SELL
Proximal Policy Optimization (PPO) : BUY
A2C (Advantage Actor-Critic) : SELL
Stacking Ensemble : BUY
CNN + LSTM : BUY
```

```
# Store all models' predictions in a list
model_predictions = [
    fundamental_analysis.split()[0].upper(),
technical_analysis.upper(), time_series_forecasting.upper(),
    linear_regression_model.upper(),
logistic_regression_model.upper(), random_forest.upper(),
    svm_model.upper(), xgboost_lightgbm_model.upper(),
ann_model.upper(), rnn_model.upper(), lstm_model.upper(),
    gru_model.upper(), transformer_model.upper(),
sarima_model.upper(), prophet_model.upper(),
    kalman_filter_model.upper(), dqn_model.upper(), ppo_model.upper(),
a2c_model.upper(),
    stacking_model.upper(), cnn_lstm_model.upper()
]

# Count occurrences of BUY, SELL, and HOLD
buy_count = sum(1 for model in model_predictions if model.upper() ==
"BUY")
sell_count = sum(1 for model in model_predictions if model.upper() ==
```

```
"SELL")
hold_count = sum(1 for model in model_predictions if model.upper() ==
"HOLD")

# Calculate total models used
total_models = len(model_predictions)

# Calculate probabilities
buy_prob = (buy_count / total_models) * 100
sell_prob = (sell_count / total_models) * 100
hold_prob = (hold_count / total_models) * 100

# Determine final decision
if buy_prob > sell_prob and buy_prob > hold_prob:
    final_decision = "BUY"
elif sell_prob > buy_prob and sell_prob > hold_prob:
    final_decision = "SELL"
else:
    final_decision = "HOLD"

# Print final decision with probability breakdown
print(f"Final Decision for {stock_ticker} based on all analysis:\n")
print(f"Fundamental Analysis : {fundamental_analysis.split()
[0].upper()}")
print(f"Technical Analysis : {technical_analysis.upper()}")
print(f"Time Series Forecasting : {time_series_forecasting.upper()}")
print(f"Linear Regression : {linear_regression_model.upper()}")
print(f"Logistic Regression : {logistic_regression_model.upper()}")
print(f"Random Forest Regressor & Classifier :
{random_forest.upper()}")
print(f"Support Vector Machine (SVM) : {svm_model.upper()}")
print(f"XGBoost & LightGBM : {xgboost_lightgbm_model.upper()}")
print(f"Artificial Neural Networks (ANN) : {ann_model.upper()}")
print(f"Recurrent Neural Networks (RNN) : {rnn_model.upper()}")
print(f"Long Short-Term Memory (LSTM) : {lstm_model.upper()}")
print(f"Gated Recurrent Units (GRU) : {gru_model.upper()}")
print(f"Transformer Models : {transformer_model.upper()}")
print(f"SARIMA Model : {sarima_model.upper()}")
print(f"Prophet : {prophet_model.upper()}")
print(f"Kalman Filter : {kalman_filter_model.upper()}")
print(f"Deep Q-Network (DQN) : {dqn_model.upper()}")
print(f"Proximal Policy Optimization (PPO) : {ppo_model.upper()}")
print(f"A2C (Advantage Actor-Critic) : {a2c_model.upper()}")
print(f"Stacking Ensemble : {stacking_model.upper()}")
print(f"CNN + LSTM : {cnn_lstm_model.upper()}")

print("\nDecision Summary :\n")
print(f"Total BUY recommendations: {buy_count}")
print(f"Total SELL recommendations: {sell_count}")
print(f"Total HOLD recommendations: {hold_count}")
```

```
print(f"Total Models used: {total_models}\n")
print(f"\nProbability of BUY : {buy_prob:.2f}%")
print(f"Probability of SELL : {sell_prob:.2f}%")
print(f"Probability of HOLD : {hold_prob:.2f}%\n")
print(f"Final Conclusion: The overall recommendation is to
{final_decision} the stock.")

print("\nWarning: This is not financial advice. Please conduct your
own research before making investment decisions.")
```

```
Final Decision for RIO based on all analysis:

Fundamental Analysis : BUY
Technical Analysis : SELL
Time Series Forecasting : SELL
Linear Regression : BUY
Logistic Regression : BUY
Random Forest Regressor & Classifier : SELL
Support Vector Machine (SVM) : BUY
XGBoost & LightGBM : SELL
Artificial Neural Networks (ANN) : SELL
Recurrent Neural Networks (RNN) : SELL
Long Short-Term Memory (LSTM) : SELL
Gated Recurrent Units (GRU) : HOLD
Transformer Models : SELL
SARIMA Model : SELL
Prophet : BUY
Kalman Filter : SELL
Deep Q-Network (DQN) : SELL
Proximal Policy Optimization (PPO) : BUY
A2C (Advantage Actor-Critic) : SELL
Stacking Ensemble : BUY
CNN + LSTM : BUY

Decision Summary :

Total BUY recommendations: 8
Total SELL recommendations: 12
Total HOLD recommendations: 1
Total Models used: 21


Probability of BUY : 38.10%
Probability of SELL : 57.14%
Probability of HOLD : 4.76%

Final Conclusion: The overall recommendation is to SELL the stock.

Warning: This is not financial advice. Please conduct your own
research before making investment decisions.
```