# Gold Project - Random Forest

Group Member: Enzo Goncalves Pereira

```
import pandas as pd
import numpy as np
import yfinance as yf
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split,
RandomizedSearchCV
from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_percentage_error
import ta

tickers = ['AAPL', 'GOOGL', 'MSFT', 'AMZN', 'META', 'TSLA', 'NFLX',
'NVDA', 'INTC', 'AMD']
all_data = []

df.head()
```


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```

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```


```
for ticker in tickers:
    df = yf.download(ticker, start='2018-01-01', end='2023-12-31')
    df['Ticker'] = ticker
    df = df.reset_index()

    df['Return'] = df['Close'].pct_change()
    df['MA5'] = df['Close'].rolling(window=5).mean()
    df['MA10'] = df['Close'].rolling(window=10).mean()
    df['Volatility'] = df['Close'].rolling(window=5).std()
```

```python
    df['Volume_Change'] = df['Volume'].pct_change()

    close_series = df['Close'].squeeze()
    df['RSI'] = ta.momentum.RSIIndicator(close=close_series).rsi()
    macd = ta.trend.MACD(close=close_series)
    df['MACD'] = macd.macd()
    df['MACD_Signal'] = macd.macd_signal()
    boll = ta.volatility.BollingerBands(close=close_series)
    df['BB_High'] = boll.bollinger_hband()
    df['BB_Low'] = boll.bollinger_lband()

    df['Target'] = df['Close'].shift(-1)

    df = df.dropna()
    all_data.append(df)

data = pd.concat(all_data, ignore_index=True)

data.head()
```

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

{"type":"dataframe","variable_name":"data"}

```python
# We select the features and the target
features = ['Close', 'MA5', 'MA10', 'Volatility', 'Volume_Change',
'RSI', 'MACD', 'MACD_Signal', 'BB_High', 'BB_Low']
X = data[features]
y = data['Target']

# I split my training and test, so I will train my model on 2018-2022
and test on 2023
train_data = data[data['Date'] < '2023-01-01']
test_data = data[data['Date'] >= '2023-01-01']

X_train = train_data[features]
y_train = train_data['Target']
X_test = test_data[features]
y_test = test_data['Target']

param_dist = {
    'n_estimators': [50],
```

```python
    'max_depth': [5, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

random_search = RandomizedSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_distributions=param_dist,
    n_iter=4,
    cv=2,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1,
    random_state=42
)

random_search.fit(X_train, y_train)
best_model = random_search.best_estimator_
```

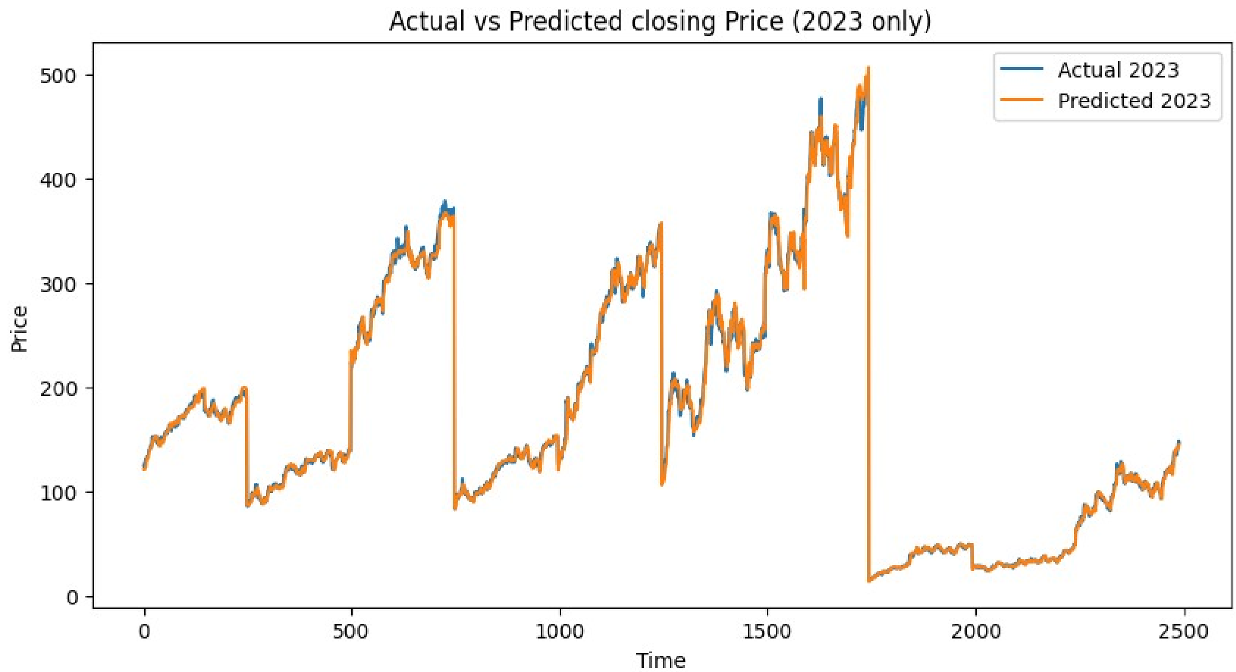
```
Fitting 2 folds for each of 4 candidates, totalling 8 fits
```

```python
# Predict and evaluate
y_pred = best_model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)

print("Best params:", random_search.best_params_)
print("Evaluation on 2023 data:")
print(f"RMSE: {rmse:.2f}")
print(f"R² Score: {r2:.2f}")
print(f"mAPE: {mape:.2%}")
```

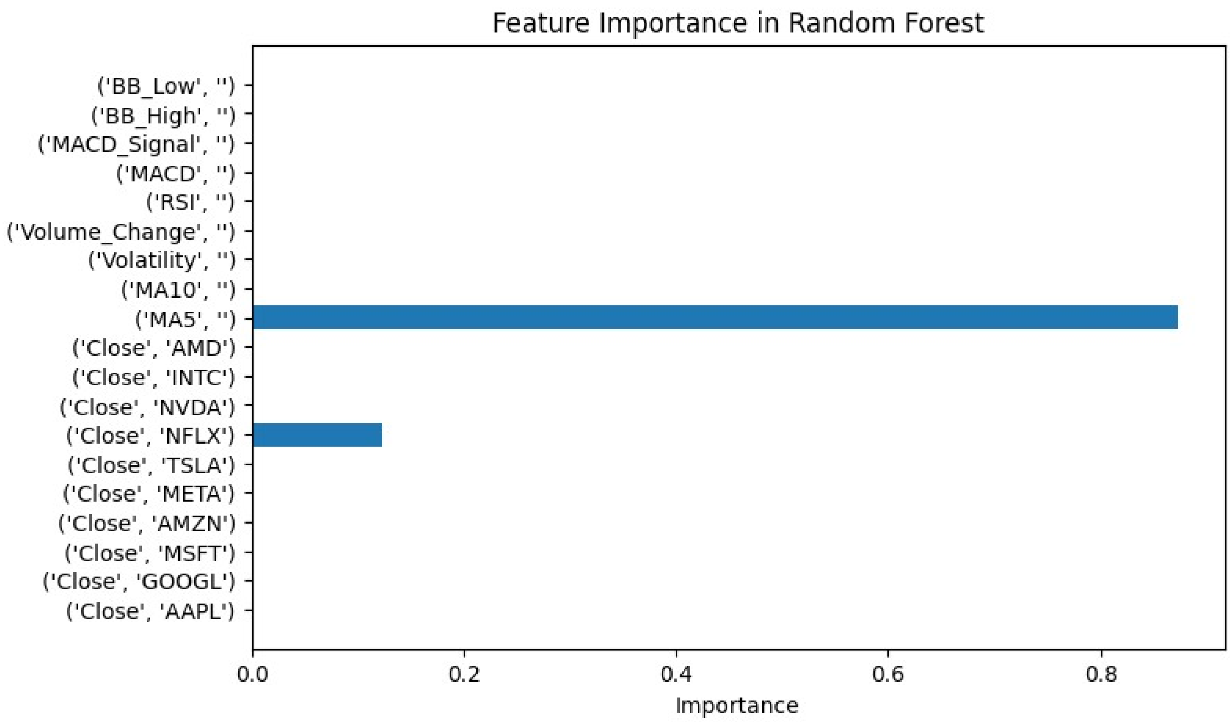
```
Best params: {'n_estimators': 50, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_depth': 10}
Evaluation on 2023 data:
RMSE: 6.07
R² Score: 1.00
mAPE: 2.37%
```

```python
# Plot predicted vs actual
plt.figure(figsize=(10,5))
plt.plot(y_test.values, label='Actual 2023')
plt.plot(y_pred, label='Predicted 2023')
plt.legend()
plt.title("Actual vs Predicted closing Price (2023 only)")
plt.xlabel("Time")
plt.ylabel("Price")
plt.show()
```




```
# Feature Importance
importances = best_model.feature_importances_
feature_names = [str(col) for col in X.columns]

plt.figure(figsize=(8,5))
plt.barh(feature_names, importances)
plt.xlabel("Importance")
plt.title("Feature Importance in Random Forest")
plt.show()
```


Feature Importance in Random Forest
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('Close', 'NVDA')
('Close', 'NFLX')
('Close', 'TSLA')
('Close', 'META')
('Close', 'AMZN')
('Close', 'MSFT')
('Close', 'GOOGL')
('Close', 'AAPL')
0.0
0.2
0.4
0.6
0.8
Importance