Predicting S&P500 ETF Closing Prices Using Historical Data and Evaluating It with The Mean Absolute Percentage Error

A. Matoug, J. Peeters, Ş. Saygılı

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# I. INTRODUCTION

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he primary objective of this task is to predict the closing price of the S&P 500 ETF (Exchange-Traded Fund) for a specified number of days based on historical data.

This paper, which constitutes a report on the task performed, will first provide a comprehensive explanation of the S&P 500 ETF. Next, the report will discuss the algorithm that will be used for forecasting (and how it will be evaluated, why this specific algorithm is chosen, …), and will include a comparison with the state of the art for such problems. Thereafter, the results will be presented and discussed in detail. Finally, a conclusion will be drawn as to whether the choice of algorithm was appropriate and what could be improved for forecasting purposes.

## S&P500 ETF (Exchange-Traded Fund)

Because they provide diversified exposure to a variety of assets in a single, easily transferable instrument, exchange-traded funds, or ETFs, have changed the investing environment. Among these, the S&P 500 ETF is one of the most prominent, designed to track the performance of the S&P 500 Index, a benchmark comprising 500 leading publicly traded companies in the United States. The S&P 500 Index is a theoretical construct that serves as a capitalization-weighted measure of the top U.S. corporations, selected based on criteria including market value, liquidity, and sector representation [1].

ETFs that track the S&P 500 Index, like the SPDR S&P 500 ETF (ticker: SPY), offer investors a way to participate in this benchmark, even though the index itself is used as a standard to evaluate the performance of the U.S. equities market. ETFs are tradable securities that mimic the index by owning the same or a representative sample of the underlying stocks, in contrast to the index, which is only a calculation [2]. Furthermore, the performance of ETFs may differ slightly from that of the index due to the introduction of real-world factors including tracking error, expense ratios, and liquidity [3].

The S&P 500 ETF's significance as a benchmark extends beyond its theoretical and practical distinctions, serving as a cornerstone of financial markets. Its capitalization-weighted design ensures that larger companies exert greater influence on the index’s performance, offering a snapshot of the U.S. economy’s largest players [4]. This dual role—as a benchmark and as an investable product—makes the S&P 500 ETF a vital tool for investors worldwide.

Historical data analysis of the S&P 500 ETF provides insights into market behaviour. By studying patterns of returns, volatility, and drawdowns, investors can refine their strategies and enhance decision-making [5]. For example, while the index data reflects theoretical market performance, ETF data incorporates the impact of trading costs, dividend distributions, and reinvestment policies, offering a more comprehensive picture of investable returns [6]. Such analyses are central to modern portfolio theory, enabling investors to optimize risk-adjusted returns through informed decisions.   
  
To sum up, the S&P 500 Index serves as a theoretical standard for the American stock market, and exchange-traded funds (ETFs) that track it offer a practical way to invest. Investors can close the gap between market performance and actual portfolio management by examining both the theoretical index and the actual ETF. This dual viewpoint emphasises how important the S&P 500 ETF is to risk management and contemporary financial markets. So, exploring algorithms for predicting this index would be of great value to investors.

## Challenges of Predicting the Closing Price

Several factors, such as the non-stationary character of financial time series, the existence of seasonality, and the unpredictability of markets, make it difficult to forecast closing prices in financial datasets. Since statistical characteristics like mean and variance can fluctuate over time, financial data is usually non-stationary, making it challenging to find consistent patterns for forecasting [7]. Furthermore, the modelling process is made more difficult by outside variables like market sentiment, macroeconomic events, and geopolitical developments, which frequently generate abrupt and unforeseen fluctuations [8].

Seasonality, which reflects repeating patterns or cycles over specific intervals, also poses a challenge. While some financial instruments exhibit clear seasonal trends—such as increased volatility around earnings reports or fiscal year-end activities—such patterns are often masked by noise in daily or intraday data [9]. In the case of the S&P 500 ETF, the presence of both short-term volatility and long-term macroeconomic influences makes it difficult to disentangle meaningful signals from noise.   
  
Additionally, predicting the closing price for the next month amplifies the difficulty since the model must generalize well to unseen data. Unlike retrospective analyses, where historical data is fully available, future data introduces uncertainty that models must approximate based on historical patterns. This task is particularly demanding in financial contexts, where the assumption of past performance being indicative of future behaviour is often invalidated by structural breaks or market shifts [10].

The combination of non-stationarity, and market randomness requires some considerations for the model design and feature selection. For example, models must balance between overfitting historical trends and capturing patterns that hold across different timeframes. These challenges highlight the importance of error metrics, such as mean absolute percentage error (MAPE), which account for variations in data scale and enable evaluation of predictive performance [11].

In conclusion, predicting the closing price for the following month is a difficult task impacted by the unstable and ever-changing nature of financial markets. Precise modelling techniques and a well-informed modelling of features are necessary to address these issues.

## Role of Historical Price Features

In this section, the given features for this project will be discussed.

The dataset provided for this project includes four features:

* date,
* opening price,
* high price,
* low price.

These collectively offer insights into the dynamics of daily market behaviour and play a role in predicting the closing price of the S&P 500 ETF.

First, the date feature, which not directly influences the closing price, can be important for identifying temporal trends and seasonal patterns. Financial markets often exhibit cyclical behaviours, with certain times of the year, month, or week displaying distinct trends. For example, the so-called "end-of-month effect" or quarterly earnings cycles may impact investor behaviour, indirectly influencing price movements [9]. Of course, relative to the other features, the date will realistically play a minor role in this project.

Secondly, the opening price, which represents the first transaction price of the day, setting the baseline for the day’s trading activity. The price is influenced by pre-market trading and after-hours market movements. It is often indicative of investor sentiment and external factors such as news or economic developments occurring prior to the market opening. In trending markets, the opening price often aligns with the closing price. Consequently, the opening price serves as a reference point for subsequent intraday fluctuations [10].

Then there is the high price and low price of the day. The high price and low price indicate the highest and lowest points of trading during the day, respectively, offering a measure of the day’s volatility. These features are helpful in capturing the variety of market swings, which might indicate uncertainty and mood in the market. For example, a wide difference between the high and low prices might be an indicator of high market volatility, which is sometimes caused by news or investor responses to fresh data [12]. These characteristics are necessary for modelling since high volatility days are frequently linked to a closing price that differs greatly from the beginning price. But of course, these assumptions will have to be detected by the model (programmed in Python), so going further into this is beyond the scope.

When combined, these features offer a basis for closing price prediction. Even while each parameter has a distinct importance, it's possible that their correlations with the closing price are not linear, requiring other modelling techniques to accurately capture dependencies, instead of simple linear regression models, and interactions. Building a precise predictive model requires an understanding of how the opening price establishes the day's baseline, how the high and low represent volatility, and how temporal patterns affect trading behaviours. The exact method and which modelling technique was used is discussed in the next section.

## Time-Series Analysis and Regression in Financial Forecasting

The modelling and estimation of financial measures, including the closing price of an asset, is important because they are essentially temporary and can sometimes be quite erratic. There are two main approaches that can be used to analyse such data: time series analysis and regression modelling. Both offer advantages depending on the characteristics of the data and the forecasting objectives.

### Time-Series Analysis

The main objective of time series analysis is to analyse the temporal characteristics of the data and use historical information and sequences to make future projections. Some of the widely used methods include statistical models such as Autoregressive Integrated Moving Average (ARIMA) and more advanced techniques such as Long Short-Term Memory (LSTM) networks.

* ARIMA predicts data with the of help its previous values and previous forecast errors. It performs particularly well where there is high autocorrelation or trends in the data and can be used to forecast future values [13]. However, ARIMA model has difficulties with non-linearity and cannot incorporate other variables that affect the system, which limits its use in analysing complex financial data.
* LSTM is a type of Recurrent Neural Network (RNN) that has been developed to deal with sequences and particularly with long-term dependencies. Its capability of capturing complex correlations and temporal structure makes it appropriate for the financial forecasting [14]. They can capture various features in the data series, for instance trends, seasonal patterns and sudden changes which are common in financial markets.

### Regression-based models

Regression models provide an alternative approach, focusing on relationships between dependent and independent variables. Using features such as the opening, high, and low prices, regression models aim to establish direct correlations with the closing price.

* Linear regression is a simple, effective approach, but only (not always) when the relationships between features are approximately linear. However, it may fail to capture non-linearities in financial datasets.
* Non-linear models, such as decision trees or support vector regression, address this limitation by modelling more complex relationships. These methods can improve accuracy but require careful tuning to avoid overfitting [15]. Also, polynomial regression is an option but it’s the same as described before. Regularization can help here but methods like this require some effort the finetune the parameters.

## Feature engineering and training

Feature engineering enhances model performance by converting raw data into useful inputs. Examples include daily price range (high minus low), percentage change from the opening price, and rolling averages. Temporal features, such as the day of the week or month, can also reveal patterns linked to seasonality or investor behaviour.

Model training uses a portion of historical data to fit parameters, while the rest is reserved for validation and testing to ensure generalization. Techniques like cross-validation, hyperparameter tuning, and regularization can also be applied to improve accuracy and avoid overfitting. Further details, whether these techniques will be applied or not, will be given in the next section.

Time-series analysis and regression are widely used in financial forecasting, each suited to different data characteristics. Effective feature engineering and training strategies help models capture market complexity and make reliable predictions. Exactly which method will be used in this project will become clear in the next section, as mentioned earlier.

# II. Method

The provided dataset for this task consists of four key features: the date, opening price, high price of the day, and low price of the day. This methodology emphasizes using the historical data for training, selecting the optimal model through grid search evaluated with a separate part of the training data, called evaluation set, and testing the model on unseen data without relying on the features of the test data, which are assumed to be unavailable.

## Data Preprocessing

Regardless of what model is used, the first step is to preprocess the raw data to ensure it is suitable for training and testing. Before any analysis can begin, the dataset must be inspected for any missing values or anomalies. Given that the stock market is closed on weekends and public holidays, there are weekly jumps in the data. The nature of the data is sequential, so it’s important that it is ordered chronologically, from old to new. This is critical for maintaining the time series structure and ensuring that the model only uses past data to predict future values. The task involves predicting future closing prices based on historical patterns, therefore the data was transformed into fixed-length sequences. Instead of predicting a day’s closing price, the system generates input sequences of past closing prices, which allows the model to learn patterns from historical data. All numerical features were normalized to a range of 0 to 1 using the MinMaxScaler. This normalization prevents features with larger magnitude from dominating the learning process. Train validation split …

## Model Selection

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# III. Results

# Citations

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   A. Matoug, J. Peeters & S. Saygili are with Hasselt University/KU Leuven, Agoralaan, 3590 Diepenbeek, Belgium (emails: abdelmalek.matoug@student.uhasselt.be, joris.peeters@student.uhasselt.be, sukru.saygili@student.uhasselt.be) [↑](#footnote-ref-2)