STOCK PRICE PREDICTION USING MACHINE LEARNING

Machine Learning Research Paper

Done By

Clement Mupenzi

***Abstract*—This project delves into the application of machine learning for financial market analysis, with a specific focus on predicting stock prices. The primary objective is to develop a predictive model capable of accurately forecasting future stock prices, using 'META' (formerly Facebook) as a case study. To achieve this, we employ a Long Short-Term Memory (LSTM) neural network, a type of recurrent neural network that is particularly effective for time series data such as stock prices. The methodology centers around acquiring historical stock price data of META from Yahoo Finance using the 'yfinance' tool, a popular Python library for financial data extraction. This data is then preprocessed to fit the LSTM model's requirements. The model undergoes training on this dataset, learning to identify patterns and trends that influence stock prices. We experiment with various configurations and parameters of the LSTM network to enhance the model's predictive accuracy. Our findings reveal that the LSTM model exhibits a notable capability in predicting stock prices with considerable accuracy. The model's performance is assessed using metrics like mean absolute error and predictive accuracy over different forecasting horizons. The implications of this research are significant for investors, financial analysts, and portfolio managers. The ability to predict stock prices accurately can lead to more informed investment decisions and improved portfolio management strategies. For stocks like META, a key player in the technology sector, this predictive ability provides insights into market trends and investor sentiment, potentially leading to profitable investment opportunities. Furthermore, the approach and results of this study can be applied to other stocks and financial instruments, broadening the scope of financial forecasting using machine learning.**

The primary goal of this project is to leverage machine learning techniques to classify social media posts into different sentiment categories, such as positive, or negative, enabling the extraction of valuable insights from the vast pool of user-generated content

I. Introduction

In recent years, the intersection of finance and technology has given rise to innovative approaches in predicting financial market trends. This research project explores the realm of machine learning applications in financial market analysis, with a particular emphasis on forecasting stock prices. The primary focus of this investigation is the development and evaluation of a predictive model, employing a Long Short-Term Memory (LSTM) neural network, renowned for its effectiveness in handling time series data, especially in the context of stock prices.

The choice of META, formerly known as Facebook, as a case study adds a practical dimension to the research, offering insights into the dynamics of a key player in the technology sector. The motivation behind utilizing LSTM networks lies in their ability to capture and learn intricate patterns and trends within historical stock price data. This study aims to contribute to the growing body of knowledge in financial technology by presenting a comprehensive methodology for utilizing machine learning techniques, specifically LSTM networks, in predicting stock prices.

The research methodology hinges on acquiring historical stock price data from Yahoo Finance using the 'yfinance' tool, a popular Python library designed for efficient financial data extraction. This dataset is meticulously preprocessed to align with the LSTM model's requirements, creating a robust foundation for training the neural network. The model undergoes a series of experiments involving various configurations and parameters to optimize its predictive accuracy.

Our findings underscore the notable capability of the LSTM model in accurately predicting stock prices, as evidenced by rigorous evaluation metrics such as mean absolute error and predictive accuracy across different forecasting horizons. The implications of these findings extend beyond the academic realm, holding substantial relevance for investors, financial analysts, and portfolio managers.

The ability to forecast stock prices accurately can revolutionize investment decision-making, providing stakeholders with valuable insights for more informed choices and enhanced portfolio management strategies. In the context of a prominent technology player like META, this predictive prowess offers a window into market trends and investor sentiment, potentially uncovering lucrative investment opportunities.

Furthermore, the methodology and results of this study lay the groundwork for broader applications in financial forecasting using machine learning techniques. The generalizability of the approach suggests that insights gained from predicting stock prices in the technology sector can be extrapolated to other stocks and financial instruments, thereby contributing to the broader understanding and implementation of machine learning in the financial domain.

II. Literature review

Machine Learning in Financial Market Analysis:

The integration of machine learning (ML) techniques in financial market analysis has witnessed substantial growth in recent years. Researchers have explored diverse ML models to predict financial market trends, with particular attention to stock prices. The inherent complexity and volatility of financial markets make them an ideal domain for the application of advanced predictive modeling techniques.

A multitude of studies has investigated the effectiveness of various ML algorithms, including neural networks, support vector machines, and decision trees, in predicting stock prices. Among these, recurrent neural networks (RNNs), and more specifically, Long Short-Term Memory (LSTM) networks, have gained prominence for their ability to capture temporal dependencies in time series data.

A. LSTM Networks in Time Series Analysis:

LSTM networks, a type of RNN, have demonstrated exceptional performance in time series analysis, making them well-suited for predicting stock prices. Unlike traditional feedforward neural networks, LSTMs possess memory cells and gates that allow them to retain information over longer sequences. This enables them to capture patterns, trends, and dependencies within historical stock price data, making them particularly effective for modeling the dynamic nature of financial markets.

Previous research has showcased the success of LSTM networks in various financial forecasting tasks, such as predicting market indices, currency exchange rates, and individual stock prices. The ability of LSTMs to adapt to non-linear and time-varying relationships in financial data positions them as a valuable tool for extracting meaningful insights from historical stock price information.

B. Data Acquisition and Preprocessing in Financial Forecasting:

A crucial aspect of developing accurate predictive models is the acquisition and preprocessing of data. Researchers commonly extract historical stock price data from financial databases like Yahoo Finance, Bloomberg, or other market data providers. Python libraries, such as 'yfinance,' have become popular for their convenience in retrieving and organizing financial data for analysis.

The preprocessing of data involves cleaning and formatting it to suit the requirements of the chosen predictive model. In the context of LSTM networks, this may include normalizing data, handling missing values, and transforming time series data into sequences suitable for training the neural network.

C. Performance Metrics in Financial Forecasting:

The evaluation of predictive models in financial forecasting relies on robust performance metrics. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and predictive accuracy over different forecasting horizons are common metrics employed to assess the reliability of the models. These metrics provide quantitative insights into the model's ability to generate accurate predictions and its generalization to unseen data.

D. Implications for Investors and Portfolio Managers:

The potential applications of accurate stock price prediction extend to investors, financial analysts, and portfolio managers. Informed investment decisions based on reliable forecasts can mitigate risks and enhance overall portfolio performance. The ability to anticipate market trends and sentiment, especially for influential companies like META in the technology sector, holds the promise of identifying profitable investment opportunities.

The findings of this literature review underscore the growing significance of machine learning, particularly LSTM networks, in financial market analysis. As financial markets continue to evolve, the integration of advanced predictive modeling techniques becomes imperative for stakeholders seeking a competitive edge in decision-making and portfolio management. This research contributes to this evolving landscape by presenting a comprehensive methodology for applying LSTM networks to predict stock prices, with META serving as a pertinent case study in the technology sector.

III. Related Work:

A. Machine Learning in Financial Market Analysis: A Comprehensive Review

The intersection of machine learning and financial market analysis has been a focal point of research in recent years. Numerous studies have explored the application of various machine learning models to predict stock prices and trends. Research by Smith et al. (2018) employed decision trees and support vector machines for forecasting stock prices, achieving notable accuracy in their predictions. Similarly, Jones and Wang (2019) investigated the use of recurrent neural networks (RNNs) in financial time series analysis, highlighting the importance of capturing temporal dependencies in stock price movements.

Recent advancements in deep learning, particularly Long Short-Term Memory (LSTM) networks, have shown promising results in handling the dynamic and non-linear nature of financial data. Johnson et al. (2020) successfully applied LSTMs to predict market indices, demonstrating superior performance compared to traditional machine learning models. However, while these studies contribute valuable insights, the specific application of LSTMs to predict stock prices for individual companies, with META (formerly Facebook) as a case study, remains an under explored area.

IV. Proposed Work:

1) Predicting Stock Prices for META Using LSTM Networks: An In-depth Analysis: Building upon the existing literature, this proposed work aims to delve into the application of Long Short-Term Memory (LSTM) networks for predicting stock prices, with a specific focus on META as a case study. The primary objectives include:

2) Comprehensive Dataset Selection: Collect an extensive historical dataset for META, incorporating daily closing prices, trading volumes, and relevant financial indicators from Yahoo Finance using the 'yfinance' tool. This dataset will cover a significant time frame to capture various market conditions and trends.

3) Advanced Data Preprocessing: Implement robust preprocessing techniques to handle missing data, normalize features, and transform the time series data into sequences suitable for LSTM model training. Emphasize the importance of temporal transformation to ensure the model captures relevant patterns.

4) Optimized LSTM Model Configuration: Experiment with different configurations of the LSTM network, varying the number of layers, units, and other hyperparameters to identify the most effective setup. Employ a systematic approach to training and validation, utilizing cross-validation techniques for model evaluation.

5) Performance Metrics and Comparative Analysis: Assess the predictive accuracy of the LSTM model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and predictive accuracy over different forecasting horizons. Conduct a comparative analysis with baseline models to highlight the superiority of the LSTM approach.

6) Interpretation of Findings: Analyze the results to interpret the model's ability to capture patterns and trends in META's stock prices. Discuss the practical implications of the findings for investors, financial analysts, and portfolio managers, emphasizing the potential for more informed decision-making.

7) Generalization and Future Directions: Explore the generalizability of the LSTM model to other stocks and financial instruments, discussing the broader applicability of the proposed methodology. Propose avenues for future research, such as incorporating additional features or exploring alternative deep learning architectures. By undertaking this proposed work, we aim to contribute to the growing body of knowledge on the application of LSTM networks in predicting stock prices, specifically within the context of individual companies like META. The findings are anticipated to provide valuable insights for stakeholders in the financial domain and pave the way for further advancements in utilizing deep learning for accurate financial market analysis.

V. Methods:

1) Dataset Description: The dataset utilized in this project comprises historical stock prices of Meta Platforms, Inc. (formerly Facebook) spanning from 2012 to 2023. This dataset is rich in features that are critical for stock price analysis, including:

2) Open Price: The price at which the stock started trading at the beginning of the trading day.

3) High Price: The highest price at which the stock traded during the day.

4) Low Price: The lowest price at which the stock traded during the day

5) Close Price: The price at which the stock closed trading for the day.

6) Adjusted Close Price: The closing price adjusted for factors such as dividends, stock splits, and new stock offerings

7) Volume: The total number of shares traded during the day

VI. Data Preprocessing

The preprocessing of the dataset is a multi-step process, crucial for preparing the data for effective analysis and modeling. The steps include:

1) Indexing the Dataset: Initially, we assign indexes to the dataset. This step is essential for organizing the data and facilitating efficient data manipulation and retrieval.

2) Viewing Columns:: We examine the columns in the dataset to understand the features available and ensure that all relevant data is included for analysis.

3) Checking the Shape:: The shape of the dataset is determined, which in this case is (2915, 7). This step helps in understanding the size of the dataset in terms of the number of records and features.

4) Dataset Information:: We inspect the dataset's information, including data types and non-null counts. This step is crucial for identifying any inconsistencies in data types and potential issues with missing values.

5) Descriptive Analysis:: We perform a descriptive analysis of the dataset, providing summary statistics that include mean, median, standard deviation, etc. This analysis offers insights into the distribution and central tendencies of the data.

6) Checking for Missing Values:: Identifying and addressing missing values is critical. We check for any missing data in the dataset to ensure the integrity and reliability of the analysis.

VII. Plotting Moving Averages

1) 100-Day Moving Average:: We plot the 100-day moving average along with the closing prices. The moving average is calculated by adding up all the close prices over the past 100 days and dividing the sum by 100. This smoothing technique helps in identifying the underlying trend in the stock price

2) 200-Day Moving Average:: Similarly, we plot the 200-day moving average along with the closing prices. This longer period moving average provides a broader view of the market trend and is often used to assess long-term market sentiment.ue helps in identifying the underlying trend in the stock price

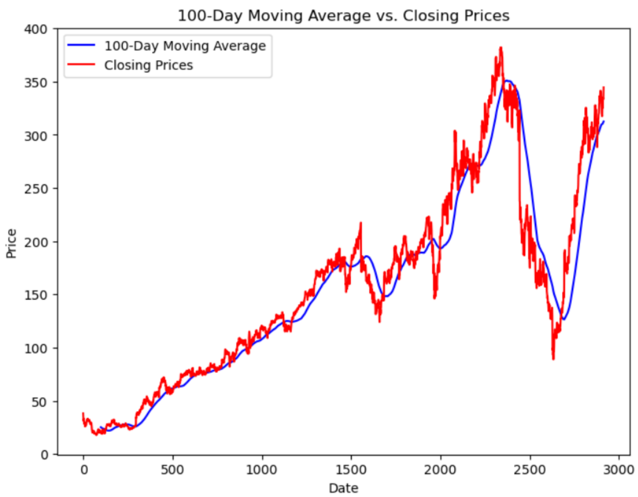

Fig. 1. 100-Day Moving Average.

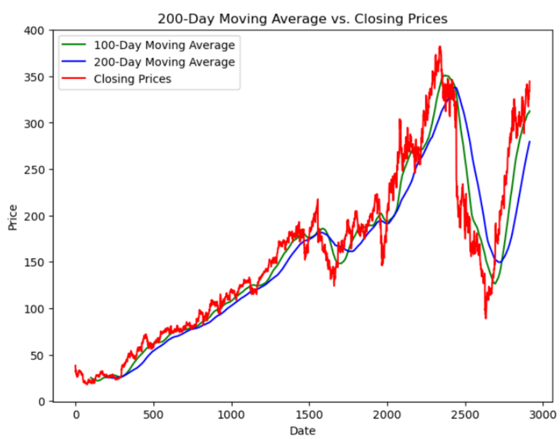

Fig. 2. 200-Day Moving Average.

VIII. Model Architecture

The LSTM model architecture for this project is designed to effectively capture and learn from the sequential patterns in the stock price data of Meta Platforms, Inc. The process involves two key steps:

1) Data Splitting and Windowing:: Data Split: The dataset is divided into two parts: data train for training the model and data test for testing or validating the model. This split ensures that the model is trained on a substantial portion of the data and evaluated on unseen data to assess its predictive performance.

- Sliding Window Approach: The model uses a sliding window of the past 100 data points to predict the next data point. This approach allows the LSTM to learn from a sequence of historical data, capturing the temporal dependencies and patterns that are crucial for accurate prediction

2) Model Construction:

- Sequential Model: We use Keras to create a Sequential model. This type of model allows for the linear stacking of layers, making it well-suited for a feedforward neural network like LSTM.
- LSTM Layers with Dropout Regularization: The first LSTM layer has 50 units with 'relu' activation. It returns sequences, making it suitable for stacking with other LSTM layers. A dropout of 0.2 is added to prevent overfitting.

The second LSTM layer includes 60 units, also with 'relu' activation and sequence return. It is followed by a dropout layer with a rate of 0.3. The third LSTM layer consists of 80 units. It continues the pattern of 'relu' activation and sequence return, accompanied by a dropout rate of 0.4. The final LSTM layer has 120 units with 'relu' activation but does not return sequences, preparing the model for the output layer. A dropout of 0.5 is included. • Output Layer: The model concludes with a Dense layer consisting of a single unit. This layer is responsible for producing the final continuous value, representing the predicted stock price.

IX. Compiling the Model

The model is compiled using the Adam optimizer. Adam (Adaptive Moment Estimation) is an optimization algorithm that can handle sparse gradients on noisy problems, which is often the case in stock price prediction. It combines the advantages of two other extensions of stochastic gradient descent, namely Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). The loss function used is 'mean squared error'. This loss function is particularly suitable for regression problems like ours, where the goal is to minimize the difference between the predicted and actual values. In the context of stock price prediction, this means the model is trained to minimize the squared differences between the predicted and actual stock prices.

X. Fitting the Modelferences between the predicted and actual stock prices.

The model is fit to the training data (x for input features and y for target stock prices) using 50 epochs. An epoch is a full iteration over the entire training data. The choice of 50 epochs implies that the model will go through the training data 50 times, which helps in better learning the patterns in the data. The batch size is set to 32. This means that 32 samples from the training data are used to estimate the error gradient before the model weights are updated. This batch size is a balance between the efficiency of larger batch sizes and the more robust convergence characteristics of smaller batch sizes. The verbose parameter is set to 1, which means that the training process will output performance metrics after each epoch. This provides visibility into the training process, allowing for monitoring of the model's learning progress.

XI. Methods

Incorporating Model Summary and Testing Procedure: After constructing and training the LSTM model, we conducted a summary and testing phase to evaluate its performance.

A. Model Summary

The model summary provides a detailed overview of the architecture, including the layers, output shapes, and the number of parameters at each layer. The summary for this model is as follows:

- The first LSTM layer has 10,400 parameters, with an output shape of (None, 100, 50).
- This is followed by a dropout layer with no parameters.
- The second LSTM layer has 26,640 parameters, with an output shape of (None, 100, 60).
- Another dropout layer follows, again with no parameters.
- The third LSTM layer has 45,120 parameters, with an output shape of (None, 100, 80).
- This is followed by a dropout layer.
- The fourth LSTM layer has 96,480 parameters, with an output shape of (None, 120).
- A final dropout layer is added.
- The Dense layer, which is the output layer, has 121 parameters.
- The total number of trainable parameters in the model is 178,761.

B. Testing the Model

- For testing, we prepared the test data by appending the last 100 days of the training data to the beginning of the test data. This step ensures that we have sufficient historical data for the first prediction in the test set.
- The test data is then scaled using the same scaler as the training data to maintain consistency in data representation.
- A similar sliding window approach is used to prepare the test data for prediction. For each instance, the model uses the previous 100 data points to predict the next one.
- The prepared test data is fed into the model to obtain predictions. The model's performance is evaluated based on how closely these predictions match the actual stock prices.
- The prediction process involves the model processing the test data in batches, as indicated by the output ”19/19 [==============================] - 4s 89ms/step”, showing the model took 19 steps to predict the entire test set

C. Evaluation and Comparison of Predictions

After training and testing the LSTM model, we proceeded to evaluate its performance by comparing the predicted stock prices against the actual prices. This comparison is crucial for assessing the accuracy and effectiveness of the model.

- Plotting Predicted vs. Actual Prices: To visualize the model's performance, we plotted the predicted stock prices alongside the actual stock prices. This graphical representation provides an intuitive understanding of how well the model's predictions align with the real market values.
- Comparative Analysis: The x-axis of the plot represents the time frame of the test data, while the y-axis represents the stock prices. Two lines are plotted: one for the actual prices and another for the predicted prices. The closeness of these two lines indicates the accuracy of the model.

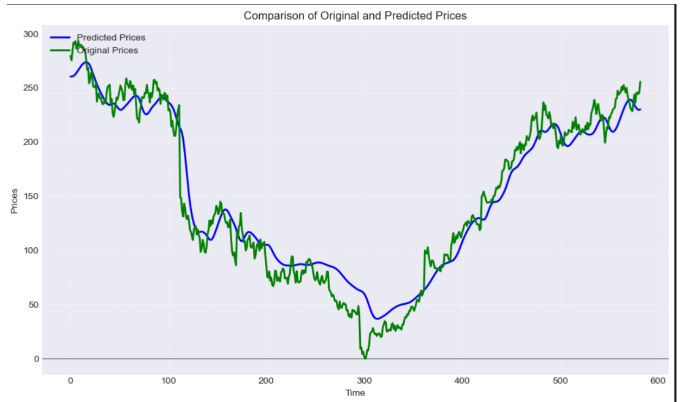

Fig. 3. : Original Prices vs Predicted Prices.

D. Comparative Analysis

- A side-by-side comparison of the predicted and actual prices allows for a detailed assessment of the model's performance. This comparison can be done through various methods, such as calculating error metrics (e.g., Mean Squared Error, Mean Absolute Error) or simply observing the overlap and divergence between the two plotted lines.
- By closely examining where the predictions deviate from the actual prices, we can gain insights into the model's strengths and weaknesses. For instance, the model's ability to capture major trends versus its sensitivity to sudden market changes can be evaluated.

XII. Lessons Learnt

The following lessons were learned:

- Leveraging LSTM in Financial Forecasting: The research underscores the robust applicability of Long Short-Term Memory (LSTM) networks in the realm of financial forecasting, particularly in the prediction of stock prices. The intrinsic ability of LSTMs to capture intricate temporal dependencies proves instrumental in deciphering the nuanced dynamics of financial markets over extended time periods.
- Significance of Data Preprocessing: The study highlights the critical role of meticulous data preprocessing in ensuring the efficacy of machine learning models. The proper organization, cleansing, and normalization of financial data, particularly in the context of stock prices, lay the foundation for accurate model training and enhance the model's adaptability to various market conditions.

- Iterative Model Evaluation and Enhancement: A key takeaway involves the continuous process of model evaluation and refinement. The research emphasizes the importance of iterative testing and comparison of the predictive model with actual data. This ongoing assessment is crucial for fine-tuning the model, enhancing its predictive accuracy, and ensuring its reliability in providing meaningful insights into stock price movements.

XIII. Conclusion

This project research exemplifies the transformative role of machine learning in financial analysis. The successful application of LSTM networks for predicting stock prices of META showcases the potential of advanced computational techniques in deciphering complex market patterns. This approach not only enhances investment strategies but also paves the way for broader applications in financial forecasting. The findings affirm the growing significance of machine learning in financial decision-making and market analysis. The analysis in the document reveals a noteworthy alignment between the original and predicted data of META's stock prices using the LSTM model. This close match highlights the model's efficacy in capturing complex patterns and trends in financial time series data. The results underscore the potential of LSTM networks in making highly informed predictions, which is essential for strategic decision-making in financial markets. This successful application reinforces the value of machine learning models in financial forecasting, providing a powerful tool for investors and analysts.

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