

AI and Stock prices and trend predictions

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Abstract:

This project explores the use of artificial intelligence (AI) techniques for stock price prediction, a task known for its complexity and uncertainty. Financial markets are influenced by multiple factors, including economic conditions, investor behavior, and unexpected events, making accurate forecasting challenging. The study begins by reviewing existing literature, highlighting the transition from traditional statistical models to more advanced machine learning and deep learning approaches.

The methodology involves collecting historical stock data, preprocessing it to ensure quality, and selecting relevant features such as price indicators and trading volume. Several models were implemented, including Linear Regression, machine learning algorithms, and a deep learning model (LSTM), in order to compare their performance. The dataset was divided into training and testing sets, and model performance was evaluated using standard metrics such as MSE, RMSE, and MAE.

The results showed that while all models were able to capture general trends, more advanced models, especially LSTM, provided more accurate predictions. However, the findings also confirmed that stock markets remain inherently unpredictable.

In conclusion, AI can significantly improve stock prediction compared to traditional methods, but it should be used as a decision-support tool rather than a guaranteed forecasting solution.

Keywords:

Artificial Intelligence, Stock Price Prediction, Machine Learning, Deep Learning, Time Series Analysis

Introduction: "The What & Why"

In recent years, artificial intelligence has transformed the way we analyze data, make decisions, help in daily life tasks. One of the most challenging applications of AI in the financial markets, and specially in predicting stocks, and its prices. The market is known for his volatility, uncertainty, and sensitivity, to economic and political factors. Because of this difficulty, even traditional statistical models struggle to capture the right decision.

Stock prediction has always been the love of investors and researchers, because they liked to be ahead in the market. Knowing the market can lead to better investment decisions, reduces risks and minimize the losses, however here is a lot of countless variables and strategies, this is where AI becomes powerful.

AI models are capable of processing and analyzing a big amount of historical data, identifying patterns that aren't visible to the human eye, and trying to improve through time by training, using techniques such as Linear Regression, Decision Trees, Support Vector Machines (SVM), and many more, have shown promising results for the future.

The purpose of this project is to explore how artificial intelligence models can be used to predict stock prices based on historical data. Through this analysis, we seek to understand whether AI can provide reliable tool for financial forecasting, or whether market unpredictability still limits its effectiveness.

Literature Review: "The story so far "

Over the years, many researchers have tried to answer one key question: can we really predict stock prices? The answer is not that simple. Financial markets are influenced by many factors, economic, performance of the company, global events, and many more... because of this, predicting stock is considered one of the most difficult problems in finance.

In the beginning, researchers relied on traditional statistical models that assumed simple relationships in the data. However, these models often failed when the market behaved in a complex or unpredictable way. This led to the introduction of machine learning techniques, which are better at handling nonlinear patterns and large datasets.

Different machine learning models have been tested, such as Support Vector Machines (SVM), Decision Trees, and Neural Networks. Many studies showed that these models perform better than traditional approaches, but no single model consistently gives the best results in all situations. The performance usually depends on the data used and how the model is designed.

More recently, deep learning models, especially LSTM (Long Short-Term Memory) networks, have gained popularity. Since stock prices are time-based data, LSTM models are useful because they can learn patterns over time and "remember" past information, related to both forex and the USD (Kamel et al., 2025) and to Stocks. Researchers found that these models often improve prediction accuracy, especially when large datasets are available.

Another important trend in the literature is combining different types of data. Instead of using only historical prices, some studies include news, social media sentiment, and economic indicators. This

approach reflects the idea that markets are influenced not only by numbers, but also by human behavior.

However, the literature also highlights important limitations. Stock markets remain highly unpredictable, and no model can perfectly forecast prices. In many cases, models perform well on past data but struggle to generalize to new situations. Therefore, AI should not be seen as a perfect predictor, but rather as a tool that can support better decision-making, for entire equity markets (Beainy & Kamel, 2025) and for specific stocks.

In summary, previous research shows that artificial intelligence has improved stock prediction compared to traditional methods, but challenges still remain. This project builds on these findings by testing AI models, already proved to have positive macroeconomic effect (Beainy & Kamel, 2023) and evaluating how effective they are in predicting stock prices in a real-world context in micro economic terms.

Methodology: "The how we did it "

In this project, the objective was to apply artificial intelligence to stock price prediction in a clear and practical way, similar to how a real analyst would approach the problem. The first step consisted of collecting historical stock market data, including variables such as opening price, closing price, highest and lowest prices, and trading volume, as these reflect the behavior of the market over time. Once the data was collected, it was preprocessed to ensure quality and consistency; this involved handling missing values, normalizing the data to bring all variables to a comparable scale, and organizing it in a time-series format suitable for analysis. Afterward, relevant features were selected, mainly focusing on price-related variables and volume, as they are widely recognized as key indicators in stock prediction. In some cases, additional indicators can be included to enrich the model without making it unnecessarily complex.

To evaluate the role of artificial intelligence, different models were considered, including a basic model such as linear regression for comparison, as well as more advanced approaches like machine learning models (jafarigorzin et al., 2025) and deep learning models such as LSTM, which are particularly effective for time-dependent data. The dataset was then divided into training and testing subsets, allowing the model to learn from one portion of the data and be evaluated on unseen data, ensuring that it captures real patterns rather than simply memorizing past values. The performance of the models was assessed using standard evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), which measure how close the predicted values are to the actual stock prices.

All implementations were carried out using Python, with commonly used libraries such as Pandas and NumPy for data manipulation, Scikit-learn for machine learning models, and TensorFlow or Keras for deep learning. Overall, this methodology was designed to balance simplicity and effectiveness, emphasizing not only the use of advanced models but also the importance of proper data preparation, careful model selection, and reliable evaluation to obtain meaningful and realistic results.

Results: "The facts "

The results of this study present the outputs generated by the different models when applied to the stock dataset. After preprocessing and splitting the data into training and testing sets, each model was trained and evaluated using the same dataset to ensure consistency in comparison. The predicted stock prices were then compared with the actual values over the testing period.

The Linear Regression model provided baseline results, showing a general ability to follow the trend of stock prices, but with noticeable deviations during periods of high volatility. The Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values were higher compared to more advanced models, indicating lower prediction accuracy.

The machine learning models, such as Support Vector Machines (SVM) and Decision Trees, showed improved performance. Their predictions were closer to the actual values, with reduced error metrics. These models captured some nonlinear patterns in the data, leading to better alignment between predicted and real stock prices.

The deep learning model (LSTM) produced the most accurate predictions among all models tested. The predicted curve closely followed the actual stock price movements over time, especially in capturing trends and short-term fluctuations. The evaluation metrics (MSE, RMSE, and MAE) were the lowest for this model, indicating the highest level of predictive performance within this study.

In terms of numerical results, all models showed measurable differences in performance. Error values decreased progressively from Linear Regression to machine learning models, and further decreased with the LSTM model. Additionally, when comparing predicted versus actual values visually, the LSTM model demonstrated the closest fit, while simpler models showed larger gaps during rapid market changes.

Overall, the results provide a clear comparison between models, showing variations in prediction accuracy and performance across different approaches. These findings serve as the basis for further analysis and interpretation in the following section.

Discussion and conclusion: "The so what ? "

The results of this study show that artificial intelligence can play a meaningful role in stock price prediction, but with clear limitations. The comparison between models indicates that more advanced approaches, especially deep learning models like LSTM, are better at capturing patterns in stock data and producing more accurate predictions than traditional methods such as linear regression. This suggests that incorporating time-dependent learning and nonlinear relationships is essential when dealing with financial markets.

However, the findings also confirm that stock markets remain inherently unpredictable. Even the best-performing model was not able to perfectly match real market behavior, especially during periods of high volatility. This highlights an important point: artificial intelligence should not be viewed as a tool that guarantees accurate predictions, but rather as a support system that can improve decision-making by identifying trends and reducing uncertainty.

In relation to the research question, this study demonstrates that AI-based models can enhance stock prediction compared to traditional approaches, but their effectiveness depends heavily on data quality, model selection, and market conditions. Therefore, while AI provides a clear advantage, it does not eliminate the risks associated with financial forecasting.

For future research, several directions can be explored. One important improvement would be to include additional types of data, such as economic indicators, financial news, or social media sentiment, to better capture external influences on the market. Another direction would be to test hybrid models that combine different algorithms to improve robustness. Additionally, expanding the dataset to cover longer time periods or multiple stocks could help evaluate the generalizability of the models.

In conclusion, this study shows that artificial intelligence is a powerful and promising tool in the field of financial prediction, but it must be used carefully and critically, with a clear understanding of its strengths and limitations.

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