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IMPROVING THE AI STOCK MARKET FORECASTING WITH CANDLESTICK PATTERNS

Abstract. In the rapidly evolving digital economy, the application of Artificial Intelligence (AI) in financial forecasting has gained significant traction. This study investigates the effect of various candlestick patterns on the performance of Long Short-Term Memory (LSTM) models in predicting stock market movements. Experiments conducted on the stock price history data demonstrate that supplementing traditional input parameters (e.g., open price) with a range of candlestick patterns enhances the predictive accuracy of LSTM models. Although the initial model architecture lacked hyperparameter optimization for solving this kind of task, our findings suggest notable improvement in prediction performance when candlestick pattern flags are incorporated. Future work will focus on incorporating additional financial indicators into the model's training data and fine-tuning it through optimization algorithms to achieve greater robustness and accuracy.

Keywords: artificial intelligence, LSTM model efficiency, stock market prediction, candlestick patterns, improving AI model accuracy.

Introduction

Digital technologies have revolutionized market dynamics, increasing financial inclusion worldwide and enabling the creation of global market services. Financial services have become independent and target regular individuals as users. The worldwide spread has introduced new data analysis methods, enabling accurate economic predictions and strategic market operations [1].

Stock market investment can be considered one of the key financial sectors that spreads accessibility and provides economic independence, whether at the high level of a country's economy or the personal level. The number of investors is growing, increasing the need to develop new algorithms and methods for predicting market dynamics. The stock market is influenced by various factors that can impact stock prices, including economic conditions, political situation, and the performance of specific companies [2].

As financial markets become increasingly data-driven, Artificial Intelligence (AI), particularly Deep Learning models, has emerged as a promising solution for enhancing market forecasting. The rise in market complexity, driven by both macroeconomic variables and behavioral patterns, necessitates the use of adaptive and intelligent models. Among the various AI techniques, Long Short-Term Memory (LSTM) networks have shown significant promise due to their ability to capture temporal dependencies in sequential data.

However, the effectiveness of such models hinges on the quality and diversity of input features. Traditional models relying solely on basic pricing data (e.g., open or close prices) often fail to capture nuanced market behaviors.

This study investigates the effect of candlestick patterns on the forecasting accuracy of LSTM models.

Literature review

Current research on the impact of digital financial technology on accelerating financial inclusion focuses on identifying the key segment that influences the development of financial institutions and economic growth.

The study [1] emphasized that digital financial technologies have fostered financial inclusion in developing economies. The work highlighted that mobile-based banking systems and digital payment solutions enable access to financial services for previously unbanked populations. This increased accessibility has enhanced economic participation and empowered marginalized communities by providing tools for savings, investments, and credit. The significant role of government policies in supporting fintech adoption highlights the importance of regulatory frameworks and partnerships between the public and private sectors in scaling these technologies.

However, digital literacy and infrastructure deficiencies persist, particularly in rural areas, where technological and educational barriers prevent widespread adoption. The study suggested that targeted educational campaigns and infrastructure investments are necessary to address these gaps effectively. The evidence presented in this section suggests that economic development and financial stability are directly dependent on modern information technologies and the latest market analysis methods [1].

Artificial Intelligence has gained importance in recent years in analyzing the market and forecasting stock prices [3, 4].

The research [5] examined techniques and case studies of advancements in Artificial Intelligence and Machine Learning for stock market prediction, demonstrating that machine learning algorithms have received considerable attention in recent years.

The most used AI models and techniques include the Support Vector Machine (SVM), the Random Forest (RF), the K-nearest neighbor (KNN), the Naive Bayes NB, the Long-Short-Term Memory (LSTM), and the Artificial Neural Network (ANN). This highlights the significance of trading as a key area for AI improvement, as evidenced by the study's results, which show that machine learning algorithms can outperform traditional data analysis methods. Nevertheless, it is essential to consider which approach yields superior accuracy. The efficiency and accuracy of each algorithm are the key parameters that should be considered and improved [5].

SVM is a promising tool for financial prediction, outperforming standard indicators when dealing with market uncertainty and complexity. SVM demonstrated higher reliability and adaptability, especially under volatile or crisis conditions in the stock market. Traditional methods were often less accurate and less responsive to sudden market shifts. The SVM model successfully captured nonlinear dependencies and complex patterns in market data [6].

On the other hand, Long Short-Term Memory (LSTM) networks have shown significant promise due to their ability to capture temporal dependencies in sequential data.

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) architecture specifically designed to model temporal sequences and long-range dependencies more effectively than standard RNNs. LSTM networks overcome the vanishing gradient problem inherent in traditional RNNs by introducing memory cells and gating mechanisms that regulate the flow of information [7].

AI algorithms were modified to enhance the accuracy of results using various techniques for the basic AI algorithms [8-10]. The research [8] argued that the deep LSTM network algorithm could be optimized with the Artificial Rabbits Optimization (ARO) algorithm. This research proposed a new deep LSTM network optimized by the ARO algorithm. The proposed model is named LSTM-ARO. The goal is to optimize LSTM model parameters using ARO to determine the most efficient architecture. To evaluate the efficiency of LSTM-ARO, it was trained on historical market data to predict price dynamics and compared with the regular LSTM model, the ANN model, and the Genetic Algorithm (GA). The results demonstrate that the LSTM-ARO model outperforms other models, delivering highly accurate predictions that can be valuable for traders and investors [8].

Similarly, the study [9] combined Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models with AI techniques, yielding high predictive performance for volatile markets. It highlighted the robustness of GARCH models in capturing market volatility and leveraging AI's adaptability to complex data patterns. The GARCH-LSTM model achieved the best performance, exhibiting the lowest RMSE (0.2002), MAE (0.1840), and MAPE (0.1570), along with the highest R-squared value (0.9995).

Overall, hybrid models combining GARCH with LSTM, GRU, and Transformer outperformed their standalone counterparts. This demonstrates that integrating the statistical properties of historical prices with RNN and Transformer architecture significantly enhances the accuracy of stock price predictions. The authors noted that basic AI models often underperform during sudden, unpredictable market shocks, highlighting the need for enhanced adaptability. The real-time market sentiment analysis was integrated with GARCH-AI models to address this limitation, thereby enabling more effective responses to sudden changes in market dynamics [9].

Reference [10] presents results suggesting that AI algorithms can be optimized by combining different models and then normalizing their results using the weighted ensemble learning method. The research described a combination of prediction models based on Artificial Neural Networks (ANN), Gaussian Process Regression (GPR), and Classification and Regression Trees (CART). This combined model was then weighted with the ensemble model based on the quality of training and using the cuckoo search algorithm. In contrast to finding the most efficient architecture for the specific AI algorithm, as described in previous publications, this study aimed to merge several algorithms to compensate for the shortcomings of each at the expense of the others. The results indicate that the proposed system can predict the price index with an average accuracy of 96.6%, representing a reduction in prediction error of at least 2.4% compared to traditional methods [10].

Together, these studies offer valuable insights into stock market prediction using AI. Considering all this evidence, AI methods are not only successfully used to predict the stock market dynamics but also have the potential to increase the accuracy of their results. Investors can use these forecasting results as key parameters to analyze and plan their investments, which simultaneously helps to develop the global economic system.

Despite these advancements, there is a limited amount of research focusing on how the inclusion of specific financial indicators affects prediction outcomes. Most studies focus on improving algorithms themselves rather than examining the data features fed into them.

Candlestick patterns can be utilized as a primary feature for stock market forecasting with LSTM models. The candlestick patterns are graphical representations of price movement in financial markets and have been used by traders for a long time to infer potential market direction. While traditionally rooted in heuristic analysis and subjective interpretation, recent research has sought to formalize and validate these patterns using computational and statistical methodologies. There are more than 103 unique candlestick patterns that were defined using first-order logic rules and fuzzy linguistic variables [11].

This research aims to verify whether candlestick patterns could be used as an additional input feature to improve the accuracy of the LSTM model for stock market forecasting.

Methodology

The methodology used was based on training the same LSTM model with varying amounts of input features.

The LSTM model was configured once for all experiments and was not optimized for solving a particular task to prevent discrepancies in the results. The LSTM model consists of three LSTM layers, each with 60 units, followed by a dropout layer to avoid overfitting and a dense output layer that predicts the closing price. The model was compiled using the Adam optimizer with an initial learning rate of 0.001 and trained using Mean Squared Error (MSE) as the loss function.

The dataset spans from 2020 to 2025, ensuring the inclusion of various market conditions, including bullish, bearish, and volatile periods.

The data was preprocessed to fill in missing values, normalize scales, and structure it into sequential input for LSTM networks.

Experiments were conducted by varying the input feature set. Two input feature sets were used to compare. The first set contains only the closing price as an input feature for the LSTM model. The second set contains close prices and candlestick patterns. The candlestick patterns were identified through rule-based classification, enabling the encoding of patterns into binary vectors that represent indicators for future increasing or decreasing trends, which are also referred to as bullish and bearish flags. The description of the input feature sets for the LSTM model is presented in Table 1.

Table 2 contains the list of the candlestick pattern names that were used in Model A. Model B contains the same candlestick patterns as Model A, but also an additional eight patterns that are listed in Table 3.

Table 1 – **Experiments' input feature set**

N	Name	Description
1	Baseline Model	Only the closing price
2	Model A	Close price and 5 bearish and 5 bullish candlestick patterns
3	Model B	Model A + 4 more bearish and 4 more bullish candlestick patterns

Table 2 – **Candlestick pattern names used in Model A**

Bearish flag	Bullish flag
Evening Star	Hammer
Dark Cloud Cover	Morning Star
Hanging Man	Engulfing Pattern
Harami Pattern	Piercing Pattern
Shooting Star	Three Advancing White Soldiers

Table 3 – **Extra candlestick pattern names used in Model B**

Bearish flag	Bullish flag
Three Black Crows	Dragonfly Doji
Gravestone Doji	Inverted Hammer
Counterattack	Three Inside Up/Dow
Advance Block	Hikkake Pattern

The model performance was evaluated using three key metrics:

- Root mean squared error (RMSE);
- Mean Absolute Error (MAE);
- Mean Absolute Percentage Error (MAPE).

Results

The observed results are represented in Table 4.

Table 4 – **Experiments' results**

Configuration	RMSE	MAE	MAPE (%)
Baseline Model	0.1755	0.1422	19.33
Model A	0.1705	0.1399	18.63
Model B	0.1687	0.1380	18.48

According to the numbers, Model B has the smallest RMSE, MAE, and MAPE error metrics.

Discussions

Based on the observed results, adding the candlestick-related features to the input layer for the LSTM model consistently improves performance.

The best overall performance was achieved by Model B, which incorporates a total of 18 separate bullish and bearish candlestick features, likely capturing more of the trend movements.

Although the LSTM model itself was not optimized for solving this problem, and only the input feature sets were modified, it still improved the efficiency of predicting trend dynamics for the selected data.

Feature research

There are several directions for the feature research related to improving the accuracy of stock market forecasting.

The first direction could involve checking other financial indicators that can be used to enhance the input layer features and improve the quality of the neural network model training.

The second promising direction involves fine-tuning the LSTM model architecture through advanced hyperparameter optimization methods such as grid search, Bayesian optimization, or nature-inspired algorithms like Genetic Algorithms.

By systematically exploring model configurations, researchers can gain a deeper understanding of the relationship between structure and performance.

Lastly, extending the model to support multi-output forecasting – predicting not just closing prices but also volatility, trend direction, or trading signals – could make the system more practical for investors and analysts.

By framing the forecasting task more broadly, future systems can offer a more comprehensive picture of market dynamics.

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Покращення прогнозування фондового ринку за допомогою штучного інтелекту з використанням свічкових патернів

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Анотація. У швидко розвиваючій цифровій економіці використання штучного інтелекту (ШІ) у фінансовому прогнозуванні набуває значної популярності. Ця робота досліджує вплив різних патернів свічок на ефективність моделей довгострокової пам'яті (LSTM) у прогнозуванні рухів фондового ринку. Експерименти, проведені на історичних даних цін на акції, показують, що доповнення традиційних вхідних параметрів діапазоном моделей свічок підвищує точність прогнозування моделей LSTM. Хоча початковій архітектурі моделі бракувало оптимізації гіперпараметрів для вирішення такого роду завдань, результати дослідження свідчать про помітне покращення ефективності прогнозування, якщо використовувати вектор патернів свічок як вхідний параметр. Подальша робота буде зосереджена на включенні додаткових фінансових показників до навчальних даних моделі та її точному налаштуванні за допомогою алгоритмів оптимізації для досягнення більшої стійкості та точності.

Ключові слова: штучний інтелект, ефективність моделі LSTM, прогнозування фондового ринку, патерни свічок, підвищення точності моделі ШІ.