Algorithmic Stock Trading: A Preliminary Exploration of Multi-Agent Systems

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**Abstract.** The highly volatile and non-linear characteristics of financial time series data make accurate stock market forecasting a significant challenge. Over the past few years, artificial intelligence (AI) has developed into a robust means of improving predictive accuracy through the identification of patterns in extensive financial datasets. This research offers a comparative analysis of several forecasting models which are Linear Regression, Prophet, ARIMA, and Long Short-Term Memory (LSTM) networks are using two distinct input configurations: traditional market data are Open, High, Low, Close and an extended feature set that includes technical indicators are RSI 50 and SMA 50. According to experimental findings on deep learning models, LSTM surpasses other models when perform evaluation with actual market trends across both feature sets. As for the multi-agent system, it boosts the reliability of decisions by producing precise “Buy” or “Sell” signals that align closely with actual market movements. It can be seen that the integrated AI architectures designed for building robust algorithmic trading systems can manage the intricacies of financial markets.

# Introduction

While the emergence of LLMs could be regarded as one of the landmark developments in AI, one of the earliest advances worth mentioning is MAS. MAS is a team of intelligent agents, each with either a somewhat different perspective, set of skills and agendas that working jointly in complex and uncertain environments, such as financial markets. Agents can work on sentiment recognition, technical analysis, or fundamental analysis in financial applications. The distributed nature of MAS and its modular construction allow better interpretability, scalability, and flexibility [1]. According to the three properties decentralization of strategy, diversity of strategies, and dynamic role assignment, MAS is then considered suitable to enhance the robustness and efficiency of trading rather than the classical algorithmic trading.

The real-world organization of financial institutions, where various teams of analysts, risk managers, and traders collaborate to maximize portfolio outcomes, is reflected in the growing adoption of MAS techniques in stock trading in recent research [1], [2], [3], [4], [5], [6], [7], [8]. LLMs interpret unstructured data such as social sentiment or financial news while deep reinforcement learning allows agents to learn from historical and real-time data. The blend of these technologies could be the key to modeling human-like reasoning, memory, and reflection, thus possibly leading to autonomous agents that can forecast market trends, and justify and modify their decisions over time.

This paper review outlines the development and present status of MAS in stock trading, spot reoccurring trends and technological shortcomings, and suggests future research trends. The reviews analyze the performance of each model under varying input conditions with fundamental market data (Open, High, Low, Close) and an expanded feature set that includes the Relative Strength Index (RSI) and Simple Moving Average (SMA). Moreover, the experiment assesses the models’ real-world applicability by comparing these predictions with actual market movements.

This research provides an important contribution to the domain of stock market forecasting. It provides an extensive comparative analysis of traditional statistical models (Linear Regression, ARIMA, Prophet), a deep learning model (LSTM), and a MAS, highlighting the superior predictive performance of AI-driven methods. MAS would definitely offer significant potential for future directions by integrating multiple information sources through specialized agents, such as technical indicators and sentiment analysis.

# Literature Review

A multi-modal, multi-agent system for financial trading tasks, FinVision is designed to process various financial inputs by a team of specialized LLM-based agents [2]. This way, a comprehensive view is created by merging several modalities together- trading signals, candlestick charts, and textual sources of news. In FinVision, each agent acts independently. The Technical Analyst Agent, for example, looks at candlestick charts with which he assesses the market for his trading strategies. The Prediction Agent forecasts different trading activities and positions from the information received from different agents. The Reflection Module has two components that help in doing historical data assessments to enhance the decision-making process: assessments of how the previous trading sessions went and what visual cues of price movements tell.

Xiao et al. presented an idea for Trading Agents as a multi-agent framework inspired by the cooperation dynamic of real trading organizations. It is said that from technical analyst, sentiment analyst, fundamental analyst, and all sorts of traders having different risk profiles-Learning Language Model will empower such agents exclusively. There is also a risk management team watching exposures and two more researcher agents: Bull and Bear, who evaluate market conditions. For intelligent trade decisions, agents collaborate and combine knowledge from conversations and past data. The potential of multi-agent LLM frameworks in financial trading has been shown experimentally, where Trading Agents have outperformed the baseline models in terms of cumulative returns, Sharpe ratio, and maximum drawdown [5].

Hedge Agents is a multi-agent financial trading system designed to be aware of balance and to become more resilient through hedging techniques. It consists of a fund manager who serves as a centralized manager and a number of hedging specialists with different specializations in financial asset classes. Hedge Agents would be built to basically act like human specialists, bringing in maybe 4x total returns with an annualized return of 70 percent over a three-year period. To achieve proper decisions, agents will utilize the cognitive powers of LLMs and cooperate with each other through three conference formats [3].

Kou et al. develop an unusual quantitative stock trading scheme through a combination of multi-agent architectures and LLMs. The system consists of three modules that first extract predictive signals from research papers, visual charts, and numerical data; second, to build a heterogeneous pool of trading agents with differing risk tolerances through ensemble learning; while the third uses a dynamic weight-gating mechanism to select and weight the most relevant agents according to the prevailing market scenario. In the experiments set in the Chinese stock markets, this method was able to outperform the state-of-the-art baselines by a wide margin in almost all financial measures.

This particular MASA framework proposes a multi-agent self-adaptive approach to balance portfolio return and associated risk. MASA has two cooperatively working agents capable of responding to market conditions via a very sophisticated multi-agent reinforcement learning (RL) mechanism [4]. The TC-MARL adds trend consistency component into multi-agent deep reinforcement learning for portfolio optimization. The system keeps shifting among agents based on market conditions by grouping stock movements into two clusters and training a different agent on each cluster. This method guarantees that the trading plan stays in line with current market patterns. The efficiency and efficacy of TC-MARL in attaining optimal portfolio strategies were confirmed by extensive testing conducted on the Chinese stock market [1].

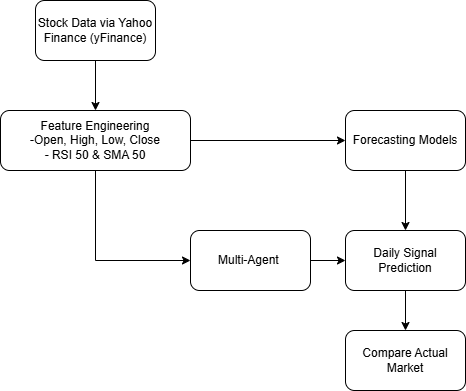
Machine Learning Model that been using recently in research, machine learning models are the Arima [9], [10], LSTM [9], Prophet [11], Linear Regression [12], [13], [14]. The author, Mo, compares with Arima and linear regression that found the Arima model has high reliable for short term forecasts.

# Method

The methodology comprises six essential elements: data acquisition, feature engineering, implementation of forecasting models, multi-agent integration This research study forecasting models and a multi-agent system to produce daily stock trading signals (Buy/Sell) for stock, and evaluation based on actual market stock The overall framework is illustrated in Figure 1.

Historical stock data was gathered using the yfinance[[1]](#footnote-1) Python package, which allows access to Yahoo Finance data. The dataset contains the standard OHLC (Open, High, Low, Close) values that are used as the basis for feature extraction and forecasting. To improve the predictive power of the models, technical indicators were calculated. In particular, the 50-day lookback Relative Strength Index (RSI) [15] and the Simple Moving Average (SMA) [15] over 50 days were chosen because the incorporation of RSI 50 (Relative Strength Index) and SMA 50 (Simple Moving Average) offered valuable context for enhancing signal reliability. While RSI 50 acts as a momentum oscillator that identifies overbought or oversold situations, SMA 50 determines mid-term trend direction by averaging price movements. On the other hand, when model predictions diverge from these indicators, it often indicates short-term volatility or misleading signals [15]. The enriched feature set used across all models was formed by these indicators and the original OHLC values.

There are four forecasting models used in this work, linear Regression, Arima, Prophet and LSTM. Each model outputs a Buy/Sell signal for the following day based on the input features. As for the MAS, the GeminiAgent module was tasked with transforming financial data into clear, human-readable summaries as part of the analytical pipeline as shown in Figure 2.

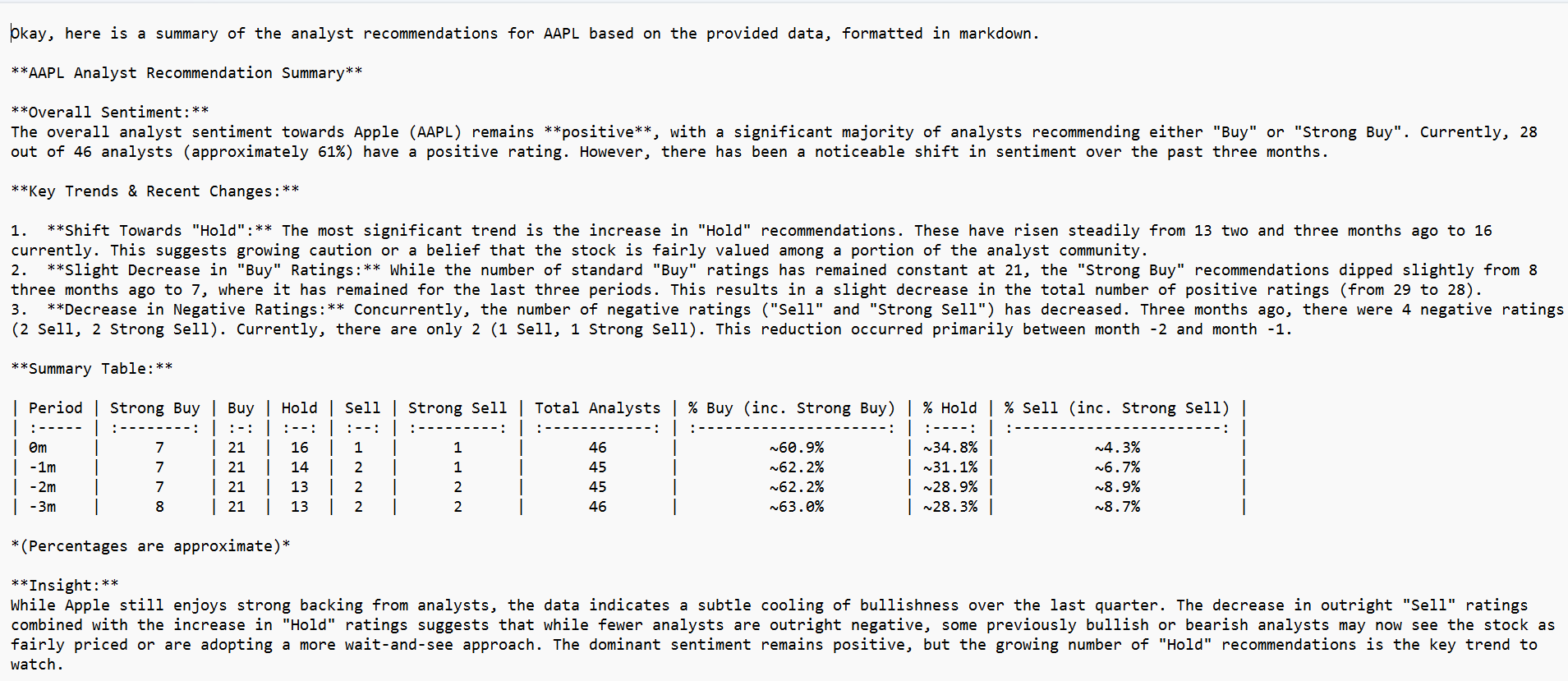


## FIGURE 1. Flowchart of framework

This was accomplished by utilizing the Gemini API, a large language model that can interpret structured data and produce insightful text. The process started by fetching recommendation data for a specific stock through the yfinance API. The data, initially formatted with time indexing in a Pandas Data Frame, underwent pre-processing to guarantee uniform date formatting and alignment. This step was essential to prevent problems arising from missing or misaligned dates in time-series data. A prompt was then added to the data, directing the Gemini model to extract essential components are the trend, overall sentiment and significant changes. This prompt-based interaction, the model was able to produce brief summaries that financial experts could easily understand.

# ExperimentAL ResultS

Apple Inc. (AAPL) is used in this work for analysis. As for the MAS, Figure 2 shows the summary and recommendation for Apple Inc. (AAPL) over the last quarter, which segments these recommendations into the current month (0 m) and the three months prior (1 m, 2 m, 3 m). Overall, the market sentiment stayed strongly positive, as around 61% of analysts (28 of 46) provided “Buy” or “Strong Buy” ratings during this period. However, this prevailing bullish stance conceals several significant changes that come to light when the monthly breakdown is analysed more closely.



**FIGURE 2.** Summarize and analyse of stock market

To begin with, a distinct tendency toward “Hold” recommendations can be observed. During the baseline period on 3 month ago, 13 analyse, which is approximately 28 % of the sample, recommended “Hold.” As of the current month which on period 0 month, the number of Hold increased to 16 analyse (approximately 34 %). This upward trend indicates that analyse are becoming more cautious: instead of fully embracing a bearish outlook, some seem to be taking a wait-and-see approach, possibly due to uncertainties regarding immediate triggers or pricing levels. Secondly, although the total count of “Buy” ratings has not changed much (21 analysts monthly), the strength of convictions has diminished a bit. The number of analysts giving “Strong Buy” recommendations has dropped from 8 three months ago to 7 this month. As a result, the total count of positive ratings (“Buy” + “Strong Buy”) decreased slightly from 29 to 28, suggesting a slight moderation of continuing positivity while not fully descending into negative territory.

Thirdly, negative sentiment has diminished. During the 3 m period, four negative ratings were recorded (“Sell” and “Strong Sell”), accounting for almost 9 % of analyse. As of this month, just three analyse provided negative assessments (“Sell,” “Strong Sell”), which has diminished the bear contingent to around 6 %. This cutback highlights that while some analysts are becoming more cautious, the number of outright bearish convictions is decreasing at a quicker rate than that of neutral positions. When considered collectively, these findings indicate that while the market remains largely supportive of AAPL’s prospects, there exists a current of caution. The rise in “Hold” recommendations, along with the slight decrease in negative ratings, indicates that a considerable number of analysts still regard the stock as fairly valued neither a clear buy nor a sell or pending further fundamental or technical confirmation. The recommendation of Final decision is buying signal after analysing the trend and ratings.

**TABLE 1.** Comparison on multi agent and forecasting models (a) Trading Data (19/3/25 - 1/4/25), (b) Trading Data (2/4/25 - 15/4/25), (c) Trading Data (16/4/25- 25/4/25)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | **19/3/25** | **20/3/25** | **21/3/25** | **24/3/25** | **25/3/25** | **26/3/25** | **27/3/25** | **28/3/25** | **31/3/25** | **1/4/25** |
| Open, Low, High, Closed | | | | | | | | | | |
| Linear Regression | Sell | Sell | Sell | Buy | Buy | Sell | Sell | Sell | Sell | Sell |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Sell | Buy | Sell | Buy | Sell | Buy | Buy | Buy |
| Open, Low, High, Closed + RSI 50+SMA 50 | | | | | | | | | | |
| Linear Regression | Sell | Sell | Buy | Buy | Buy | Buy | Sell | Sell | Sell | Sell |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt 1) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt II) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Actual Market | Buy | Sell | Buy | Buy | Buy | Sell | Buy | Sell | Buy | Buy |

(a)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | **2/4/25** | **3/4/25** | **4/4/25** | **7/4/25** | **8/4/25** | **9/4/25** | **10/4/25** | **11/4/25** | **14/4/25** | **15/4/25** |
| Open, Low, High, Closed | | | | | | | | | | |
| Linear Regression | Buy | Buy | Sell | Sell | Sell | Buy | Buy | Sell | Sell | Sell |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Sell | Buy | Sell | Buy | Sell | Buy | Buy | Buy |
| Open, Low, High, Closed + RSI 50+SMA 50 | | | | | | | | | | |
| Linear Regression | Sell | Sell | Buy | Buy | Buy | Buy | Sell | Sell | Sell | Sell |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt I) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt II) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Actual Market | Buy | Sell | Sell | Sell | Sell | Buy | Sell | Buy | Buy | Sell |

(b)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Model** | **16/4/25** | **17/4/25** | **18/4/25** | **21/4/25** | **22/4/25** | **23/4/25** | **24/4/25** | **25/4/25** |
| Open, Low, High, Closed | | | | | | | | |
| Linear Regression | Sell | Sell | Sell | Buy | Buy | Sell | Sell | Buy |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Sell | Buy | Sell | Buy | Buy | Buy |
| Open, Low, High, Closed + RSI 50+SMA 50 | | | | | | | | |
| Linear Regression | Sell | Sell | Buy | Buy | Buy | Sell | Sell | Sell |
| Prophet | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| Arima | Sell | Sell | Sell | Sell | Sell | Sell | Sell | Sell |
| LSTM | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt 1) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Multi agent AI (Prompt II) | Buy | Buy | Buy | Buy | Buy | Buy | Buy | Buy |
| Actual Market | Sell | Buy | Sell | Buy | Buy | Buy | Buy | Buy |

**(c)**

These experiments carried out a comparative analysis using daily market data from March 19, 2025, to April 25, 2025, as can be seen in Table 1, to assess how effective various forecasting models were at predicting the stock market. The models analysed include Linear Regression, Prophet, ARIMA, LSTM, and a Multi-Agent AI system. Two sets of features were employed: (1) Open, Low, High, and Close prices, and (2) the same features enhanced with RSI (Relative Strength Index 50) and SMA (Simple Moving Average 50). The model's predictions were compared with actual market movements from Yahoo Finance, which were classified as either "Buy" or "Sell". Particularly in the extended feature set scenario, the LSTM model was able to generate Buy signals that corresponded closely with actual market behaviours. Utilizing technical indicators (RSI + SMA), the LSTM model matched actual market movements perfectly which showcasing its strong predictive capability and robustness against noise.

**TABLE 2**. Summarize of each model match with actual market

|  |  |
| --- | --- |
| **Model** | **19/3/2025 – 25/4/2025 (28 days), Matched with Actual Market Movement** |
| Linear Regression (OHLC) | 16 |
| Prophet (OHLC) | 11 |
| Arima (OHLC) | 11 |
| LSTM (OHLC) | 17 |
| Linear Regression (OHLC + RSI 50 +SMA 50) | 12 |
| Prophet (OHLC + RSI 50 +SMA 50) | 11 |
| Arima (OHLC + RSI 50 +SMA 50) | 11 |
| LSTM (OHLC + RSI 50 +SMA 50) | 17 |
| Multi agent AI (Prompt I) | 17 |
| Multi agent AI (Prompt II) | 17 |

As for the MAS, two different prompts which are the prompt I “*Please provide a detailed summary with insights*.” and prompt 2 “*As a senior financial analyst with 30 years of experience specializing in {ticker}, analyses this data and provide ONLY a final trading decision (Buy /Sell) with a one-sentence rationale:*”.

Table 2 shows the summary of comparison between all models against actual market movement. Although LSTM and MAS currently show similar outcomes, it is important to recognize that LSTM’s performance is heavily rooted in pattern recognition within historical sequences—a field that has already been extensively explored in past research. In contrast, MAS offers significant potential for future directions by integrating multiple information sources through specialized agents, such as technical indicators and sentiment analysis.

This ability to incorporate diverse, real-time inputs positions MAS as a promising and evolving approach, capable of addressing the limitations of purely historical models and adapting to the increasingly complex dynamics of real-world environments. Thus, MAS is well worth deeper exploration and development.

# CONCLUSION

This experiment demonstrates that LSTM and Multi-Agent AI models excel at short-term stock trend prediction, especially when technical indicators are included in the feature set. Although traditional statistical methods such as Prophet and ARIMA are easier to interpret and computationally efficient, they have difficulty adapting to rapid market changes, leading to consistently conservative (Sell) recommendations.

The LSTM model exhibited higher temporal learning capabilities by accurately shadowing the actual market movement where technical indicators were in use. While the model retained an admirable level of predictive accuracy with observance of daily trends, also illustrating an easy fit to daily trends, these results testify to the benefits of sequence-aware deep-learning architectures for financial forecasting. Most impressively, the multi-Agent AI system made predictions in good agreement with the actual market course and the complete observation period. This might affirm that including various agent roles like sentiment analysts, fundamental interpreters, and technical strategists contributes heavily to forming a complete stock market picture. With the impetus for the multi-Agent system built on an arrangement of reasoning, it merges the inputs of specialized agents concentrating on various financial perspectives like technical analysis, sentiment analysis, and fundamental assessment. The risk of overfitting to price patterns alone is reduced by this modular-like decision-making system, which is a drawback of conventional LSTMs that are mainly trained on sequential numerical data.

Future work building upon this would look into possibilities of specialization and better adaptation to seasonal market conditions by increasing agent autonomy and agent diversity in the multi-agent architecture. For the system to better respond to market shocks, real-time streams of macroeconomic data, social media sentiment, and live news feeds can also be integrated.

In conclusion, the results present great promise for the application of multi-agent and AI-based architectures to stock market behaviours prediction. These complexities in market trends and instant adjustments to profit from technical and behavioural cues are indeed mastered better by these compared to the conventional frameworks. Given an increasingly complex financial market, intelligent cooperative AI frameworks such as the one this study discusses are perhaps the most promising candidates for scalable and robust algorithmic trading strategies in the coming future.

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