IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁐ Peer-reviewed & Refereed journal ⁐ Vol. 13, Issue 2, February 2026

DOI: 10.17148/IARJSET.2026.13252

An AI-Based Stock Market Trading Strategy Advisor Integrating LSTM Prediction, FinBERT Sentiment Analysis and Deep Q-Network (DQN) Reinforcement Learning

Puja Patil[1], Mrinal Kadam[2], Chetan Baviskar[3], Chaitanya Raut[4]

Professor, Department of Computer Engineering, TSSM's Bhivarabai Sawant College of Engineering and Research, Narhe, Pune, India[1]

Student, Department of Computer Engineering, TSSM's Bhivarabai Sawant College of Engineering and Research, Narhe, Pune, India[2]

Student, Department of Computer Engineering, TSSM's Bhivarabai Sawant College of Engineering and Research, Narhe, Pune, India[3]

Student, Department of Computer Engineering, TSSM's Bhivarabai Sawant College of Engineering and Research, Narhe, Pune, India[4]

Abstract: Financial markets can be influenced by quantitative price movements or by qualitative behavioral factors such as news sentiment and investor psychology. Historical stock prediction models are traditionally based on data, but they are usually not good for finding any trading decisions and tend to fail us. This paper presents an AI stock market trading strategy advisor system that combines Long Short-Term Memory (LSTM) networks (for price prediction) with FinBERT-based Natural Language Processing (NLP) using financial sentiment and Deep Q-Network (DQN) reinforcement learning as deep neural networks for intelligent decision making. It simulates actual trading conditions using historical market data and financial news. The LSTM module predicts future price trends, FinBERT estimates sentiment based on financial headlines, and the DQN agent learns with regard to the return and sentiment signal the best trading decisions including Buy / Sell / Hold in the market based on the expected values and direction of the returns. Experimental study shows that the integrated strategy of this approach in their experimental implementation enables better decision-making support than the classic strategies based on combining technical forecasting with behavior-based decision support, because their combination is more effective than the application-level forecasting approach.

Keywords: AI Trading Advisor, Deep Q-Network (DQN), FinBERT, LSTM, Reinforcement Learning, Sentiment Analysis, Stock Market Prediction

I. INTRODUCTION

Stock market prediction has long been considered a complex task due to its volatile and non-linear nature. Traditional forecasting approaches primarily rely on historical price trends and technical indicators to estimate future market behavior [4], [5]. However, real-world financial markets are influenced not only by past data but also by qualitative factors such as financial news, investor sentiment, and market perception [8], [9].

Recent advancements in Natural Language Processing (NLP), particularly models like FinBERT, have enabled the extraction of sentiment from financial text data, providing valuable contextual insights into market trends [20]. In parallel, reinforcement learning techniques such as Deep Q-Networks (DQN) have been explored for automated trading decisions by learning optimal strategies through interaction with market environments [14].

This paper proposes an AI-based stock market trading strategy advisor that integrates LSTM-based price prediction, FinBERT-driven sentiment analysis, and a Deep Q-Network (DQN) reinforcement learning agent into a unified framework for intelligent trading decision support.

DOI: 10.17148/IARJSET.2026.13252

II. LITERATURE SURVEY

Machine learning models such as LSTM have demonstrated effectiveness in capturing time-series patterns in stock price prediction [6], but they often overlook external influences such as market sentiment. Sentiment analysis techniques using NLP have been applied to understand the impact of financial news on stock movements [9]; however, they lack the capability to generate trading decisions.

Reinforcement learning approaches such as DQN enable automated trading strategies [24], yet many existing systems rely solely on technical indicators without integrating predictive insights or behavioral signals. Therefore, there is a need for an integrated framework combining prediction, sentiment analysis, and intelligent decision-making.

III. PROPOSED SYSTEM

This paper proposes an AI-based stock market trading strategy advisor that integrates prediction, sentiment analysis, and intelligent decision-making into a unified framework. The system consists of three core modules. The first module uses a Long Short-Term Memory (LSTM) network to analyze historical stock data and forecast future price trends. The second module employs FinBERT-based Natural Language Processing to evaluate financial news sentiment and capture behavioral market signals. The third module utilizes a Deep Q-Network (DQN) reinforcement learning agent to generate trading decisions such as Buy, Sell, or Hold based on predicted returns, sentiment scores, and technical indicators. By combining time-series forecasting with sentiment understanding and adaptive learning, the proposed system moves beyond traditional prediction models and provides a decision-support mechanism for trading strategy formulation.

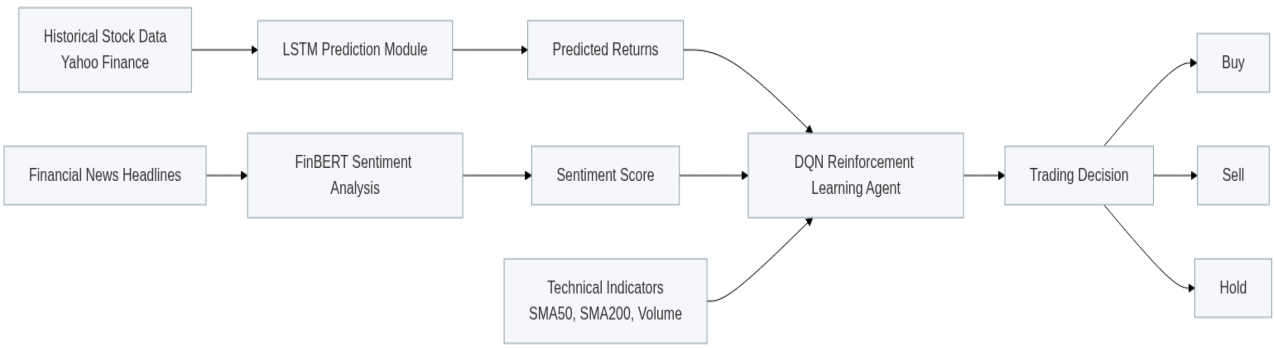

Fig 1: Architecture of the Proposed AI-Based Trading Strategy Advisor

IV. SYSTEM ARCHITECTURE

The proposed system is designed as a multi-layer framework that integrates prediction, sentiment analysis, and decision-making components to generate intelligent trading strategies. The architecture begins with the collection of historical stock market data and financial news headlines from reliable sources such as Yahoo Finance. The historical price data is processed by the LSTM module to forecast future price movements, while the financial news headlines are analyzed using the FinBERT-based sentiment analysis module to extract positive, negative, or neutral sentiment signals.

The outputs from both the LSTM prediction module and the sentiment analysis module are combined with technical indicators such as SMA50, SMA200, and trading volume to form the input state for the Deep Q-Network (DQN) reinforcement learning agent. The DQN agent learns optimal trading policies by evaluating market conditions and generates actionable decisions in the form of Buy, Sell, or Hold signals.

This layered architecture enables the system to integrate technical trends with behavioral insights, allowing adaptive and informed trading strategy formulation rather than relying solely on traditional prediction models.

V. METHODOLOGY

The methodology includes data collection, prediction, sentiment analysis, and decision-making stages. Historical market data is used to train the LSTM model, while financial news is processed using FinBERT to determine sentiment. The predicted returns are calculated using:

$$\textbf{Predicted Return} = (\textbf{Predicted Price} - \textbf{Current Price}) / \textbf{Current Price}$$

DOI: 10.17148/IARJSET.2026.13252

These values, along with technical indicators, form the state input for the DQN agent, which learns optimal trading strategies.

The predicted returns from the LSTM model and sentiment scores from FinBERT are combined with technical indicators to form the state input for the Deep Q-Network (DQN) reinforcement learning agent. The DQN agent learns optimal trading strategies based on market conditions and generates trading decisions in the form of Buy, Sell, or Hold actions, enabling the integration of quantitative forecasting with behavioral insights for improved decision support.

VI. IMPLEMENTATION

The proposed system was implemented through the following stages:
• Historical stock data was collected using financial APIs for training and evaluation.
• Data preprocessing was performed to extract relevant features such as price trends, volume, SMA50, and SMA200.
• An LSTM model was developed to forecast future stock price movements.
• Financial news headlines were processed using the FinBERT model to extract sentiment scores.
• Sentiment outputs were categorized into positive, negative, or neutral signals.
• The predicted returns and sentiment scores were combined with technical indicators to form the state input.
• A Deep Q-Network (DQN) reinforcement learning agent was implemented to learn optimal trading strategies.
• The DQN agent generated trading actions in the form of Buy, Sell, or Hold decisions.
• The overall system was developed using machine learning and reinforcement learning libraries to integrate prediction, sentiment analysis, and decision-making into a unified framework.

VII. EXPERIMENTAL SETUP

The proposed system was evaluated using historical stock market data obtained from Yahoo Finance. The dataset includes key market indicators such as price and volume along with technical indicators like SMA50 and SMA200. The model was tested on selected global and Indian stocks to analyze performance under different market conditions.

The LSTM model was used for price prediction, FinBERT for sentiment analysis of financial news, and a Deep Q-Network (DQN) agent for generating trading decisions. The system performance was evaluated by comparing the AI-based strategy with a traditional Buy-and-Hold approach.

VIII. RESULT ANALYSIS

The performance of the proposed AI-based trading strategy advisor was evaluated by comparing its outcomes with a traditional Buy-and-Hold approach. The system utilized LSTM for price prediction, FinBERT for sentiment analysis, and a Deep Q-Network (DQN) agent for generating trading decisions based on market conditions.The implementation results are demonstrated through system interface visualization, model training progress, and strategy performance comparison.

Table 1: Performance Metrics of Proposed AI Strategy

Metric	Value
Sharpe Ratio	0.6110
Max Drawdown	-0.3440
Total Return	0.3030

The performance metrics indicate stable returns and controlled risk under the proposed AI-based strategy.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 13, Issue 2, February 2026

DOI: 10.17148/IARJSET.2026.13252

Table 2: Model Comparison

Model Used	Prediction Capability	Sentiment Awareness	Decision Making
LSTM	Yes	No	No
FinBERT	No	Yes	No
DQN	Limited	No	Yes
Proposed System	Yes	Yes	Yes

The proposed integrated system outperforms individual models by combining prediction, sentiment analysis, and decision-making capabilities.

Fig 2: Streamlit-Based Interface for AI Trading Strategy Analysis

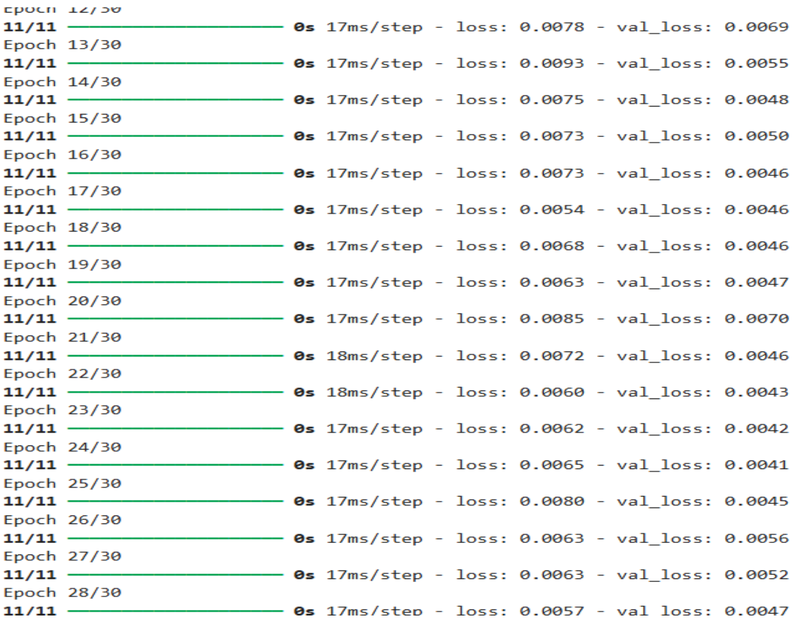

Fig 3: LSTM Model Training Performance

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 2, February 2026

DOI: 10.17148/IARJSET.2026.13252

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - los
Training RL agent...
Episode 1/20 completed
Episode 2/20 completed
Episode 3/20 completed
Episode 4/20 completed
Episode 5/20 completed
Episode 6/20 completed
Episode 7/20 completed
Episode 8/20 completed
Episode 9/20 completed
Episode 10/20 completed
Episode 11/20 completed
Episode 12/20 completed
Episode 13/20 completed
Episode 14/20 completed
Episode 15/20 completed
Episode 16/20 completed
Episode 17/20 completed
Episode 18/20 completed
Episode 19/20 completed
Episode 20/20 completed
RL model saved to models/rl_model.keras
```

Fig 4: Training Progress of DQN Reinforcement Learning Agent

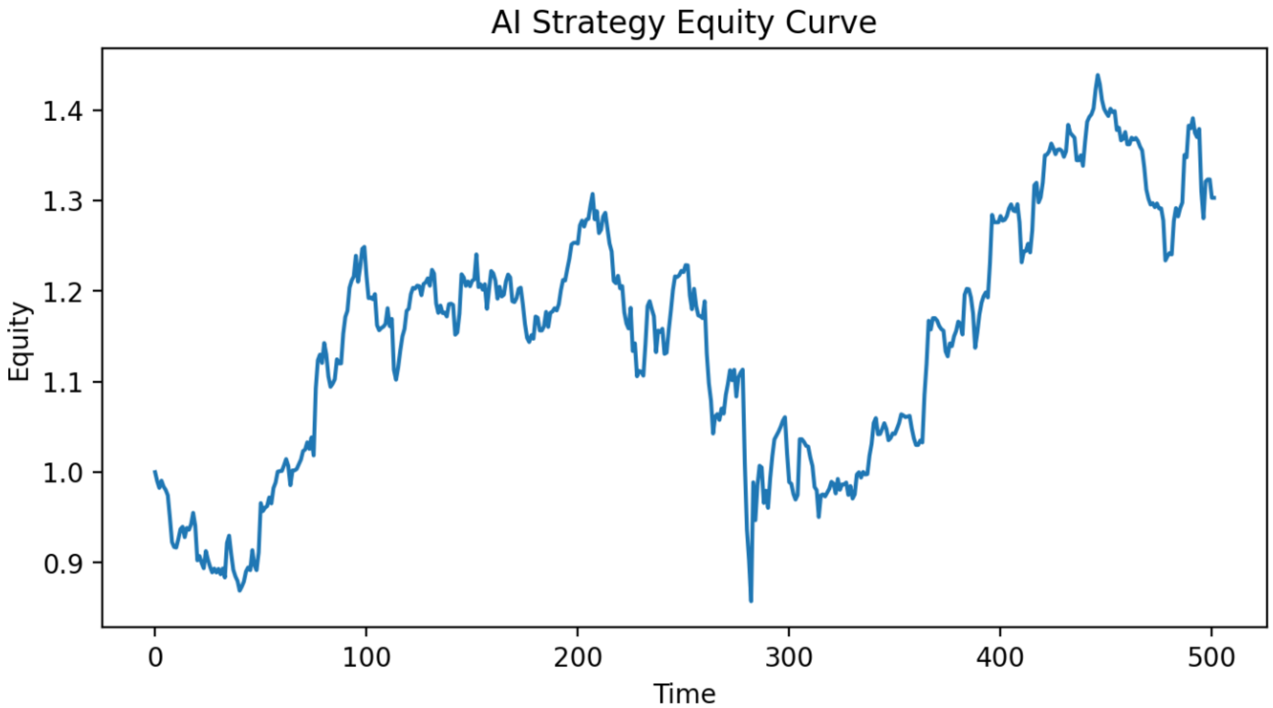

Fig 5: Equity Growth using AI-Based Trading Strategy

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 13, Issue 2, February 2026

DOI: 10.17148/IARJSET.2026.13252

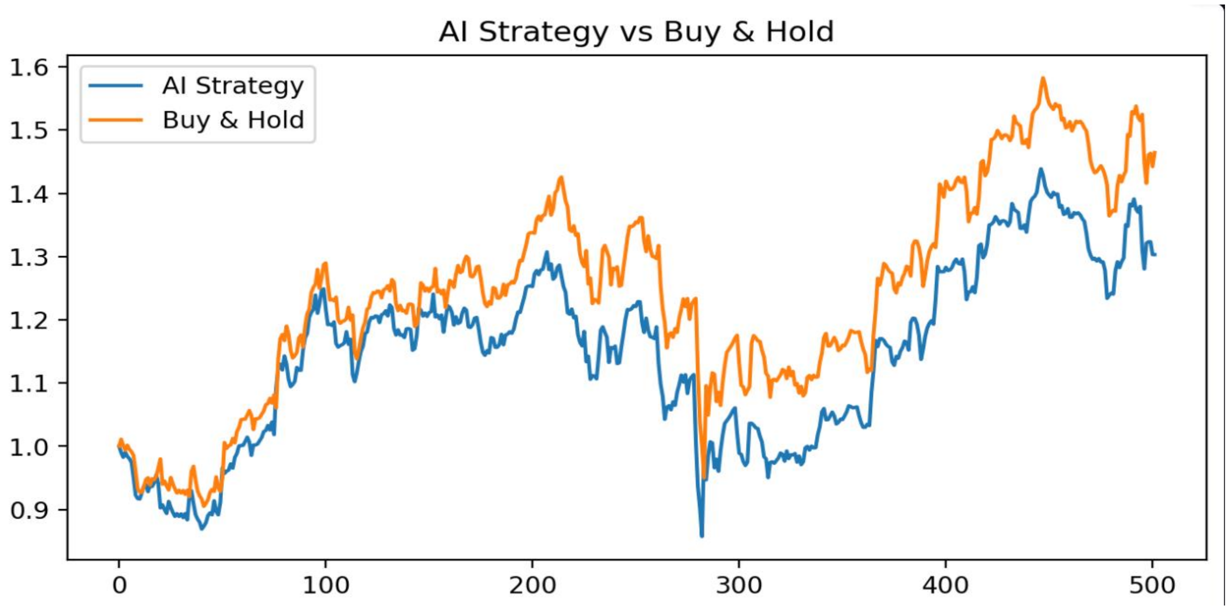

Fig 6: Comparison between AI Strategy and Traditional Buy-and-Hold Approach

The results indicate that the proposed system provides improved decision-support capability by adapting to both technical trends and sentiment signals. Unlike traditional strategies that rely solely on market trends, the AI-based approach dynamically adjusts trading actions in response to predicted returns and market sentiment.

The integration of prediction, sentiment understanding, and reinforcement learning enabled the system to make informed Buy, Sell, or Hold decisions, contributing to more stable trading behavior under varying market conditions.

IX. ADVANTAGES

The proposed AI-based trading strategy advisor offers several advantages over traditional prediction systems:
• Combines technical price trends with behavioral sentiment analysis
• Provides actionable trading decisions instead of only predictions
• Adapts dynamically to changing market conditions using reinforcement learning
• Reduces reliance on manual interpretation of market signals
• Supports both global and Indian stock market analysis
• Integrates forecasting, sentiment understanding, and decision-making into a unified framework

X. CONCLUSION

This paper presented an AI-based stock market trading strategy advisor that integrates LSTM-based price prediction, FinBERT sentiment analysis, and a Deep Q-Network (DQN) reinforcement learning agent into a unified framework. Unlike traditional models that focus only on forecasting, the proposed system combines technical trends with behavioral insights to generate actionable trading decisions.

The integration of prediction, sentiment understanding, and adaptive learning enables the system to respond effectively to changing market conditions. The results demonstrate that the proposed approach enhances decision-support capability and contributes toward intelligent trading strategy formulation.

XI. FUTURE WORK

The proposed system can be further enhanced by incorporating real-time data integration for live trading analysis. Future improvements may include portfolio optimization using multi-stock strategies and the implementation of advanced reinforcement learning techniques for improved decision-making. Additionally, integrating risk management mechanisms and expanding the system to support multi-agent trading environments can further strengthen its practical applicability.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 2, February 2026

DOI: 10.17148/IARJSET.2026.13252

REFERENCES

[1]. B. Huang, Y. Huan, L. D. Xu, L. Zheng, and Z. Zou, "Automated trading systems statistical and machine learning methods and hardware implementation: A survey," *Enterprise Information Systems*, vol. 13, no. 1, pp. 132–144, 2018.

[2]. R. B. Wiranata and A. Djunaidy, "The stock exchange prediction using machine learning techniques: A comprehensive literature review," *Jurnal Ilmu Komputer dan Informasi*, vol. 14, no. 2, pp. 91–112, 2021.

[3]. M. Saberironaghi, J. Ren, and A. Saberironaghi, "Stock market prediction using machine learning and deep learning techniques: A review," *AppliedMath*, vol. 5, no. 3, 2025.

[4]. J. Shen and M. O. Shafiq, "Short-term stock market price trend prediction using a deep learning system," *Journal of Big Data*, vol. 7, no. 1, 2020.

[5]. N. Rouf et al., "Stock market prediction using machine learning techniques: A decade survey," *Electronics*, vol. 10, no. 21, 2021.

[6]. S. Chaku et al., "Stock price prediction using stacked LSTM algorithm," *IARJSET*, vol. 10, no. 5, 2023.

[7]. K. Saini, "A study on stock price prediction using LSTM model," *IJRASET*, vol. 9, no. VI, 2021.

[8]. K. Mishev et al., "Evaluation of sentiment analysis in finance: From lexicons to transformers," *IEEE Access*, vol. 8, pp. 131662–131682, 2020.

[9]. K. Du et al., "Financial sentiment analysis: Techniques and applications," *ACM Computing Surveys*, vol. 56, no. 9, 2024.

[10]. W. Lin, L. Xie, and H. Xu, "Deep-reinforcement-learning-based dynamic ensemble model for stock prediction," *Electronics*, vol. 12, no. 21, 2023.

[11]. W. Zhang et al., "Reinforcement learning for stock prediction and trading," *IEEE Access*, vol. 11, 2023.

[12]. S. Du and H. Shen, "A stock prediction method based on deep reinforcement learning and sentiment analysis," *Applied Sciences*, vol. 14, no. 19, 2024.

[13]. T. L. Meng and M. Khushi, "Reinforcement learning in financial markets," *Data*, vol. 4, no. 3, 2019.

[14]. T. Kabbani and E. Duman, "Deep reinforcement learning approach for trading automation," *IEEE Access*, 2022.

[15]. J. Shah et al., "A comprehensive review on hybrid deep learning approaches for stock prediction," *Intelligent Systems with Applications*, 2022.

[16]. K. Cui et al., "CNN for stock trading based on DDQN algorithm," *IEEE Access*, vol. 11, 2023.

[17]. S. Carta et al., "Multi-DQN: Ensemble of deep Q-learning agents for stock forecasting," *Expert Systems with Applications*, vol. 164, 2021.

[18]. W. Jun Gu et al., "Predicting stock prices with FinBERT-LSTM," 2024.

[19]. Y. Shen and P. K. Zhang, "Financial sentiment analysis using FinBERT," 2024.

[20]. J. Kim et al., "Forecasting S&P 500 using FinBERT and LSTM," *Axioms*, vol. 12, 2023.

[21]. S. Gössi et al., "FinBERT-FOMC: Fine-tuned FinBERT model," 2023.

[22]. O. Shobayo et al., "Sentiment analysis using FinBERT," *Big Data and Cognitive Computing*, 2024.

[23]. S. B. Priya et al., "Advanced financial sentiment analysis using FinBERT," 2025.

[24]. M. Massahi and M. Mahootchi, "Deep Q-learning based trading system," *Expert Systems with Applications*, 2024.

[25]. A. K. Bhati et al., "DQN Trader: Reinforcement learning for trading," 2025.

[26]. J. Bollen et al., "Twitter mood predicts the stock market," *Journal of Computational Science*, 2011.

[27]. G. Cohen, "Algorithmic trading using AI methodologies," *Mathematics*, 2022.

[28]. W. Afua et al., "Algorithmic trading and AI," *World Journal of Advanced Engineering*, 2024.

[29]. M. Patil, "Impact of AI in algorithmic trading strategies," *SJRT*, 2025.

[30]. Z. S. Zulkifli et al., "Algorithmic trading system based on technical indicators," 2023.