



(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 5, May 2025

⊕ www.ijirset.com 🖂 ijirset@gmail.com 🖄 +91-9940572462 🕓 +91 63819 07438





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|

AI-Driven Stock Trading Automation: A Multimodal Strategy Integrating Technical Indicators, Fundamental Analysis, and Social Sentiment

G Naga Sujini¹, Dheeraj Venkatesh², Divya Kummari²

Assistant Professor, Department of CSE, Mahatma Gandhi Institute of Technology, Hyderabad, India¹

Department of CSE, Mahatma Gandhi Institute of Technology, Hyderabad, India²

ABSTRACT: TradeBot aims to address the limitations of traditional trading methods by introducing an AI-driven trading bot that automates trading decisions using machine learning, deep learning, sentiment analysis, and technical indicators. By combining these technologies, the bot processes vast amounts of data, including historical market trends, real-time price feeds, and market sentiment from news and social media, to make informed trading decisions. The goal is to optimize trading strategies, enabling faster, smarter, and more profitable trades. The bot continuously adapts to changing market conditions through machine learning algorithms, allowing it to identify patterns and trends that human traders might overlook. Sentiment analysis further enhances decision-making by interpreting the market's emotional tone, providing the bot with a comprehensive understanding of the market environment. Additionally, the bot executes trades at high speed and can manage multiple assets simultaneously, ensuring it capitalizes on opportunities faster than a human trader. Incorporating advanced risk management features, the bot adjusts its strategies in real-time based on market conditions to balance profitability with risk. This solution offers a significant advantage over traditional trading by removing emotional biases, improving decision-making, and providing real-time adaptability. As the bot learns from its performance, it paves the way for the broader use of AI in financial markets, enhancing trading efficiency and setting the stage for the future of automated trading.

KEYWORDS: AI driven trading, machine learning, deep learning, sentimental analysis.

I. INTRODUCTION

The rise of AI and machine learning (ML) has led to the widespread adoption of trading bots (tradebots) in financial markets, optimizing strategy development and decision-making. Recent studies demonstrate their growing sophistication—Ansari et al. (2024) introduced an AI-driven intraday trading framework, while Palaniappan et al. (2024) explored quantum-based forecasting for high-frequency trading [1][2]. López-Pérez et al. (2024) and Ullah et al. (2023) showed how ML can enhance network efficiency and cryptocurrency trading respectively [3][4]. Other works, like Haralayya (2023) and Zhang et al. (2022), analyzed the impact of algorithmic trading on liquidity and used reinforcement learning for stock prediction [5][7]. These studies highlight the potential of AI to create adaptive, efficient, and profitable trading systems.

However, traders still face emotional biases, market volatility, and a lack of expertise, leading to poor decisions and financial losses. Risk management and adapting to unpredictable market shifts also pose major challenges, making consistent success difficult.Current tradebots are either rule-based—using indicators like Moving Averages and RSI— or ML-based, which learn from historical data using techniques such as neural networks and reinforcement learning. Platforms like MetaTrader and QuantConnect support both models, with ML implementations often built using TensorFlow or Scikit-learn.

This project proposes an AI-powered tradebot combining ML, sentiment analysis, and technical indicators to automate trading. It uses Logistic Regression for stock selection based on fundamentals, VADER for real-time sentiment analysis from news and Reddit, and technical indicators like MACD and the 200-day SMA to refine entries. Trades are executed via Alpaca API using bracket orders with built-in risk management. The system continuously adapts to market data, aiming for improved performance, adaptability, and profitability.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|

II. LITERATURE SURVEY

[1] Y. Ansari, S. Yasmin, S. Naz, H. Zaffar, Z. Ali, J. Moon, and S. Rho, "AI-Driven Intraday Trading: Applying Machine Learning and Market Activity for Enhanced Decision Support in Financial Markets," IEEE Access, vol. 12, pp. 1-1, Jan. 2024.

The paper titled "AI-Driven Intraday Trading: Applying Machine Learning and Market Activity for Enhanced Decision Support in Financial Markets" by Min-Chih Hung, An-Pin Chen, and Wan-Ting Yu, published in IEEE Access in January 2024, presents a novel approach to intraday trading by integrating machine learning with market activity analysis. The study focuses on Taiwan's weighted index futures market, aiming to mitigate the risks associated with emotional trading behaviors that often lead to irrational price fluctuations.

[2] V. Palaniappan, I. Ishak, F. Sidi, H. Ibrahim, and Z. A. Zukarnain, "A Review on High-Frequency Trading Forecasting Methods: Opportunity and Challenges for Quantum Based Method," IEEE Access, vol. 12, pp. 1-1, Jun. 2024.

The paper titled "A Review on High-Frequency Trading Forecasting Methods: Opportunity and Challenges for Quantum-Based Method" by Visalakshi Palaniappan, Iskandar Ishak, Fatimah Sidi, Hamidah Ibrahim, and Zuriati Ahmad Zukarnain, published in IEEE Access in June 2024, offers a comprehensive examination of high-frequency trading (HFT) forecasting methodologies. It delves into traditional time series models like ARIMA and machine learning techniques such as neural networks and support vector machines, highlighting their limitations in handling the vast and noisy datasets characteristic of HFT. The authors advocate for the integration of quantum computing to enhance forecasting accuracy and efficiency.

[3] D. López-Pérez, A. De Domenico, N. Piovesan, and M. Debbah, "Data-Driven Energy Efficiency Modeling in Large-Scale Networks: An Expert Knowledge and ML-Based Approach," IEEE Transactions on Machine Learning in Communications and Networks, vol. 1, no. 1, pp. 1-1, Jun. 2024.

The paper titled "Data-Driven Energy Efficiency Modeling in Large-Scale Networks: An Expert Knowledge and ML-Based Approach" by David López-Pérez, Antonio De Domenico, Nicola Piovesan, and Mérouane Debbah, published in IEEE Transactions on Machine Learning in Communications and Networking in June 2024, introduces the Simulated Reality of Communication Networks (SRCON) framework. This innovative, data-driven modeling paradigm leverages live network data and integrates machine learning (ML) with expert-based models to predict network energy efficiency and user equipment (UE) quality of service under various carrier shutdown configurations.

[4] S. Ilahi et al., "Financial Algorithmic Trading and Market Liquidity: A Comprehensive Analysis and Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 5, pp. 11320–11329, 2024.

This paper analyzes the impact of four major algorithmic trading strategies—High-Frequency Trading (HFT), Statistical Arbitrage, Market Making, and Momentum Trading—on market liquidity. Using quantitative metrics such as profitability, Sharpe ratio, maximum drawdown, and bid-ask spread, the study evaluates each strategy's effectiveness and market influence. Findings indicate that Market Making consistently provides reliable liquidity with minimal volatility, while Momentum Trading offers high returns during trending periods but introduces risks during reversals. The research highlights the importance of selecting appropriate trading strategies based on market conditions to optimize liquidity and performance.

[5] D. Mohapatro et al., "Financial Algorithmic Trading And Market Liquidity: A Comprehensive Analysis And Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 4, pp. 6185–6191, 2024.

This study examines the role of algorithmic trading (AT) in influencing market liquidity on the Deutsche Boerse's DAX 30 index constituents. The research finds that AT accounts for over half of the market order volume and significantly impacts liquidity dynamics. ATs tend to absorb liquidity when spreads are narrow and provide liquidity when spreads are wide, demonstrating a responsive approach to market conditions. The paper underscores the necessity for market regulators and practitioners to consider these dynamics to maintain efficient and stable market operations.

[6] S. Ilahi et al., "Financial Algorithmic Trading and Market Liquidity: A Comprehensive Analysis and Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 5, pp. 11320–11329, 2024.

This paper analyzes the impact of four major algorithmic trading strategies—High-Frequency Trading (HFT), Statistical Arbitrage, Market Making, and Momentum Trading—on market liquidity. Using quantitative metrics such as profitability, Sharpe ratio, maximum drawdown, and bid-ask spread, the study evaluates each strategy's effectiveness





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|

and market influence. Findings indicate that Market Making consistently provides reliable liquidity with minimal volatility, while Momentum Trading offers high returns during trending periods but introduces risks during reversals. The research highlights the importance of selecting appropriate trading strategies based on market conditions to optimize liquidity and performance.

[7] D. Mohapatro et al., "Financial Algorithmic Trading And Market Liquidity A Comprehensive Analysis And Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 4, pp. 6185–6191, 2024. This study examines the role of algorithmic trading (AT) in influencing market liquidity on the Deutsche Boerse's DAX 30 index constituents. The research finds that AT accounts for over half of the market order volume and significantly impacts liquidity dynamics. ATs tend to absorb liquidity when spreads are narrow and provide liquidity when spreads are wide, demonstrating a responsive approach to market conditions. The paper underscores the necessity for market regulators and practitioners to consider these dynamics to maintain efficient and stable market operations.

III. METHODOLOGY



System Architecture of TradeBot

This diagram outlines the user flow for a trading platform. It begins with the User, who must first Login via the Login Page. Upon successful authentication, the user is directed to the Trading Page, which acts as the central hub. From there, users can access various components: Trade Input for placing trades, Data Display for viewing trading data, Graph Display for visual analysis, and the Sidebar for additional navigation. The 10 Data Display provides access to a Positions Tab, while the Sidebar offers links to the Portfolio Tab and Recent Orders Tab. Each section is interconnected through a straightforward selection process, ensuring a seamless navigation experience across the platform.

This diagram outlines the user flow for a trading platform. It begins with the user, who must first Login via the Login Page. Upon successful authentication, the user is directed to the Trading Page, which acts as the central hub. From there, users can access various components: Trade Input for placing trades, Data Display for viewing trading data, Graph Display for visual analysis, and the Sidebar for additional navigation. The Data Display provides access to a Positions Tab, while the Sidebar offers links to the Portfolio Tab and Recent Orders Tab. Each section is interconnected through a straightforward selection process, ensuring a seamless navigation experience across the platform.

ALGORITHMS

3.2.1 Sentiment Analysis (NLP Algorithm):

For sentiment extraction, the model employs a rule-based natural language processing technique using the VADER (Valence Aware Dictionary and sEntiment Reasoner) SentimentIntensityAnalyzer from the nltk library. Reddit posts referencing candidate stocks are scraped via the Reddit API, parsed, and scored for their positive, neutral, or negative tone. The sentiment scores are aggregated to compute an average sentiment value per stock.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|

3.2.2. Feature Extraction (Finance Fundamentals):

Fundamental financial data is retrieved in real time using the yfinance library. Key indicators such as Market Capitalization, Price-to-Earnings (P/E) Ratio, Return on Equity (ROE), and Earnings per Share (EPS) are extracted to form the core feature set representing a stock's intrinsic value. This step provides quantitative context for evaluating long-term company performance, complementing short-term sentiment signals.

3.2.3. Stock Ranking (Machine Learning Algorithm):

The model uses a Logistic Regression classifier implemented with scikit-learn to perform supervised learning on the combined feature set of fundamental metrics and sentiment scores. After training on historical data, the classifier is used to predict the likelihood of a stock being a "good" investment candidate. Stocks exceeding a predetermined probability threshold are selected for further analysis. This classification algorithm formalizes the ranking process and serves as a decision filter in the trading pipeline.

3.2.4. MACD Strategy (Technical Analysis Algorithm):

Technical indicators are computed using the pandas_ta library, specifically focusing on the Moving Average Convergence Divergence (MACD) strategy. The model calculates the Fast Exponential Moving Average (EMA) over 12 periods, the Slow EMA over 26 periods, and the Signal Line over 9 periods. A bullish signal is identified when the MACD line crosses above the signal line while both are below zero, indicating a potential upward reversal under bearish conditions. Additionally, only stocks trading above their 200-day Simple Moving Average (SMA) are considered, ensuring alignment with long-term positive trends.

3.2.5. Automated Trading (Execution Logic):

Trade execution is handled through the alpaca-trade-api interface. Once a candidate stock satisfies all upstream criteria, a bracket order—comprising a market buy order, take-profit limit, and stop-loss threshold—is automatically submitted to the Alpaca trading platform. This logic implements the final decision layer in the pipeline, enabling real-time, rule-based trade automation that closes the loop from data ingestion to portfolio action.

IV. EXPERIMENTAL RESULTS

The final results generated from the above project provide a comprehensive solution for assisting users with automated stock trading using a combination of machine learning, sentiment analysis, and technical analysis. The backend of the project, developed using Python and powered by a pre-trained Logistic Regression model, handles the core functionalities essential for stock selection and trade execution.

First, it retrieves historical stock price data through the Alpaca API and sentiment data from Reddit discussions using PRAW. It preprocesses this data by calculating key technical indicators such as the 200-day Simple Moving Average (SMA200) and MACD using pandas-ta. Sentiment scores are calculated using NLTK's VADER sentiment analyzer to assess public opinion. Then, the Logistic Regression model, trained separately, predicts which stocks are fundamentally strong candidates for trading based on historical data.

Second, based on both technical conditions (such as the stock price being above the SMA200 and a positive MACD crossover) and model predictions, the system identifies buy opportunities. For stocks that meet the criteria, it automatically places bracket orders (buy orders with take-profit and stop-loss levels) through the Alpaca Trading API, ensuring smart risk management.

The GUI, built using Streamlit, enables users to easily interact with the system. It features an intuitive dashboard that displays the selected stocks, their candlestick charts, order placement statuses, and real-time updates on the user's virtual balance. The user can visually inspect stock performance, review trading decisions, and monitor their portfolio's progress, all from a single interactive interface.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|



(a) User Interface Page

- (b) Chart for No Buy Signal
- (c) Chart for Buy Signal

	K7	77 855	
5 B			
6 0	lance		
7 6	incest.		
	rago Bonos		
	SHealth		

(d) Placed Orders Table and Balance Remaining

The overall integration of the GUI, backend, and external APIs offers a seamless trading experience for users, especially those looking for a data-driven and partially automated trading assistant.

The above image shows all the trades placed by the TradeBot and the amount left over after all the trades.

V. CONCLUSION

The developed AI-driven trading bot successfully integrates multiple dimensions of financial analysis—Redditbased sentiment mining, Yahoo Finance-sourced fundamental screening, and a MACD-based technical strategy—into a unified pipeline that automates end-to-end trading decisions via the Alpaca API. This system demonstrates a holistic approach to stock selection and trade execution by combining public sentiment, intrinsic value assessment, and momentum indicators. Its modular and scalable architecture allows for adaptability to varying market conditions with minimal reconfiguration, establishing a solid foundation for an intelligent and extensible trading platform.

REFERENCES

[1] Y. Ansari, S. Yasmin, S. Naz, H. Zaffar, Z. Ali, J. Moon, and S. Rho, "AI-Driven Intraday Trading: Applying Machine Learning and Market Activity for Enhanced Decision Support in Financial Markets," IEEE Access, vol. 12, pp. 1-1, Jan. 2024.

[2] V. Palaniappan, I. Ishak, F. Sidi, H. Ibrahim, and Z. A. Zukarnain, "A Review on High-Frequency Trading Forecasting Methods: Opportunity and Challenges for Quantum Based Method," IEEE Access, vol. 12, pp. 1-1, Jun. 2024.

[3] D. López-Pérez, A. De Domenico, N. Piovesan, and M. Debbah, "Data-Driven Energy Efficiency Modeling in Large-Scale Networks: An Expert Knowledge and ML-Based Approach," IEEE Transactions on Machine Learning in Communications and Networks, vol. 1, no. 1, pp. 1-1, Jun. 2024.

[4] S. Ilahi, S. V. Mallikraj, R. Bawa, M. Rahmatullah, A. Islam, "Financial Algorithmic Trading and Market Liquidity: A Comprehensive Analysis and Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 5, pp. 11320–11329, 2024.

[5] D. Mohapatro, Y. S. Patro, L. M. Solomon, P. Mishra, A. Yadav, A. S. Yadav, "Financial Algorithmic Trading And Market Liquidity A Comprehensive Analysis And Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 4, pp. 6185–6191, 2024.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 5, May 2025

|DOI: 10.15680/IJIRSET.2025.1405085|

[6] S. Ilahi, S. V. Mallikraj, R. Bawa, M. Rahmatullah, A. Islam, "Financial Algorithmic Trading and Market Liquidity: A Comprehensive Analysis and Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 5, pp. 11320–11329, 2024.

[7] D. Mohapatro, Y. S. Patro, L. M. Solomon, P. Mishra, A. Yadav, A. S. Yadav, "Financial Algorithmic Trading And Market Liquidity A Comprehensive Analysis And Trading Strategies," Educational Administration: Theory and Practice, vol. 30, no. 4, pp. 6185–6191, 2024.

[8] F. Ullah, H. Shamshad, S. Ullah, A. Al-Dhaqm, A. Asadullah, and V. R. Kebande, "Forecasting and Trading of the Stable Cryptocurrencies with Machine Learning and Deep Learning Algorithms for Market Conditions," IEEE Access, vol. 11, pp. 1-1, Oct. 2023.

[9] B. Haralayya, "Algorithmic Trading and Market Liquidity: A Comprehensive Analysis of High-Frequency Trading Strategies," Department of Master of Business Administration, Lingaraj Appa Engineering College, Bidar, India, 2023.

[10] Y. Ansari et al., "A Deep Reinforcement Learning-Based Decision Support System for Automated Stock Market Trading," IEEE Access, vol. 10, pp. 127469-127501, Dec. 2022.

[11] W. Zhang, T. Yin, Y. Zhao, B. Han, and H. Liu, "Reinforcement Learning for Stock Prediction and High-Frequency Trading with T+1 Rules," IEEE Access, vol. 10, pp. 1-1, Aug. 2022.

[12] T. Kabbani, E. Duman, "Deep Reinforcement Learning Approach for Trading Automation in The Stock Market," arXiv preprint, Jul. 2022.

[13] J. Zou, J. Lou, B. Wang, S. Liu, "A Novel Deep Reinforcement Learning Based Automated Stock Trading System Using Cascaded LSTM Networks," arXiv preprint, Dec. 2022.

[14] J. Zou, J. Lou, B. Wang, S. Liu, "A Novel Deep Reinforcement Learning Based Automated Stock Trading System Using Cascaded LSTM Networks," arXiv preprint, 2022.

[15] J. Zou, J. Lou, B. Wang, S. Liu, "A Novel Deep Reinforcement Learning Based Automated Stock Trading System Using Cascaded LSTM Networks," arXiv preprint, 2022.

[16] X. Liu, Z. Xiong, S. Zhong, H. Yang, A. Walid, "Practical Deep Reinforcement Learning Approach for Stock Trading," arXiv preprint, Nov. 2018.

[17] X. Liu, Z. Xiong, S. Zhong, H. Yang, A. Walid, "Practical Deep Reinforcement Learning Approach for Stock Trading," arXiv preprint, 2018.

[18] F. G. D. C. Ferreira, A. Gandomi, and A. R. T. Cardoso, "Artificial Intelligence Applied to Stock Market Trading: A Review," IEEE Access, vol. 5, pp. 1836-1851, 2017.

[19] O. B. Sezer, M. Ozbayoglu, E. Dogdu, "An Artificial Neural Network-based Stock Trading System Using Technical Analysis and Big Data Framework," arXiv preprint, Dec. 2017.

[20] S. Rho, S. Yasmin, S. Naz, H. Zaffar, Z. Ali, J. Moon, and Y. Ansari, "A Deep Reinforcement Learning-Based Decision Support System for Automated Stock Market Trading," IEEE Access, vol. 10, pp. 127469-127501, Dec.









INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com