E-ISSN: 2583-9667
Indexed Journal
Peer Reviewed Journal
https://multiresearchjournal.theviews.in

Received: 03-02-2025
Accepted: 08-03-2025

INTERNATIONAL JOURNAL OF ADVANCE RESEARCH IN MULTIDISCIPLINARY

Volume 3; Issue 2; 2025; Page No. 159-162

Stock market prediction using deep reinforcement learning

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DOI: https://doi.org/10.5281/zenodo.15575174

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Abstract

The stock market exhibits complex, volatile behavior influenced by a multitude of factors ranging from economic indicators to investor sentiments. Accurate prediction remains a significant challenge. In this project, we propose an advanced framework leveraging Deep Reinforcement Learning (DRL), specifically the Deep Deterministic Policy Gradient (DDPG) algorithm, to model intelligent trading strategies. The system incorporates real-time financial data, sentiment analysis of market news using VADER, and a continuous retraining pipeline to adapt to changing market conditions. Our experimental results demonstrate notable improvement in prediction accuracy and investment returns compared to traditional machine learning approaches.

Keywords: Stock market prediction, deep reinforcement learning, DDPG, sentiment analysis, financial forecasting, continuous learning

Introduction

The stock market, being a complex adaptive system, poses significant challenges for prediction due to nonlinearity, noise, and time-varying factors. Traditional prediction models, including statistical regressions and supervised machine learning algorithms, often struggle to accommodate the dynamic nature of financial markets. Recent advancements in Reinforcement Learning (RL) offer a promising avenue, particularly with the emergence of Deep RL methods capable of handling high dimensional data spaces.

In this work, we explore the application of the DDPG algorithm, integrating real-time data and market sentiments to predict stock trends and optimize trading decisions. The use of continuous training allows the system to evolve and adapt in near real-time, giving it an edge over static models.

Literature survey

Previous works in stock prediction utilized methods such as ARIMA models for time series forecasting and technical indicators like Moving Averages for trend analysis. Machine Learning models such as Support Vector Machines (SVM) and Random Forests provided moderate success but required extensive feature engineering and retraining. Reinforcement Learning methods like Q-learning were introduced to model the decision-making process; however, they were limited to discrete action spaces. The introduction of DRL algorithms like DQN and later DDPG provided capabilities to operate in continuous action spaces, making them ideal for financial trading where actions (buy/sell amounts) are continuous.

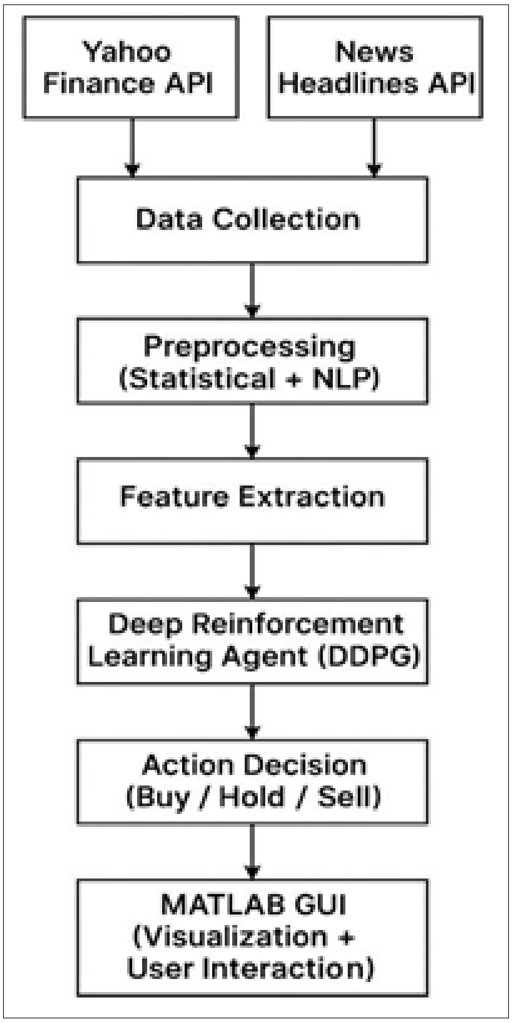
System analysis

a. **Existing system:** Most current stock prediction systems rely heavily on historical price trends, ignoring external factors such as news sentiments or global events. Machine Learning models often suffer from model drift as market behavior changes over time.
b. **Proposed system:** Our proposed system is a hybrid approach combining statistical analysis, natural language processing for sentiment extraction, and a DDPG agent for decision-making. Real-time financial data and news sentiments are fed into the DRL agent, which continuously updates its trading strategy.
c. **Feasibility study:** Deep Reinforcement Learning models, especially those allowing continuous retraining with new data, demonstrate high adaptability. Moreover, the inclusion of sentiment analysis provides

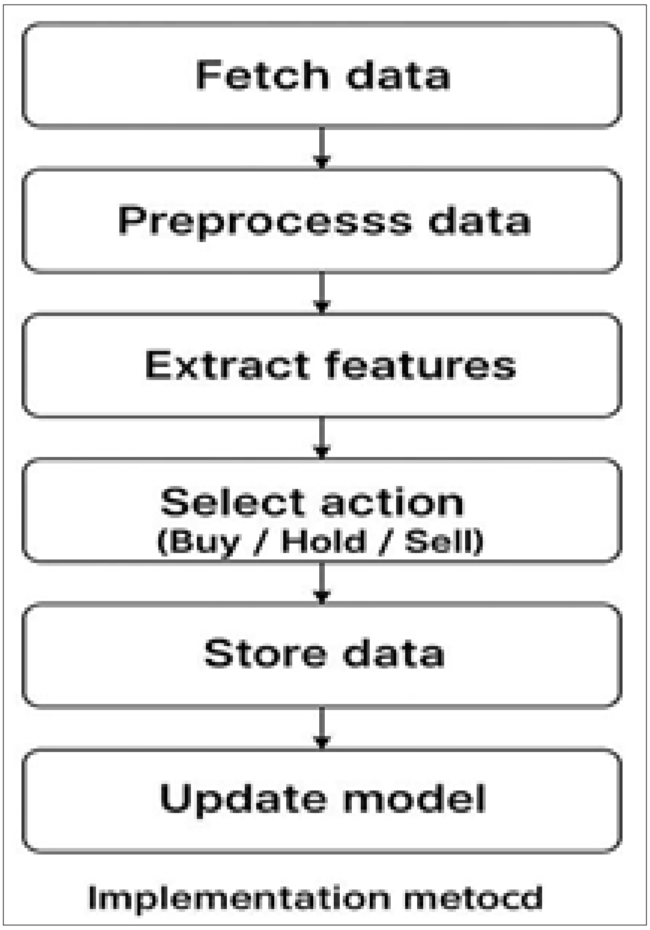
a richer feature set, allowing the system to better anticipate market movements

System design and implementation

- **a. Data collection:** Live financial data is sourced from Yahoo Finance APIs, and real-time news headlines are fetched using news APIs.
- **b. Preprocessing:** The collected news data undergoes sentiment analysis using the VADER model to generate positive, neutral, or negative scores. Financial data undergoes statistical preprocessing to calculate relevant features.
- **c. Continuous training pipeline:** The DDPG agent is designed to retrain at fixed intervals as new data flows in. This continuous training mechanism ensures that the model stays relevant to the most recent market behavior.
- **d. System architecture:** Inputs include normalized stock prices, trading volume, technical indicators, and sentiment scores. The DDPG agent then outputs actions: buy, sell, or hold, with corresponding confidence levels.
- **e. System architecture diagram**



f) System implementation diagram



System testing

- **a. Testing objectives:** Testing ensures the reliability, accuracy, and efficiency of the system components. Special focus is given to validating real-time data handling and training stability.
- **b. Testing strategies:** Both white-box testing (internal logic validation) and black-box testing (functional output validation) strategies were employed. System performance was benchmarked under simulated live trading conditions.
- **c. Unit testing and integration testing**: Each module, including data ingestion, preprocessing, model training, and prediction, was tested independently (unit testing) and in combination (integration testing).

Results and Discussions

Performance evaluation shows that the DDPG-based model outperforms conventional methods by achieving improved returns and higher Sharpe ratios. Incorporating sentiment scores notably enhanced the model's decision-making during high-volatility periods.

Classification models like KNN and SVM were also tested separately for trend prediction tasks and achieved over 70% accuracy, validating the quality of the feature engineering process.

Fig 1

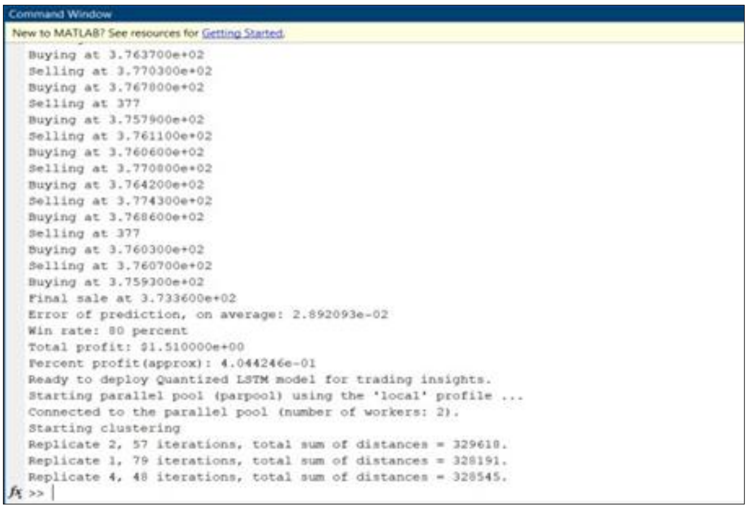


Fig 2

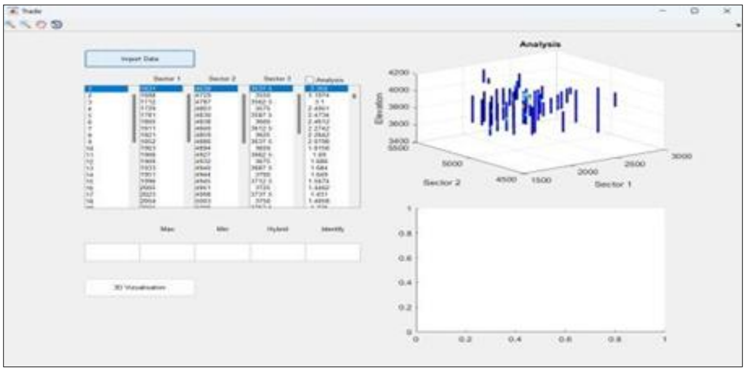


Fig 3: Data sources like social media feeds, extending the model to multi-agent environments, and optimizing

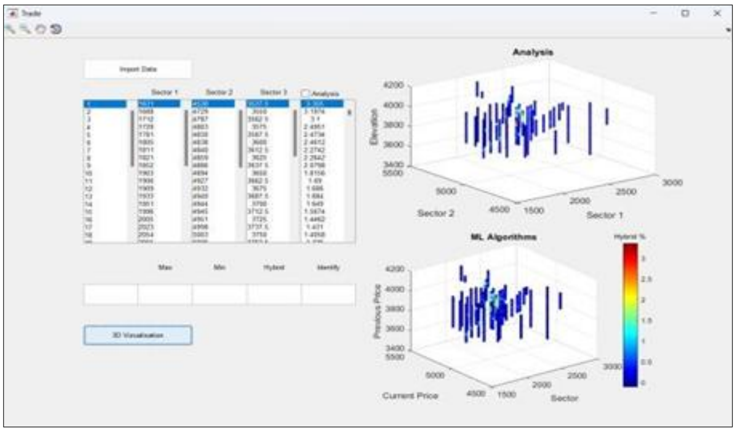


Fig 4

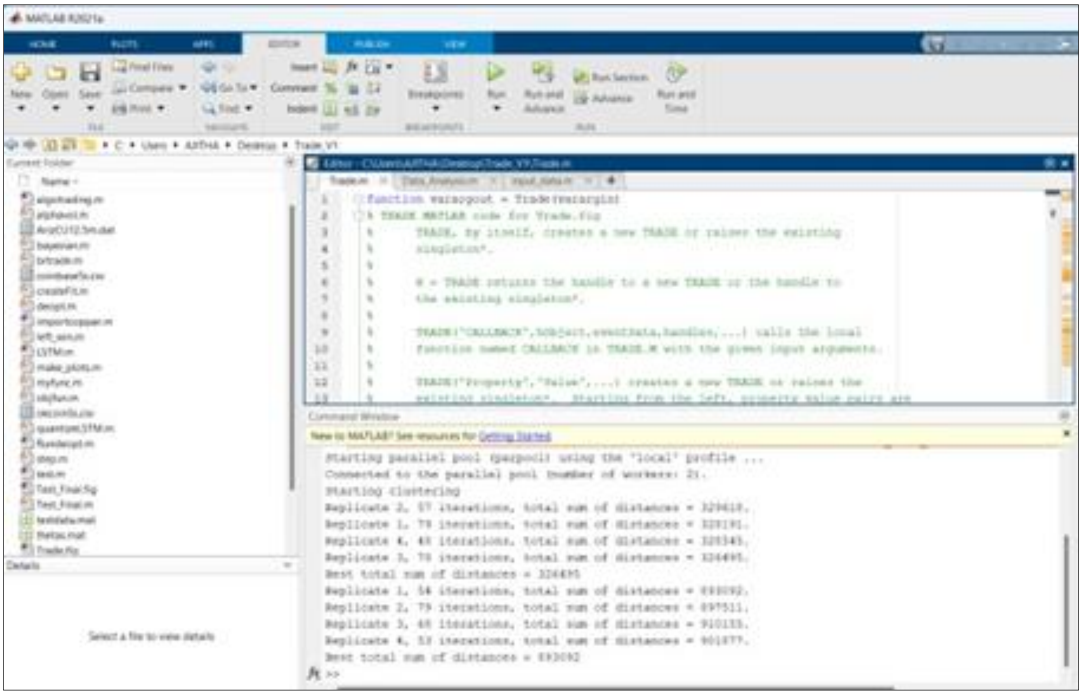


Fig 5: Phenomena and motifs of networks induced from time series," *Proceedings of the National Academy of Sciences*, vol. 105, no. 50, pp. 19601–19605, 2008. [4] T. Lillicrap *et al.*, "Continuous control with deep reinforcement learning," *arXiv preprint*

Conclusion and future enhancements

This work demonstrates that Deep Reinforcement Learning, particularly DDPG, when combined with real-time data ingestion and sentiment analysis, can serve as a powerful framework for stock market prediction and trading automation. Future enhancements could involve integrating alternative training with ensemble methods.

Acknowledgments

The author expresses heartfelt gratitude to Dr. R. Parameswari for her invaluable guidance and constant encouragement. The author also thanks the Department of Computer Science and Information Technology, VISTAS, for providing the resources and support for this research

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