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An Empirical Assessment of Artificial Intelligence-Based Deep Reinforced Learning in Automatic Stock Trading

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Abstract: Stock trading is the process of buying and selling stocks to boost financial returns. The secret to effective stock trading is making the proper trading decisions at the right moments or developing a competent trading plan. In a lot of recent studies, machine learning (ML) approaches have been utilised to predict stock movements or prices in order to conduct stock trading. This research aims to examine the possibilities of deep reinforcement learning powered by Artificial Intelligence (AI) for enhancing the precision and efficiency of automated stock trading systems. It analyses the difficulties in performing automated stock trading and suggests a brand-new Deep Reinforcement Learning (DRL)method to overcome them. To forecast stock prices and make trading decisions, the suggested method combines a deep neural network and a Reinforcement Learning (RL) algorithm. Based on actual stock data, experiments are run to assess how well the suggested technique performs. The outcomes demonstrate that the suggested technique beats current trading strategies and can generate large increases in profitability.

Keywords: *Stock trading,deep reinforcement learning, artificial intelligence, efficiency*

1. Introduction

Stock trading is one of the most used financial arbitrage strategies and is unquestionably rewarding. However, it is also true that earning money through stock trading is difficult due to the inability in foreseeing real-time movements in the stock market. Because of this, there have been numerous efforts to develop an automated stock trading system that ensures a profit, and *Reinforcement Learning*

(RL) is one of the most frequently used key concepts in these endeavours. There are various benefits built into this branch of artificial intelligence (AI) that have fuelled the rise of RL in the banking sector. RL makes it possible to combine the "forecasting" and "portfolio construction" duties into a single integrated step, which directly ties ML issues to the goals of investors. (Fischer, 2018). One of the obstacles for financial engineers and officials is creating a reliable automated stock trading system because it is difficult to include all necessary aspects in a model for a complex and volatile stock market (Bekiros, 2010).

The use of ML and Deep Learning (DL) techniques for asset management and stock trading by organisational and individual investors has increased in the past few years. Techniques like stock price prediction using Random Forests (RF), Neural Networks, or Support Vector Machines (SVM) enable traders to develop the most profitable online trading techniques and outperform those that rely solely on conventional variables (Fang et al., 2019).

Stock trading is the process of buying and selling stocks to boost financial returns. The secret to effective stock trading is making the proper trading decisions at the right moments or developing a suitable trading plan. In recent years, many studies have employed ML approaches to predict stock movements or prices in order to conduct stock trading. However, making long-term predictions about stock prices or trends is risky. Furthermore, according to Li et al. (2019a), the trading technique that relies on stock price prediction is dominant. The stock market is influenced by a variety of variables, such as shifts in investor psychology and corporate policies, natural catastrophes, and other emergencies, as well as alterations to investor psychology generally. A dynamic trading method offers greater advantages than a static trading technique since it may make trading decisions pre-emptively in response to stock market swings.

The three primary drawbacks of ML techniques for stock market prediction are as follows: (i) The noise and instability of financial market statistics, as well as the interactions of other immeasurable elements, make them unreliable. As a result, it is extremely challenging to consider all necessary elements in complicated and volatile stock markets Kim et al., 2017) (ii) Several additional factors, like political developments, the behaviour of other stock markets, or even investor psychology, can affect stock prices (Zhang & Wu,, 2009). (iii) The majority of approaches rely on supervised learning and demand training sets that are tagged with market conditions; nevertheless, these ML classifiers are

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susceptible to overfitting, which decreases the model's capacity for generalisation. ML algorithms that can provide investment signals or forecast a company's future possibilities are paired with underlying data from financial records and other sources, such as business news, to identify potential investment targets (Carta et al., 2021). The stock screening issue is resolved by such an algorithm, but it is unable to resolve the issue of how to distribute holdings among the investment targets. To put it another way, it is still up to the trader to decide when to enter and quit a position.

A growing number of investigations are presently using dynamic trading tactics based on DRL. Alpha Zero's victory against humans has increased interest in RL. It is capable of independent learning and decision-making and has been extensively used in the fields of game play, unmanned vehicle operation, and helicopter control (Ng et al., 2006). RL may be used to resolve the sequential decision-making problem, which can subsequently be applied to stock trading to develop dynamic trading methods. RL is unable to comprehend the environment around it, though. Since DRL integrates the perceptual powers of DL with the decision-making characteristics of RL, this problem is solved providing additional advantages.

One of the challenges in putting DRL-based stock trading into action is the need for precise stock market analysis. Financial data is nonlinear and erratic. Most of the current research on stock trading that uses DRL examines the stock market using stock data (Bao et al., 2017). Nevertheless, there is noise in stock data, which influences the results of the final analysis. Technical indicators help lessen the impact of noise and represent developments in the stock market from many angles. Investigations exist that use two-dimensional graphics created from financial data to analyse the stock market (Sezer and Ozbayoglu, 2018). Numerous data sources depict changes in the stock market from different perspectives. Multisource data, as opposed to stock market analysis relying on a single data source, may integrate the characteristics of various data sources, making it more useful for stock market analysis. However, the synthesis of data from several sources is challenging.

1.1 Research Gap

Currently, AI based DRL has been playing an important role in automatic stock trading. It has been used to predict stock prices and identify profitable trading strategies. While the research in this field has been growing rapidly, there is still a lack of understanding of how the DRL models are implemented in real-world applications. Moreover, there is a lack of research that investigates the effectiveness of different DRL models in the context of automatic stock trading. For example, research comparing the performance of different DRL models has not been conducted. Additionally, there is also a lack of research that investigates the potential risks of using DRL models in automatic stock trading. Further study is needed to understand the implementation of the DRL models and to compare their performance in the context of automatic stock trading. Moreover, research is needed to identify and mitigate the potential risks associated with using DRL models in automatic stock trading.

2. Literature Review

Reinforcement-learning is a way of learning through trial and error with an explicit objective incorporating a feedback system, just like a toddler who first acts, observe and then depending on the feedback he gets from any adult learns what's to do or not (Naeem, et al., 2020). RL finds application in many fields like simulation technologies, robotics, gaming, healthcare and transportation etc (Mendi et al., 2021).

Aboutorab et al. (2022) applied RL to understand how it can hep managers to enhance their efficiency in performance and identify risk associated within the supply chain operations. Kober et al. (2013) investigated the generation of behaviour in robotics focussing on its learning as well as challenges faced.

Li et al., while studying driving of vision-based autonomous cars simulation made use of the reinforcement-learning based control meant for taking a control decision. Subsequently, a novel deep RL visual TORCS (VTORCS) was proposed. The controller thus obtained outperformed the linear quadratic regulator (LQR) controller and model predictive control (MPC) controller on different tracks.

The role of RL has also been investigated in stock analysis as well as stock prediction by many scholars. He et al, (2022) used DRL approaches to handle the intricate stock trading decision-making problem. They discussed 2 trading approaches 1) In order to maximise the return for the acquisition and sale of a particular blue chip stock, they created a novel trading agent relying on Double Deep Q-Network (DDQN); 2) Also, they used the twin-delayed deep deterministic policy gradient (TD3) approach to construct a multi-stock collaborative trading agent for fulfilling the objectives of risk hedging and return maximisation in order to further lower the risk of stock trading for the more typical multi-stock trading situations.

The overall financial market is significantly influenced by the stock market. In the stock market, there has long been discussion over how to get reliable trading signals. The DRL theory and model are reviewed by Li et al, (2019). The model's validity was verified using actual data, and the advantages of the three traditional Deep RL models are contrasted. It was observed that DRL model served as an invaluable resource for the development of investor automation investment approach, stock market investment tactics, the use of AI in the field of financial investment, and the enhancement of investor strategy yield from the viewpoint of the automated stock market investment transactions decision-making mechanism.

DRL has produced notable outcomes amongseveral ML benchmarks Machine learning methods according to Millea (2021). The aim of his study was to identifying similar trading community frameworks, and identifying problems and drawbacks of machine learning methods It also explained how to utilise a hierarchy to partition the issue area and how to use model-based RL to develop a predictive world model for the trading environment. Additionally, numerous risk metrics were described and explored, which can be used to shape the agent's rewards in a (dense) fashion in addition to providing a way to evaluate the success of different algorithms.

Jyothi & Krishnamurthy, (2022) opined that the stock price can be predicted using a variety of approaches, however due to their computational complexity, these methods provide a significant challenge when using real financial data in decision-making. So, thay suggested the Recurrent Q Network Learning (RQNL) for determining the best course of action based on stock price changes. A neural network was used to build the forgotten memory in order to address the computational complexity limitation. It was observed that RL lessened correlations in time series data while improving prediction ability.

The stock market plays a crucial part in the broader financial industry. A long time has been spent researching how to obtain useful trading signals during the transaction process in order to maximise the rewards (Li et al., (2020). This study by Li et al. (2020) presented a theory of DRL for stock trading decisions and stock price prediction. This research demonstrated the viability of DRL in financial markets as well as the legitimacy and benefits of strategic decision-making from the viewpoints of stock market forecasting and intelligent decision-making mechanisms.

3. Research Methodology

The objective is to nurture the AI agent in a manner that, when faced with a trading scenario, it may offer an optimum parameter set of the trading method and possibly obtain the highest pay out after a specified number of rounds. We modify the Deep Q-Learning (DQN) algorithm instead of using conventional optimisation techniques. This approach is suggested because it can effectively optimise a trading strategy without the need for prior knowledge, and because the learning algorithm can change on its own when subjected to novel situations. The decision to employ DRL was made because it boosts the automation possibilities for a variety of decision-making issues that were unsolvable due to their multivariate state and action spaces. This study discusses the learning method, some implementation considerations, and a brief description of our learning environment and AI agent. In order to improve the trading techniques used in the tests conducted for this work, an automated trading system is established.

To avoid the circumstance where the optimisation techniques are over-fitted or the gathered parameters do not yield any gain in succeeding intervals, we consider 100 intervals, each with 3456 data. 20% of the dataset is utilised to evaluate the effectiveness for each interval, the start and end dates of which change, with the first 80% of the dataset being set aside for training reasons.

The Pareto principle, which is frequently used to guide optimisation attempts in computer science, guided the selection of this ratio. Other ratios can likewise be used without losing generality.

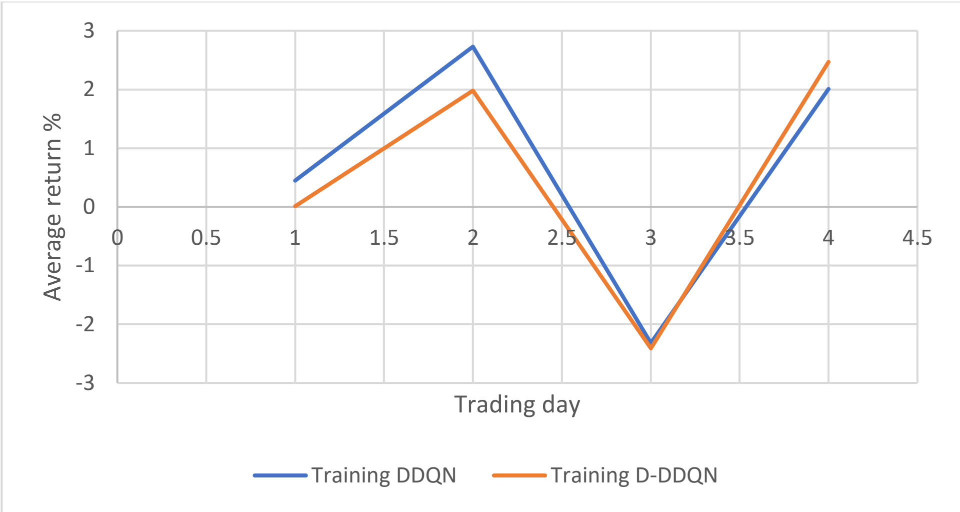
Double Deep Q-Network (DDQN) and Duelling D-DDQN power the learning process of agents. The networks in both situations consist of two Convolutional Neural Network (CNN), each with 120 neurons. Following the CNN tiers in the case of D-DDQN, two sets of entirely linked tiers are included, the first of which has 60 neurons set apart for predicting the value function and the second of which has 60 neurons set aside for predicting the benefit function. The cumulative return and the Sharpe ratio are two objective functions that we use to measure the system's performance against.

4. Results and Discussion

Table 41. Average efficiency of the return reward function

Period	Setting	Avg%	Max%	Min%	SD.
Training	DDQN	0.45	2.73	-2.32	2.01
	D-DDQN	0.01	1.98	-2.41	2.47
Testing	DDQN	0.27	2.45	-3.79	1.32
	D-DDQN	-0.02	1.09	-1.02	1.01

More particularly, Table 1 displays statistical findings in which the cumulative return serves as the incentive function. The increased standard deviation, however, also shows how unstable the outcomes are when trading using short-term time frames. In contrast to the real market, where trading efficiency is assessed by the gain made over a longer time frame, such as a week or month, this study concentrates on the regular profit, hence excessive volatility is appropriate. The system may consider several time periods in the future to contrast the stability of the profit generated.



a) Training period

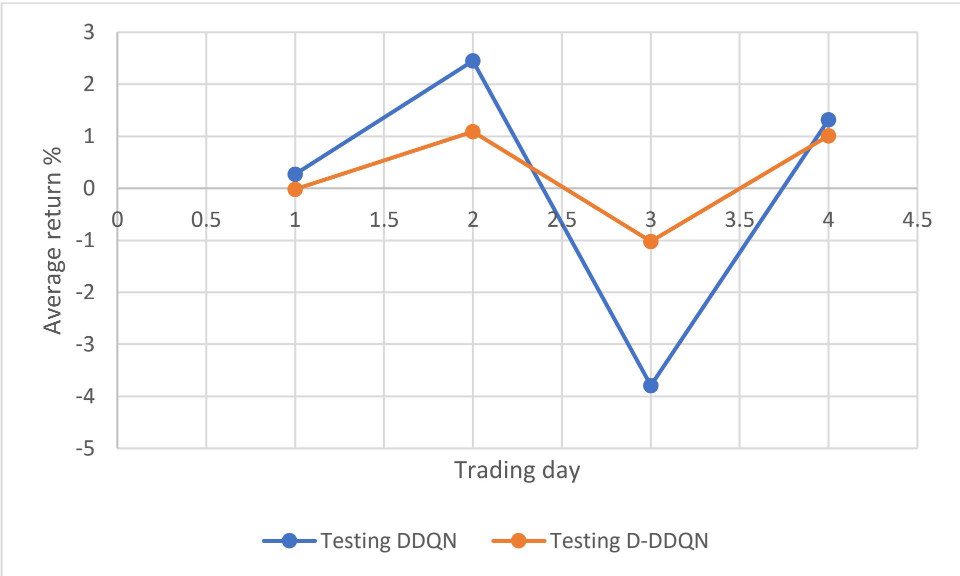
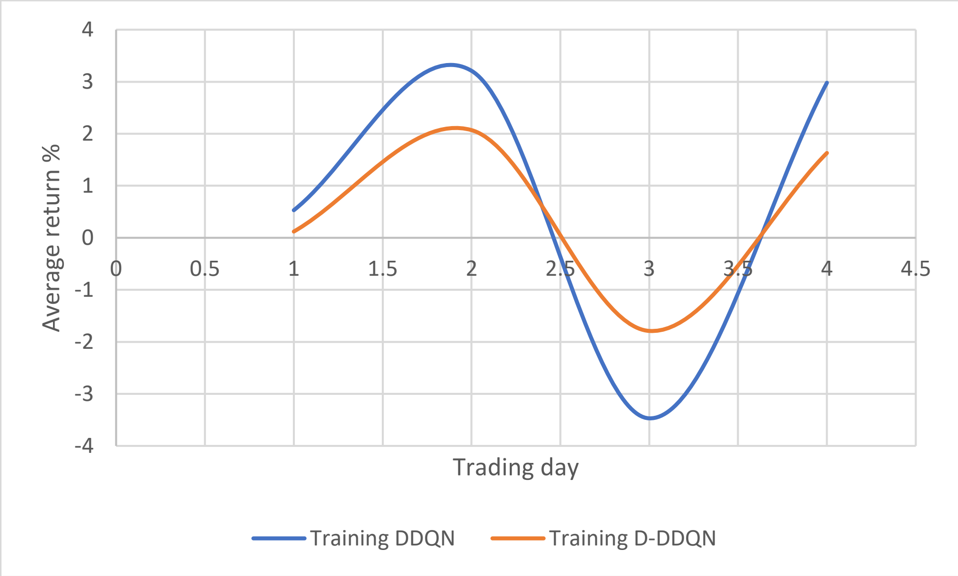


Fig 1. Average returns using the return reward function of the DRL technique. **(**a) Training period; (b) Testing period

The outcomes with various settings are shown in the above figure 1. The trading system with the reward return function is first taken into consideration. Figure 1a depicts the average percentage returns for the training data sets, and Figure 1b shows the average percentage returns for the 100 testing sets with various start and end dates.



(a) Training period

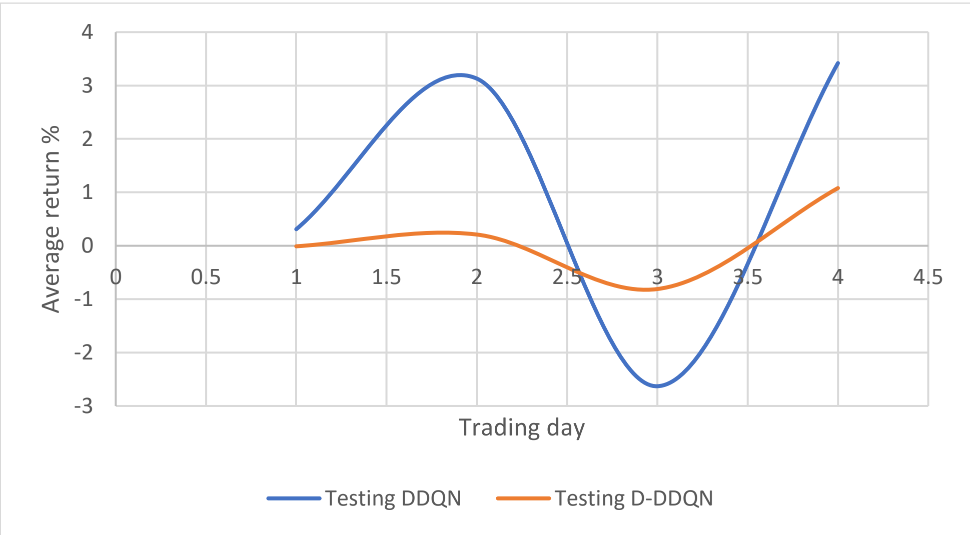


Fig 2. Average returns from DRL approach with Sharpe reward function. (a) Training period; (b) Testing period

The average Sharpe value throughout all eras is presented in Figure .2 provides a summary of statistical data. Although DDQN performs better overall than the D-DDQN setting, all other statistical indicators point to DDQN as having superior efficiency. The DDQN configuration also offers positive returns and lower volatility over the course of all periods.

The performance of the BO technique is then summarised in Table 2 across 100 distinct testing sets, with the findings indicating a positive average return. The biggest gap between the best return, 28.88%, and the lowest outcome, 22.45%, shows the volatility of the trading performance.

Table 2. Statistics of the BO approach's average return efficiency

Avg return (%)	Max return (%)	Min return (%)	SD
2.34	37.42	-11.32	8.52

Table 3 displays the typical execution time for the trading system using various strategies. Smaller volatility is provided by DDQN setting than by BO method, but execution time is longer. In order to trade on the real market, traders must choose from among or integrate several trading methods, which generates a sizable set of variables that must be optimised.

Table 3. Execution time for trading system using various approaches

Approach	Execution time (s)
DDQN	7823
D-DDQN	219
BO	579

5. Conclusion

The use of AI and DRL in the automatic stock trading system has revolutionized the financial markets. It has provided an efficient and accurate way of predicting stock prices, which has helped traders make more informed decisions. AI-based DRL also could recognise patterns, trends and anomalies that may not be visible to the human eye, enabling traders to make more informed decisions. AI-based DRL has also dramatically reduced the amount of time and effort required to conduct stock trading. By automating the process, traders can be more efficient and profitable. Furthermore, AI-based DRL can be used to customize the trading process to fit the individual needs of the traders, allowing them to make decisions based on their own preferences and strategies, rather than relying on the general advice of analysts. Overall, AI-based DRL has made a huge impact on the automatic stock trading system. It has enabled traders to make more informed decisions and has improved their chances of making successful trades. Furthermore, AI-based DRL has simplified the trading process by automating it, thus reducing the amount of time and effort required to conduct stock trading. As such, AI-based DRL is a great addition to the existing trading system and should be used by all traders looking to maximize their potential for success.

6. Challenges

The stock market is an ever-evolving and dynamic industry, making it difficult to effectively manage and trade stocks. With the rapid growth of artificial intelligence (AI) technology, many financial institutions have begun to incorporate AI-based deep reinforcement learning (DRL) into their trading strategies. While DRL has been shown to be a powerful tool for stock trading, there are still numerous challenges that must be addressed to make it an effective and reliable tool. Firstly, one of the major challenges with using AI-based DRL in stock trading is the lack of data. Since stock prices fluctuate rapidly, it’s difficult to obtain enough data points to accurately train an AI model. Additionally, the lack of historical data further complicates this problem as the AI model must be able to accurately learn from current and past stock prices. Secondly, another challenge when using AI-based DRL in stock trading is the inability to accurately forecast future stock prices. As stock prices can be affected by a variety of external factors, it is difficult to accurately predict how the stock market will react to certain events or changes in the economy. Additionally, since stock prices can be influenced by human sentiment, it is difficult to accurately forecast future stock prices. Finally, AI-based DRL can be very computationally intensive, as it requires a large amount of processing power and memory. This can be especially challenging for financial institutions that may not have the resources to use AI-based DRL. Additionally, since AI-based DRL is an emerging technology, there is a lack of reliable tools and techniques for using it in stock trading.

7. Limitations

One of the major limitations of using artificial intelligence-based deep reinforced learning in automatic stock trading is the lack of robustness. The algorithms and models used in artificial intelligence-based deep reinforced learning are often highly sensitive and can easily be affected by small changes in the data, which can lead to inaccurate predictions or decisions. As such, it is difficult to ensure that the results of the deep reinforced learning model are reliable and valid. Another limitation of artificial intelligence-based deep reinforced learning in automatic stock trading is the lack of transparency. The methods used in artificial intelligence-based deep reinforced learning are often highly complex and difficult to understand, which means that it is difficult to explain the decisions that the model is making. This lack of transparency can lead to mistrust in the model and its results.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Declaration of conflicts of interests

Authors declare that they have no conflict of interest.

Data Availability Statement

Not applicable

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

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