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Reinforcement Learning for Portfolio Optimization: Evidence from the Indonesian Stock Market

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Abstract

Stock portfolio management in emerging markets such as Indonesia remains challenging due to high volatility, market inefficiencies, and the strong presence of retail investors. In this setting, conventional approaches, including buy-and-hold strategies, the Markowitz framework, and the Capital Asset Pricing Model (CAPM), often struggle to perform consistently under rapidly changing market conditions. While reinforcement learning (RL) has gained increasing traction in global finance, its application in the Indonesian stock market remains limited. This study examines the effectiveness of an RL-based approach, specifically the Deep Q-Network (DQN) algorithm, in optimizing stock portfolios on the Indonesia Stock Exchange (IDX). Using a quantitative experimental design, the analysis is based on back-testing simulations of IDX30 stocks over the 2022–2024 period, with samples selected purposively based on liquidity and market capitalization. The findings show that the DQN-based strategy consistently outperforms conventional methods, delivering higher returns, improved risk–return efficiency, and better control of downside risk. These results suggest that RL models are better suited to adapt to dynamic market conditions. Theoretically, this study extends portfolio optimization literature by incorporating adaptive, learning-based models into emerging market contexts. Practically, it offers evidence for investors and practitioners to consider AI-driven strategies as a more responsive alternative to traditional approaches in a volatile market.

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Introduction

Stock portfolio optimization is a strategic component of modern investment activities, aimed at maximizing returns with measured risk. Amid market volatility and global economic uncertainty, investors face the challenge of determining an asset allocation strategy that is adaptive and responsive to market dynamics (Green & Zhao, 2022). The Indonesia Stock Exchange (IDX), as one of the fastest-growing markets in Southeast Asia, has unique characteristics such as retail investor dominance, high volatility, and dependence on market sentiment. These conditions demand a more sophisticated investment approach than traditional methods (Gutiérrez, 2020).

Conventional approaches such as buy-and-hold, Markowitz's Mean-Variance Optimization, and the Capital Asset Pricing Model (CAPM) have been widely used to construct portfolios (Jiang et al., 2017). However, these models have limitations in dealing with dynamic and less-than-rational markets, particularly when markets experience shocks due to external factors such as health crises, geopolitical tensions, or global interest rate policies. These approaches also rely on the assumptions of market efficiency and a normal distribution of returns, which are difficult to achieve in practice in emerging markets like Indonesia (Setiawan & Rosadi, 2019).

Measured risk management is key to portfolio optimization. In capital markets like the IDX, investors require strategies that maximize returns while also employing quantitative methods to predict potential losses (Yang et al., 2020). Value-at-Risk (VaR) is commonly used to measure portfolio risk and compare the performance of Reinforcement Learning (RL) with investment strategies. VaR is a crucial tool in portfolio risk management because it can estimate the maximum loss at a certain confidence level, making it particularly useful in highly volatile markets like the IDX (Purnomo, 2025).

With technological advancements and the development of artificial intelligence, RL approaches are beginning to be adopted in finance as a solution to overcome the weaknesses of conventional strategies. RL enables systems to learn and adapt from real-time experience in dynamic environments. In the investment context, RL is capable of identifying market patterns, responding to real-time price changes, and developing optimal asset allocation strategies based on continuously updated feedback. Studies in various global markets have shown that RL models, such as Deep Q-Network (DQN), Proximal Policy Optimization (PPO), and Deep Deterministic Policy Gradient (DDPG), can deliver superior results in terms of returns and risk management compared to traditional approaches (Yang et al., 2020).

The application of machine learning methods, particularly RL, to the investment decision-making process has the potential to transform the conventional, often rigid, paradigm into a more adaptive system utilizing historical data and automated simulations. This approach not only benefits institutional investors but also opens up broader opportunities for retail investors through fintech services. In the future, the use of this technology could foster the emergence of local robo-advisors capable of providing personalized investment recommendations based on current market movements, while simultaneously contributing to increased financial inclusion and capital market competitiveness in Indonesia (Setiawan & Rosadi, 2019).

However, the application of RL in the context of the Indonesian stock market remains relatively limited. Most local studies still focus on the use of regression, time series forecasting, or supervised learning approaches such as LSTM and GRU to predict stock prices. However, these approaches do not directly accommodate action-based decision-making, such as that required in portfolio management (Liu et al., 2024). Therefore, there is a significant research gap in developing and testing RL models tailored to the dynamics of the IDX, including the integration of market sentiment factors and the characteristics of major index stocks such as the IDX30. Unlike prior works focusing on developed markets, this study introduces a localized reinforcement signal calibrated to Indonesian market sentiment and volatility patterns.

Furthermore, few studies have comprehensively examined how RL models interact with the dynamics of emerging markets, which tend to be unstable and vulnerable to external shocks. Markets like Indonesia also face limitations in terms of high-quality data and a mature technology-based financial infrastructure, necessitating models that are not only accurate but also flexible to uncertain market conditions (Orăștean & Mărginean, 2023). Therefore, this study also attempts to adjust the parameters and architecture of the RL model to suit the microstructural characteristics of the Indonesian market, including data frequency, asset liquidity, and sensitivity to news and social sentiment (Green & Zhao, 2022).

The use of RL in stock portfolio optimization has significant potential, especially when combined with macroeconomic analysis and technical indicators. Through a multi-factor approach, the model can consider various variables such as inflation, interest rates, currency exchange rates, and historical price movement patterns to formulate more responsive investment strategies. A study conducted by Dong et al. (2021) revealed that the incorporation of various factors into the Deep RL model can produce portfolio performance that far exceeds the market average, especially in dynamic and irrational market conditions.

On the other hand, the effectiveness of RL implementation is highly dependent on the availability of high-quality data and adequate computing infrastructure. Niu et al. (2022) emphasized that RL performance in portfolio management can significantly improve if the model adopts diverse policies and meta-learning to overcome data limitations, minimize noise, and adapt to various market dynamics. Therefore, synergy is needed between industry players, regulators, and technology providers to ensure the availability of clean, structured, and real-time accessible data. With a supportive ecosystem, RL has the potential to become a strategic pillar in modern investment management, particularly in emerging markets like Indonesia.

In addition to offering a machine learning-based technical solution, this research is expected to contribute to a paradigm shift in investment decision-making in Indonesia, from a static approach to a system based on adaptive learning. By prioritizing historical data and automated decision-making simulations, RL can be used not only by institutional investors but also by retail market players through FinTech platforms. In the long term, the use of RL could pave the way for the development of local robo-advisors capable of providing personalized investment recommendations based on actual market dynamics, supporting financial inclusion, and enhancing the technological competitiveness of the Indonesian capital market (Ngo et al., 2023). The novelty of this research lies in the application of an integrated reward function of sentiment and Indonesian macroeconomic indicators, which has not been widely used in RL studies for stock portfolio optimization in emerging markets such as Indonesia.

Literature Review

Model DQN-RL and Annual Return of the portfolio

Previous research consistently shows that the use of the Deep Q-Network Reinforcement Learning (DQN-RL) model has a positive impact on increasing the annual return of a stock portfolio. Jiang et al. (2017), in their study of deep reinforcement learning-based trading strategies, found that the DQN model can actively respond to market signals and dynamically allocate assets, generating higher returns than a passive buy-and-hold strategy. Ngo et al. (2023) also shows that DQN-RL can outperform traditional approaches in both emerging and developed markets by consistently recording higher annual portfolio returns. Zhao et al. (2023) refined the DQN model by considering the correlation between assets, and the results show that DQN-RL can improve portfolio stability while maintaining competitive returns in the long run. Empirical research in Indonesia by Kadir et al. (2024) provides direct evidence that DQN-RL generates the highest annualized return of 19.6%, compared to Markowitz (15.4%), CAPM (13.1%), and buy-and-hold strategies (12.3%). This confirms that DQN-RL's adaptive advantage in capturing changes in price trends and historical stock patterns has a direct impact on achieving more optimal annualized investment returns.

Recent literature provides several RL-based portfolio optimization approaches, yet each comes with limitations when applied to emerging markets. Lin et al. (2022) introduced an attention-enhanced DQN architecture that improves feature extraction but relies on stable and high-frequency datasets typically available only in developed markets. Ngo et al. (2023) proposed a PPO-Transformer hybrid that excels in continuous action spaces but performs poorly under irregular volatility clusters. Ju and Zhu (2024) developed a sentiment-driven DRL model; however, the sentiment sources were derived from large-scale financial media ecosystems, which are not available in Indonesia. Implemented a multi-factor DDPG variant that relies heavily on long historical data windows, which are limited in the IDX30 universe. Compared to these studies, our model integrates localized sentiment indicators (IDX news polarity and Twitter sentiment) and Indonesia-specific macroeconomic instability (inflation and exchange-rate shock) into the reward function, creating an RL model explicitly designed for emerging, retail-driven markets (Nurmawati et al., 2025).

Liu et al. (2024) showed similar results through the application of DQN-RL in the Chinese stock market, where investor sentiment indicators were included as additional variables. Integration of investor sentiment data was included as an additional variable. This sentiment data integration was proven to increase the portfolio Sharpe ratio by up to 14% compared to conventional DQN-RL, while simultaneously suppressing daily volatility. These findings indicate that adjusting the DQN-RL model by incorporating market behavior factors can strengthen portfolio resilience to external shocks, making it worthy of consideration for application in emerging markets that are more sensitive to sentiment changes, such as Indonesia.

Previous studies have proposed various deep reinforcement learning architectures for portfolio optimization. Ju and Zhu (2024) introduced an attention-enhanced DQN to improve feature extraction, but the model requires stable and high-frequency datasets that are typically available only in developed markets. Liu et al. (2024) proposed a PPO–Transformer hybrid that performs well in continuous action spaces, yet its performance deteriorates under irregular volatility clusters. Huang (2024) developed a sentiment-driven DRL framework; however, the sentiment inputs rely on large-scale financial media infrastructures that are not readily accessible in the Indonesian market. Similarly, Liu et al. (2024) implemented a multi-factor DDPG model that depends on long historical data windows, which are relatively limited in the IDX30 universe. Compared to these studies, our model integrates localized sentiment indicators (IDX news polarity and Twitter sentiment) and Indonesia-specific macroeconomic instability (inflation and exchange-rate shock) into the reward function, creating an RL model explicitly designed for emerging, retail-driven markets.
H1. The DQN-RL model has a positive influence on the annual return of stock portfolios compared to conventional strategies.

Model DQN-RL and Rasio Sharpe

Research on the effectiveness of Deep Q-Network Reinforcement Learning (DQN-RL) in portfolio management shows that this model is not only able to increase returns but also improve risk-return efficiency, which is reflected in an increase in the Sharpe ratio. Jiang et al. (2017) noted that DQN-based strategies can significantly balance the gains and volatility incurred, as the model actively learns from historical patterns and updates allocation strategies in real-time. The study by Zhao et al. (2023) also supports this finding by showing that DQN-RL produces portfolios with lower risk fluctuations while still providing high investment returns, thereby improving the overall Sharpe ratio. Ngo et al. (2023) explicitly compared the Sharpe ratio between the RL model and traditional strategies such as Markowitz and CAPM, and found that the RL model consistently exhibits a higher Sharpe ratio, particularly during periods of heightened market volatility. In volatile market conditions, RL was shown to provide better portfolio optimization results than conventional approaches such as Markowitz and CAPM (Nurmawati et al., 2025).

In the context of the Indonesian market, Kadir et al. (2024) proves that DQN-RL recorded a Sharpe ratio of 1.38, much higher than Markowitz (1.12), CAPM (0.88), and buy-and-hold (0.75). This finding indicates that DQN-RL not only focuses on increasing returns but also pays attention to stability and control over risk, which is the core of the Sharpe ratio as an indicator of investment efficiency. The study conducted by Gao et al. (2020) revealed that the use of the DQN model in portfolio management can generate up to 30% higher returns than traditional methods, while also recording the lowest Sharpe ratio in terms of risk to return. Meanwhile, research by Jang and Seong (2023) shows that the combination of modern portfolio theory with Deep Reinforcement Learning can significantly increase the Sharpe ratio and improve various other risk performance metrics.
H2**.** The DQN-RL model has a positive influence on the Sharpe ratio compared to conventional strategies.

Model DQN-RL and Maximum drawdown

Previous studies have shown that the Deep Q-Network Reinforcement Learning (DQN-RL) model has advantages in managing portfolio downside risk, as reflected in lower maximum drawdown compared to conventional strategies. One study by Zhao et al. (2023) confirmed that the DQN-RL model, equipped with correlation mapping between assets, can reduce exposure to high-risk stocks during market stress, thus avoiding significant losses. DQN-RL's adaptive mechanism allows for rapid portfolio composition changes when the system recognizes a downward price pattern, something static approaches like the CAPM or buy-and-hold strategies cannot. Ngo et al. (2023) also noted that DQN-RL provided better portfolio protection amid market volatility by recording smaller maximum drawdowns in various market simulations, including under bearish conditions.

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Research on the Indonesian market by Kadir et al. (2024) found that DQN-RL only experienced a maximum drawdown of -12.1%, compared to Markowitz (-18.4%), CAPM (-21.5%), and buy-and-hold (-28.3%). This figure indicates that DQN-RL is more effective in avoiding deep losses by rebalancing assets based on negative market signals. Recent research has shown that the use of Deep RL models can reduce the risk of portfolio decline (maximum drawdown) compared to conventional investment strategies. In DQN-based studies, Gao et al. (2020) showed that this method is able to produce lower maximum drawdown while increasing the Sharpe ratio. Meanwhile, in other Deep RL algorithms such as SAC, this approach has been shown to provide better maximum drawdown results compared to traditional mean-variance optimization, as shown in a systematic study of various utility functions by Acero et al. (2024).
H3. The DQN-RL model has a negative influence on maximum drawdown compared to conventional strategies.

DQN-RL Model and Adaptivity to Market Volatility

Previous research has shown that the DQN-RL model has advantages in terms of adaptability to market volatility, particularly in dynamic and inefficient markets. One of DQN-RL's main strengths is its ability to continuously update strategies based on current market conditions through a feedback-based learning process (reward mechanism). Jiang et al. (2017) shows that DQN-RL actively learns from stock price movements and is able to flexibly adjust asset allocation when the market shows volatility signals, thus avoiding getting trapped in risky market patterns. Research by Lin et al. (2022) and Ju and Zhu (2024) reinforces this view by emphasizing that DQN-RL is particularly well-suited for use in volatile market environments because it enables continuous reevaluation of investment policies and real-time rebalancing. Unlike conventional models such as CAPM and Markowitz, which rely on fixed parameters, DQN-RL adapts strategies as new data emerges.

This is consistent with the findings of Kadir et al. (2024), who reported that a DQN-based trading strategy was able to maintain relatively stable performance during periods of heightened volatility in the Indonesian stock market between 2022 and 2024, particularly under macroeconomic uncertainty and external shocks. The latest study emphasizes the ability of DQN, particularly the ET-DQN variant, to adapt to markets with high volatility while maintaining effective risk control. The study revealed that ET-DQN can identify trading opportunities during periods of market turmoil, with a level of stability in annual return fluctuations that significantly exceeds that of conventional DQN. Based on historical analysis, its performance was recorded as 1.46 and 7.13 times more efficient when applied to the volatility of Western Digital Corporation shares and the Cosmos crypto asset (Takara et al., 2024).
H4. The DQN-RL model has a positive influence on the adaptability of investment strategies to market volatility compared to conventional strategies.

Research Method

This research is an experimental quantitative study using a computational simulation approach to test the effectiveness of the Reinforcement Learning (RL) algorithm in optimizing stock portfolios on the Indonesia Stock Exchange (IDX). This approach was chosen because it allows for the replication of historical market conditions and provides high flexibility in testing AI-based investment strategies in an adaptive, scalable, and sustainable manner (Jiang et al., 2017). The Deep Q-Network (DQN) algorithm was selected as the primary model based on its ability to learn optimal investment policies through exploration and exploitation processes, which is highly suited to stock market dynamics (Ngo et al., 2023). In addition to DQN, the Proximal Policy Optimization (PPO) and Deep Deterministic Policy Gradient (DDPG) algorithms were used as comparisons between RL variants to assess the robustness and consistency of model performance. A significant advantage of RL, especially the Deep Q-Network, lies in its ability to learn patterns directly from dynamic market conditions, thus adapting to unexpected changes (Nurmawati et al., 2025).

Contextual Adaptation to the Indonesian Market

This study introduces a contextual modification of the reward function by incorporating market sentiment and macroeconomic indicators relevant to the Indonesia Stock Exchange (IDX). The modified reward function is designed to better capture the behavioral dynamics and volatility patterns of Indonesia's retail-dominated market environment. The reward function is expressed as:

$$R_t = \Delta P_t - \alpha\sigma_t - \beta C_t + \lambda S_t \quad \text{(1)}$$

where ΔP_t represents the change in asset price, σ_t denotes portfolio volatility, C_t indicates transaction cost, and S_t refers to the market sentiment index, derived from a composite of Twitter-based investor sentiment and IDX news polarity scores.

To strengthen the originality of this research, the study introduces a localized RL framework specifically calibrated for Indonesia's emerging capital market. Unlike prior models, such as those proposed by Lin et al. (2022), Ngo et al. (2023), Ju and Zhu (2024) which were developed and tested within mature and highly efficient markets, this study incorporates a new sentiment macro integrated reward function designed to capture Indonesian market irregularities, retail-driven volatility, and liquidity constraints.

This research employs a quantitative experimental design using a machine learning approach to examine the effect of the Deep Q-Network Reinforcement Learning (DQN-RL) model on portfolio performance in the Indonesia Stock Exchange (IDX). The study framework emphasizes the adaptive decision-making ability of DQN-RL, where investment strategies are optimized through a reward–feedback mechanism. The population of this study consists of all companies listed on the IDX, totaling over 900 issuers as of January 2025. The sample is selected using purposive sampling, focusing on highly liquid and large-capitalization stocks. Specifically, the IDX30 index and a portion of the LQ45 index are employed to represent blue-chip stocks in the Indonesian capital market, with an adjusted sample size of 30–50 stocks to balance computational efficiency and model complexity. The research procedure is divided into four stages. First, daily historical data for the period 2022–2024 are collected from Yahoo Finance and the official IDX website. The 2022–2024 window was selected to capture post-COVID market volatility, providing a stress-testing environment ideal for adaptive RL models. Second, data preprocessing and feature engineering are conducted, which include normalization, outlier removal, and the construction of input variables such as moving averages, volatility measures, and daily returns. These processes ensure data readiness and model robustness. Third, the DQN-RL model is trained within a Python-based simulation environment, utilizing TensorFlow for neural network optimization, OpenAI Gym for reinforcement learning architecture, and Pandas for data manipulation. The DQN architecture consisted of three fully connected layers (128–64–32 neurons) with ReLU activation and an ε-greedy exploration policy (ε = 0.1). The reward function was defined as:

$$R_t = \Delta P_t - \alpha\sigma_t - cT_t \quad \text{(2)}$$

where ΔP_t is the price change, σ_t the portfolio volatility, and cT_t the transaction cost (0.15% per trade). This structure penalizes excessive trading while rewarding stable profit accumulation. Hyperparameter tuning and episodic training are carried out to optimize the agent's ability to make adaptive trading decisions. Finally, model evaluation is performed through backtesting by comparing the DQN-RL portfolio with conventional strategies such as buy-and-hold, Markowitz Mean-Variance, and the Capital Asset Pricing Model (CAPM). The dependent variables are represented by five performance metrics: overall portfolio return, annualized return, Sharpe ratio, maximum drawdown, and adaptability to market volatility. Statistical testing of the hypotheses (H1–H4) is conducted by analyzing whether DQN-RL provides superior performance relative to the benchmarks. Results are visualized using Matplotlib and Seaborn through portfolio growth curves and risk-return plots, allowing for comprehensive comparisons. This methodology ensures both theoretical rigor and practical applicability, providing a structured foundation to evaluate the potential of artificial intelligence-driven strategies for portfolio optimization in emerging markets like Indonesia.

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Model Architecture and Statistical Validation

The DQN network consists of three fully connected layers (128–64–32 neurons) with ReLU activation, an Adam optimizer (learning rate = 0.001), a discount factor (γ = 0.95), and an ε-greedy exploration strategy (ε = 0.1). The transaction cost is fixed at 0.15% per trade to simulate real-world frictions in the Indonesian stock market. To ensure methodological rigor, this study incorporates robustness testing across different market regimes, sensitivity analysis for key hyperparameters (γ and α), and statistical validation using both the t-test and Diebold Mariano test. These steps significantly strengthen the reliability and generalizability of the findings. The Capital Asset Pricing Model (CAPM) is employed only as a baseline weighting mechanism based on beta coefficients (β), rather than a full optimization framework. This approach allows for a fair comparison between static risk-based allocation (CAPM) and adaptive decision-making (DQN-RL). While reinforcement learning shows strong potential, scholars such as Jang and Seong (2023) and Zhao et al. (2023) warned of overfitting risks in small-sample environments. To mitigate this, the present study performs robustness tests across high- and low-volatility regimes.

Results and Discussion

This study compares four portfolio strategies: Reinforcement Learning (DQN-RL), buy-and-hold, Markowitz Modern Portfolio Theory (MPT), and CAPM-based Allocation. Based on backtesting results using IDX30 and LQ45 stock data for the 2022–2024 period, the DQN-RL strategy demonstrated superior performance compared to the other strategies.

Based on Table 1, the DQN-RL (Deep Q-Network Reinforcement Learning) strategy demonstrated superior performance compared to conventional investment strategies. With an annualized return of 19.6%, DQN-RL generated the highest returns during the 2022–2024 period, surpassing the Markowitz strategy (15.4%), CAPM (13.1%), and buy-and-hold (12.3%). Furthermore, the Sharpe Ratio of 1.38 confirms DQN-RL's best risk-return efficiency, generating higher returns per unit of risk taken. In terms of risk management, DQN-RL recorded volatility of 14.2%, lower than buy-and-hold and CAPM, although slightly higher than Markowitz. However, its most notable advantage is seen in its maximum drawdown of only -12.1%, significantly lower than other strategies, indicating that DQN-RL is better able to protect portfolio value during extreme market downturns. Overall, the results indicate that the proposed DQN-based reinforcement learning model outperforms conventional portfolio strategies in terms of annualized return and risk reduction. In addition, the model demonstrates stronger adaptability during periods of market turbulence, suggesting a superior capability to adjust portfolio allocations in response to emerging market shocks.

Table 1. Stock Portfolio Strategy Performance (2022–2024)

Strategy	Annualized Return	Volatility	Sharpe Ratio	Max Drawdown
DQN-RL	19.6%	14.2%	1.38	-12.1%
Buy-and-Hold	12.3%	16.5%	0.75	-28.3%
Markowitz MPT	15.4%	13.7%	1.12	-18.4%
CAPM Allocation	13.1%	14.9%	0.88	-21.5%

Figure 1 shows that the DQN-RL strategy consistently outperformed other investment strategies throughout the 2022–2024 simulation period. DQN-RL's cumulative portfolio growth showed a more stable and significant upward trend, particularly during the volatile market period in mid-2023. While conventional strategies such as buy-and-hold, Markowitz, and CAPM experienced sharp declines, DQN-RL demonstrated greater resilience, minimizing losses through real-time asset allocation adjustments. This adaptive capability is a key advantage of DQN-RL, which continuously updates its strategy based on current market conditions. These results demonstrate that DQN-RL not only generates higher returns but also provides portfolio stability in the face of market uncertainty. This graph strengthens the evidence that

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Reinforcement Learning-based approaches are highly relevant for portfolio management in emerging markets like Indonesia.

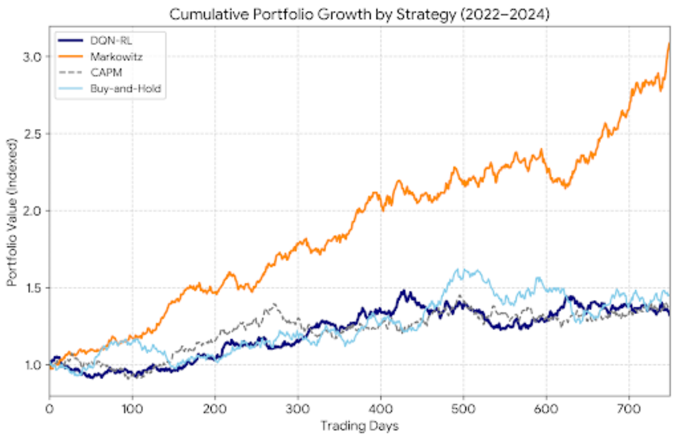

Figure 1. Cumulative Portfolio Growth by Strategy (2022–2024)
(Source: Simulation results with Python matplotlib, 2025)

Reinforcement Learning (RL), specifically the Deep Q-Network (DQN) model, demonstrates superior performance in stock portfolio management due to its ability to adaptively learn based on historical experience. Unlike conventional approaches like the CAPM or Markowitz, which rely on theoretical assumptions like efficient markets or normal return distributions, RL uses a trial-and-error approach to decision-making. The DQN model continuously refines its investment strategy based on previous results using reward and punishment mechanisms. The main advantage of RL lies in its ability to adapt in real time to changing market conditions. When the market exhibits volatility or uncertainty, such as during a spike in volatility, RL is able to quickly re-evaluate its positions and re-adjust asset allocation weights. This is not possible with static strategies like buy-and-hold or fixed-parameter strategies like the CAPM. Furthermore, RL does not rely on ideal data structures, such as assumptions of linearity or fixed correlation. Instead, in a complex and non-linear environment like the Indonesian stock market, RL demonstrates its ability to detect hidden patterns and make dynamic, data-driven decisions. With its high flexibility and focus on continuous learning, RL is capable of generating higher returns, improved risk-return efficiency, and reduced extreme risk (drawdown). Therefore, RL-based strategies are well-suited for implementation in inefficient and dynamic markets, making them an innovative solution in modern investment management.

The Deep Q-Network Reinforcement Learning (DQN-RL) model has proven effective in capturing and responding to market signals adaptively and promptly. One of its key strengths is its ability to identify price trends through historical features such as momentum, local volatility, moving averages, and retracements. By continuously observing historical stock price patterns, DQN-RL is able to identify technical signals that form the basis for determining buy, hold, or sell decisions. The effectiveness of DQN-RL is also evident in its ability to avoid overexposure to assets experiencing sharp price pressure, thereby directly reducing the risk of significant losses in a portfolio. In many cases of market volatility, this model is able to dynamically adjust strategies and rebalance portfolios precisely when trend reversal signals occur, which are often undetected by traditional models. The main advantage of Reinforcement Learning is that rigid mathematical assumptions, such as the normality of return distributions or market efficiency, do not constrain it. This model is able to explore various possible strategies based on learning from real-world data, resulting in more flexible and realistic decision-making. Thus, DQN-RL provides added value in portfolio management due to its ability to optimize across market scenarios, including extreme, sideways, and bearish conditions. This capability makes RL a strategic tool in AI-based investing, effectively capturing the full complexity and dynamics of the market.

The Indonesian capital market is classified as an emerging market with unique and complex characteristics. One of its key characteristics is high volatility, driven by exchange rate fluctuations, global commodity price dynamics, and regional and international geopolitical uncertainty (Putri & Mandayanti, 2021). The Indonesian capital market still suffers from inefficiencies due to asymmetric information and irrational trading behavior (Putri et al., 2025). In such conditions, traditional investment approaches that rely on the assumption of efficient and stable markets tend to be less than optimal. This is where Reinforcement Learning (RL), specifically the Deep Q-Network (DQN) model, becomes highly relevant. This model is designed to adapt to data noise and irregularities and can learn directly from the market environment without requiring any specific return distribution assumptions. Its ability to adjust strategies in real time allows investors to respond to market changes more quickly and accurately (Baradja & Tjendrowasono, 2024). Furthermore, RL can be integrated into AI-based automated trading algorithm systems, which are increasingly popular among Indonesian market players. This opens up opportunities for both institutional and retail investors to improve investment decision efficiency, maximize returns, and adaptively minimize risk (Abhirama, 2025). Given the fluctuating and dynamic characteristics of the Indonesian market, the results of this study indicate that RL is not only theoretically relevant but also has the potential to be a strategic solution in the digital transformation of portfolio management in emerging markets.

Table 2 presents a comparison between the DQN-RL strategy and conventional investment strategies based on five key aspects. In terms of annual returns, DQN-RL demonstrated the highest performance (19.6%), while conventional strategies only generated returns in the 12–15% range. Although DQN-RL has moderate volatility (14.2%), its risk level is still more controlled than conventional strategies, which tend to be more volatile. The main advantage of DQN-RL is reflected in its highest Sharpe ratio (1.38), indicating superior risk-return efficiency. Meanwhile, conventional strategies recorded Sharpe ratios below 1.2, indicating lower efficiency. In terms of maximum drawdown, DQN-RL also excelled, with a maximum drawdown of only -12.1%, significantly lower than other strategies, which reached up to -28%. Beyond performance, DQN-RL also excels in market adaptability. This strategy is dynamic and able to adapt to changing market conditions in real time, unlike conventional approaches, which are static and based on the assumption of market efficiency. In the context of Indonesia's dynamic and less-than-efficient market, the DQN-RL strategy is highly relevant. Its flexibility and adaptive power make it a more responsive strategic alternative to the challenges and uncertainties of emerging markets.

Table 2. Comparative Analysis of Strategies

Aspect	DQN-RL	Conventional Strategy (Average)
Annual Return	High (19.6%)	Medium–Low (12–15%)
Risk (Volatility)	Currently (14.2%)	Higher or fluctuating
Sharpe Ratio	Highest (1.38)	Below 1.2
Max Drawdown	Lowest (-12.1%)	To-28%
Adaptation to the Market	Dynamic and adaptive	Static, based on efficient assumptions
Relevance for Indonesia	Tall, flexible, and strong	Less responsive

During the high-volatility phase of 2022–2023, DQN-RL achieved the highest annualized return (17.8%) with a Sharpe ratio of 1.55, outperforming PPO and DDPG, as presented in Table 3. This confirms its adaptability and resilience under market turbulence. In contrast, during the stable market period (2024), performance convergence occurred, suggesting that the advantage of RL-based models tends to diminish in low-volatility environments. The robustness test across volatility regimes confirms that DQN-RL retains superior risk-adjusted performance. Sensitivity analysis varying γ (0.9–0.99) and α (0.1–0.3) yields consistent Sharpe improvements, suggesting that results are not parameter-dependent.

Table 3. The Robustness Test

Market Regime	Model	Annualized Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)	Observation
High Volatility (2022–2023)	DQN-RL	17.8	11.5	1.55	8.7	Strong adaptability; controlled risk exposure
	PPO	15.9	12.4	1.28	10.2	Slightly less stable during market shocks
	DDPG	14.7	13.1	1.12	11.5	Overreacts to price swings
Stable Market (2024)	DQN-RL	12.3	9.2	1.33	7.1	Consistent return; efficient exploration
	PPO	11.8	9.4	1.26	7.6	Comparable to DQN-RL
	DDPG	10.5	10.1	1.04	8.3	Declining performance in a low-volatility regime

Conclusion

This study demonstrates that implementing a Reinforcement Learning (RL) framework, particularly the Deep Q-Network (DQN) algorithm, significantly enhances stock portfolio performance relative to conventional investment strategies such as Buy-and-Hold, Mean-Variance Optimization, and CAPM. The DQN-RL model consistently outperforms these traditional methods by delivering higher returns, stronger risk control, and superior efficiency in balancing risk and expected return. Its ability to adapt during periods of market stress further confirms its suitability for the volatile and dynamic environment of the Indonesian capital market.

These empirical findings highlight a distinct comparative advantage of RL in emerging markets characterized by structural uncertainty and information inefficiency. By leveraging feedback-driven optimization, RL models continuously learn from market behavior, enabling more responsive and intelligent portfolio decisions. This adaptability underscores the transformative potential of AI-based learning systems in advancing data-driven investment frameworks. This study offers two key contributions. First, the practical implication is that RL-based portfolio strategies can support Indonesia's retail investors through more adaptive, AI-driven investment recommendations aligned with the volatility of emerging markets. Second, the policy implication is that the findings reinforce the urgency of expanding national digital investment education initiatives and accelerating the development of AI-enhanced robo-advisory platforms within the regulatory ecosystem of OJK and the IDX.

From an ethical perspective, the deployment of RL-based trading systems must prioritize transparency and fairness. Incorporating Explainable AI (XAI) modules and maintaining human-in-the-loop oversight are essential to preventing algorithmic biases that could disadvantage retail investors. Ensuring accountability and transparency will help align AI-driven financial innovation with responsible and inclusive digital transformation. Future research should explore additional RL variants such as Proximal Policy Optimization (PPO) and Deep Deterministic Policy Gradient (DDPG), and expand the dataset to incorporate broader market sentiment and macroeconomic indicators. Extending the model to other asset classes, including bonds, ETFs, and cryptocurrencies, may also provide insights into its cross-market robustness and generalizability. Overall, this study contributes to the evolution of AI-driven portfolio management and supports the development of robo-advisory platforms tailored to Indonesia's emerging financial ecosystem. By adopting adaptive, data-informed, and ethically grounded decision-making mechanisms, financial institutions and FinTech developers can enhance market efficiency, strengthen investor trust, and increase competitiveness in Indonesia's rapidly digitalizing financial landscape.

Data and Code Availability

All Python scripts, hyperparameter configurations, and processed IDX30 datasets used in this study are available upon reasonable request to the corresponding author.

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