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Event-driven Automated Equity Trading using Simple Moving Average (SMA) Crossovers Integrated in Proximal Policy Optimization (PPO) Algorithm

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Abstract:
There is growing use of reinforcement learning within automated trading systems in order to be able to adapt to dynamic financial markets. This research suggests an automated framework of equity trading involving events that combine Simple Moving Average (SMA) crossover indicators with Proximal Policy Optimization (PPO) reinforcement learning algorithm to improve the process of trading decisions. The interaction between SMA crossover events as technical triggers to produce market state signals, and PPO as a learner of optimal trading policies through interaction with the market environment and maximization of cumulative trading rewards, is proposed in the model. The system processes past price history information of the equity to detect short-term and long-term crossovers of SMAs, which are converted to event signals of possible buy and sell. The PPO agent examines these signals and other market characteristics in order to dynamically adapt trading positions and risk exposure. The benchmark equity experimental analysis shows that the proposed hybrid framework has better performance in terms of profitability, lower drawdown risk, and strategy stability than the conventional rule-based SMA strategies. Reinforcement learning on adaptive policies in non-stationary markets is made possible by the combination of event-based technical signals and reinforcement learning. The findings emphasize the success of technical analysis indicator integration with current reinforcement learning algorithms in intelligent and automated equity trading systems.

Keywords:
Financial Time Series Analysis; Data-Driven Portfolio Decision Making; Algorithmic Trading Strategies; Proximal Policy Optimization (PPO); Automated Equity Trading; Reinforcement Learning in Finance.

1. Introduction

The use of automated and algorithmic trading systems has revolutionized financial markets at a very high rate. The numerous innovations in the field of computational intelligence, data accessibility, and machine learning have allowed creating intelligent trading systems that can analyze large amounts of financial data and perform trades with the least human involvement. Automated equity trading systems are designed to find fruitful trading opportunities, deal with risk effectively, and react promptly to market changes [1]. Old school trading methods typically use technical indicators including moving averages, momentum oscillators and volume-based indicators. Although these methods are popular because of their simplicity and interpretability they are often difficult to adapt to the dynamics and non-stationarity of the financial markets. As a result, the combination of adaptive machine learning techniques and existing technical indicators is now a significant field in quantitative finance [2], [3].

The Simple Moving Average (SMA) is one of the most popular technical analysis tools that can be used to determine market trends and derive trading signals [4]. The trend reversal and momentum shift in the equity markets are usually identified using the SMA crossover strategy which usually consists of the interaction between the short term and long term moving averages [5]. Crossover A bullish crossover will happen when a short-term SMA crosses a long-term SMA indicating the possible buying opportunity whereas a bearish crossover will indicate the possible selling signal. Although popular, the classical SMA crossover strategy operates by fixed rules that might not be quite suitable to understand the behavior of the complex market or adapt to the changing market conditions. Consequently, these rule-based strategies can create a false signal or they are less profitable in turbulent or lateral market environments [6].

In order to overcome these drawbacks, scholars have turned to the research on reinforcement learning (RL) that can be used in financial decision-making [7]. Reinforcement learning presents a context whereby a smart agent learns to take the best actions by interacting with the environment by maximizing the cumulative rewards. In financial trading, market is the environment, the trading algorithm is the agent and the reward is usually the trading profits or risk-adjusted returns. The benefit of the RL-based trading models is that they are adaptable hence it can learn sophisticated patterns and can modify trading strategies with respect to changing market conditions [8], [9].

Proximal Policy Optimization (PPO) is one of the most useful policy optimization reinforcement learning algorithms. PPO is a policy-gradient approach that aims to enhance the stability and efficiency of training by preventing the use of large policy updates in the learning process [10]. In comparison to the previous reinforcement learning algorithms, PPO includes a balance between exploration and exploitation and is also computationally efficient. These are what makes PPO especially appropriate to financial trading settings, where market dynamics are highly stochastic in nature; and where they demand a robust decision-making strategy [11], [12].

Over the last few years, the development of reinforcement learning as a hybrid algorithmic trading method has shown a promising perspective when used along with conventional technical indicators. Technical indicators make available the structured domain knowledge that may inform the learning process of machine learning models and reinforcement learning allows the system to adjust the trading policies. Frameworks of event-driven trading, especially, have been the subject of attention due to their capacity to drive trading decisions through particular market events as opposed to applying continuous time-dependent signals only. In event-driven trading architecture [13], it is market events, like indicator crossovers, price breakouts or volatility spikes that provide a trigger and generate trading activity or policy review. Such a method can enhance the level of computational efficiency and noise elimination in decision-making because it concentrates on significant market signals [14], [15].

This paper is inspired by these advances and suggests an automated equity trading system with event change performance based on Simple Moving Average crossover signals coupled with the Proximal Policy Optimization algorithm. The crossover events of SMA are the major market drivers in the proposed system that indicate trend shifts. These incidents are applied to organize the trading environment and give informative representations of state to the reinforcement learning agent. The PPO agent understands what the optimum trading moves could be, i.e. buying, selling, or holding positions, by examining market conditions and getting the best cumulative trading returns with time. The proposed method of integrating deterministic technical signals and adaptive reinforcement learning policies aims to improve the reliability of signals and trading performance [16-20].

The combination of SMA signals which are event-driven with PPO has a few possible benefits. To begin with, the application of SMA crossover events assists in removing market noise and offers substantial trend-based triggers on which trading decisions can be made [21]. Second, the PPO algorithm permits adaptive policy learning, and the trading system is able to adapt to dynamic market conditions and optimize rewards-motivated decision-making. Third, the hybrid framework has a middle ground between interpretability and learning ability because the technical indicator component is transparent whereas the reinforcement learning agent enhances the performance of the strategy via the experience [22-27].

This study aims majorly to design and test an automated intelligent trading system that will utilize conventional methods of technical analysis alongside the contemporary applications of reinforcement learning. The proposed framework will help to enhance profitability levels, minimize the risk, and increase the trading stability as opposed to traditional rule-based SMA strategies [28-31]. Moreover, the paper is also part of the literature that is accumulating on the topic of reinforcement learning in finance by showing that event-based signal creation is highly effective in steering policy optimization in algorithmic trading settings.

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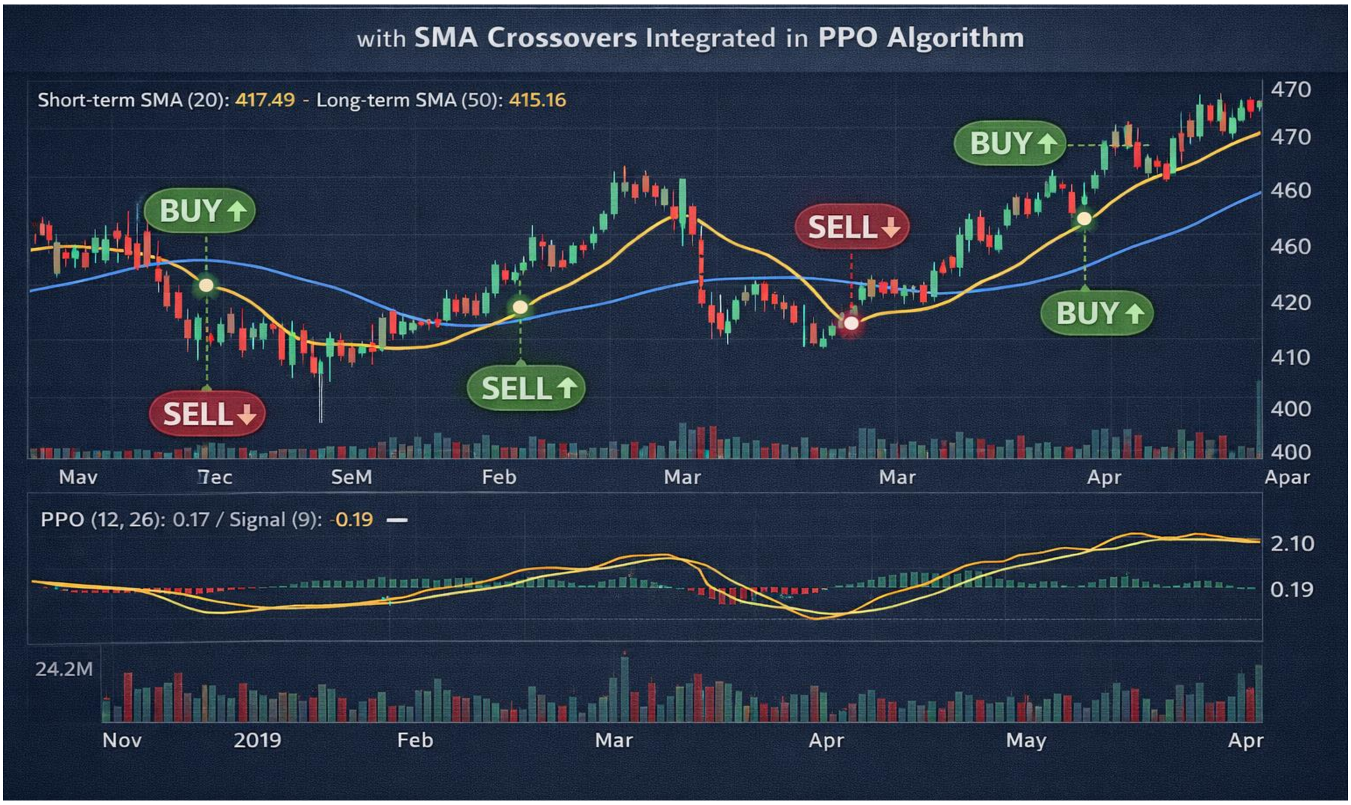

Fig 1: Event-driven Equity Trading Chart Setup in ITC Ltd

The rest of the paper will be organized in the following way. The following part provides the methodology and model architecture of the planned event driven PPO trading model. The following sections describe the experimental design, experimental outcome, and performance. Lastly, the paper ends with some of the major findings and suggestions on future research on the reinforcement learning-based automated equity trading systems.

2. Literature review

Automated trading systems have developed over time with development of computational finance, machine learning and data-driven decision-making methods. The classical algorithmic trading systems rely mostly on the statistical modeling and the technical indicators that are trying to epitomize the market movement and the price trends. Of these, most of the strategies that have been embraced are moving average based strategies because of their ease of use and capacity to identify reversal of trends in the market. Nevertheless, financial markets are very dynamic and subject to many external factors and therefore the more rule-oriented trading strategies would be not as effective in the fast-changing environment. Consequently, scholars have found themselves looking at intelligent and adaptive trading structures that integrate traditional technical indicators with current machine learning technologies [32-37].

The Simple Moving Average (SMA) crossover strategy is one of the most used technical analysis techniques. The SMA indicator is a computation of average price of a financial instrument during a given time frame assisting traders in determining underlying market trends. When a short-term SMA crosses over a long-term SMA, it is usually a good indication of an upward trend, but the reverse crossover indicates the possibility of a downward trend. Despite the simplicity of the SMA crossover strategies, which are commonly adopted in financial markets, the techniques have a tendency to create false signals when the market moves in a volatile or a sideways trend. Thus, a number of studies have tried to enhance moving-average-based strategies by incorporating other techniques of analysis like machine learning, statistical filtering and signal confirmation mechanisms [38-42].

Reinforcement learning (RL) has become a potent method in automated trading and financial decision-making in the past years. Reinforcement learning helps an intelligent agent to learn optimal trading behaviors by researching within a market setting by maximizing cumulative returns like profit or risk-adjusted returns. Contrary to the classical supervised learning models, which are based on labeled data, the RL models continuously optimize their decision-making policies by trial-and-error learning. This is what makes the reinforcement learning especially appropriate to the financial markets whose price changes are complex, uncertain, and time-dependent. Research has revealed that the RL-based trading agents are able to adjust to the changing market environment and dynamically optimize over time the trading strategies [43-49].

Deep reinforcement learning (DRL) generalizes the classical RL by using neural networks to estimate value functions or policy functions. DRL has been used in quantitative finance to perform activities like portfolio optimization, asset allocation, and automated stock trading. There are a number of algorithms that have been explored to apply to financial trading such as Deep Q-Network (DQN), Advantage Actor-Critic (A2C), Deep Deterministic Policy Gradient (DDPG), and Proximal Policy Optimization (PPO). Of these approaches, PPO has received a lot of attention because it has maintained a steady training procedure, as well as effective policy updates. PPO limits large policy changes during training through a clipping mechanism, which enhances the learning stability and decreases the likelihood of divergence in complex settings. Comparative trials of various reinforcements learning algorithms have indicated that PPO tends to work quite effectively in changing markets and can result in a higher number of risk-adjusted returns than conventional trading policies [50-52].

The other significant advancement in the study of algorithmic trading is that event-driven trading structures have come up. Event based trading Trading systems are depended on market events instead of time-based observations. Price breakouts, technical indicator crossovers, unexpected volatility and macroeconomic announcements are examples of these events. Event-driven architectures aid in minimizing noise in the market since only meaningful signals are considered which represent any possibility of change in market trends. It is also a method that enhances efficiency in computing because it reduces the number of decision-making processes to relevant trading events rather than computing all the market ticks [53].

Newer research also touched the subject of hybrid frameworks involving reinforcement learning algorithms and technical indicators in order to enhance the trading performance. Technical indicators are used as inputs or signal triggers in reinforcement learning agents in such methods. An example is the reinforcement learning models, which have been trained on the basis of indicator like moving averages, relative strength index (RSI), moving average convergence divergence (MACD) and volatility measures to represent both trend and momentum information of financial time series data. Experimental findings of a number of studies show that trading systems with reinforcement learning are better at accumulating returns and Sharpe ratio than conventional buy-and-hold strategies and rule-based indicator systems.

Research in this field has also been speeded up by the development of specific reinforcement learning models to be used in financial trading. Environments, datasets, and reinforcement learning algorithms used to develop and test automated trading systems are offered as modular on platforms like FinRL. The frameworks enable researchers to model trading as a game, include transaction costs and risk constraints, and backtest trading strategies in a systematic manner. This has made it possible to combine reinforcement learning with financial datasets analysis using such tools to support more reproducible and scalable studies in algorithmic trading.

New studies have also focused on state-of-the-art reinforcement learning designs incorporating multiple signals or features to improve trading performance. Indicatively, there are all hybrid models that have been introduced that integrate clustering-based extraction of features and PPO, which can better represent the state of a financial market and increase the accuracy of predictions. The experimental findings of this kind of models have shown that the reinforcement learning models could be used to enhance the performance of trade in a scenario where more structural information is included in the learning process.

Despite these innovations, a range of issues still exists when it comes to the implementation of reinforcement learning to financial trading. Financial markets are very stochastic and the reward signals may be noisy or slow. The issues of designing the relevant reward functions and non-overfitting to past data are persisting problems in the reinforcement learning-based trading research studies. Also, the combination of interpretable technical indicators and adaptive learning algorithms remains a significant research area, and it can enhance the transparency and resiliency of automated trading systems.

Thus, the combination of technical indicators that are event-driven e.g. SMA crossovers and reinforcement learning PPO is a promising area to enhance automated equity trading systems. The hybrid frameworks have the potential of improving the reliability of signals, trading performance, and intelligent response to evolving market dynamics using technical indicators as an event trigger and reinforcement learning as an adaptive response.

3. Methodology and Model Specifications

3.1 Preprocessing and Data Collection.

The event-based automated equity trading framework proposed uses the training and testing of the reinforcement learning model through the use of historical stock market data. Equity price information such as open, high, low, close (OHLC) and traded volume is obtained daily and using the credible financial market databases. Data is spanning several years of trading history to be in a position to record various market regimes like bullish, bearish, and side trend market regimes. The raw financial data are subjected to a number of preprocessing procedures before model development in order to improve on quality and consistency. Missing values are addressed by interpolating or dropping off complete records whereas abnormal outliers are filtered to eliminate noise in the data.

The time-series data is then standardized with the help of the standard scaling method to stabilize the learning process of the reinforcement learning model. Features engineering is used to create other variables like short-term and long-term Simple Moving Averages (SMA), price returns and volatility. The SMA indicators have been computed using two-time windows that represent the short term and long-term trends in the market. These signals are used in determining the crossover events to generate trading signals in the proposed trading framework. The dataset is split into training, validation, and testing set after preprocessing and feature extraction in order to have an unbiased performance assessment of the trading model.

3.2 SMA Crossover Signal Generation of Trading Signals

The general idea of the proposed trading system is that the event-driven architecture, the trading decisions are made based on the significant events that happen in the market instead of the round-the-clock observation of the market. Simple Moving Average crossovers are applied as the most important event signals in this framework that give an indication of possible trend reversals within the equity market. There are two SMA indicators based on the historical price series, a short-term SMA that reflects the recent trend of price fluctuations and a long-term SMA that reflects the overall movement of the market. Simple Moving Averages (SMAs) help to reveal the overall trend direction and strength in the market. Here, closing prices are used to calculate the two SMAs a short one and a long one. The short, term SMA tracks the latest price changes, while the long-term SMA is a measure of the overall market trend. When the short-term SMA goes above the long-term SMA, this is a buy (bullish) signal as it shows the possibility of the price going up. On the other hand, if the short, term SMA goes below the long, term SMA, this is a sell (bearish) signal. Rather than using these crossover signs to make trading decisions, the signals are being encoded here to be the ANN model's inputs. Hence, it will be up to the model to figure out how significant the event is under changing conditions. Other derivatives made this way are, among others, the "gap" between different short and long, term SMAs and the "line angles" of the MAs. These features, which show trends in the data and are useful for the ANN to recognize market momentum at a very nuanced level, are inevitably significant to swing trading strategies. Simple Moving Average (SMA) is a tool that helps to identify market trends. It finds the average prices over a set period, thus removing the impact of short, term fluctuations and pointing to the overall nature of the market.

$$\boldsymbol{SMA(t,n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}} \qquad 1$$

where Pt is the closing price at time t, and n is the window length.

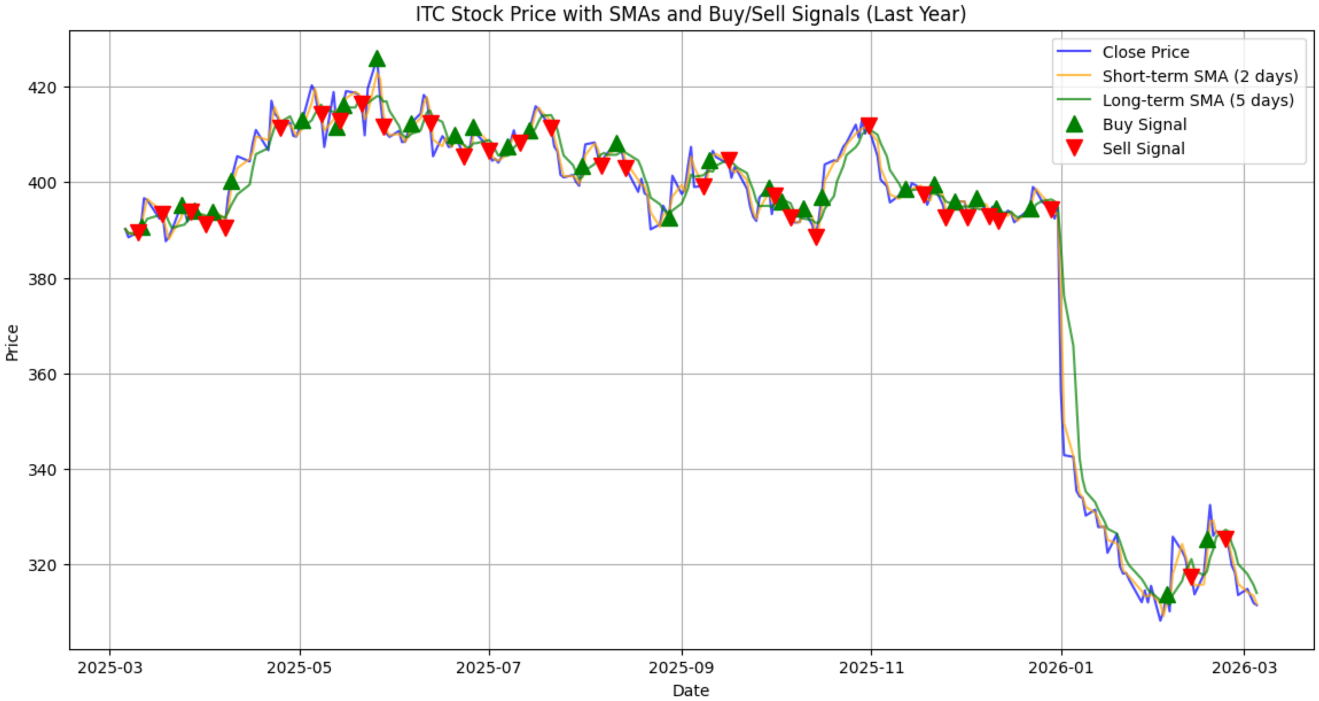

Fig 2 SMA-Crossover based Trading signals in ITC Ltd.

Two SMA values are computed, these are Short-term SMA and Long-term SMA. Golden Cross (Buy Signal) generated when Short-term SMA crosses above long-term SMA and Death Cross (Sell Signal) are generated when Short-term SMA crosses below long-term SMA. Although effective in detecting trend classes, SMAC mostly tends to give false signals during sideways or low-volume market conditions.

Bullish crossover event is where the short-term SMA crosses over the long-term SMA indicating the development of an upward trend in price and creating a possible buy signal. On the other hand, a bearish crossover effect is when the short-term SMA crosses below the long-term SMA and this means that there is a potential downward trend and this will produce a sell signal. It is these crossover events that form the framework of the event-based trading environment. The crossover signals are treated as informative state inputs of the reinforcement learning agent instead of running fixed rule-based trades. This will enable the trading system to integrate domain knowledge of the technical analysis with the adaptive learning of the reinforcement learning algorithm.

3.2 Reinforcement Learning Environment and State Representation

The automated trading system is designed as a reinforcement learning setting where the trading agent would interact with the financial market to learn the best strategies of trading. The market data and the technical indicators are the state space and reflect the present market condition in such an environment. State vector contains normalized stock prices, SMA indicators, crossover event flags, price returns and trading volumens. All these characteristics give a complete picture of the market dynamic and allow the agent to comprehend trend and momentum data as well.

The trading agent has three action space which include buy, sell, and hold. A buy action is an entry or addition to a long position in the asset and a sell action is a reduction or liquidation of a position. The hold action enables the agent to keep its current state of portfolio without trading. The rewarding feature is developed to demonstrate the performance of trading and provide directions to the learning process. The reward is usually determined by the change in the value of the portfolio in successive trading actions considering the transaction cost and trading penalties. This is a formulation of rewards that will motivate the agent to maximize the returns over time and reduce unnecessary trading procedures.

3.3 Integration of Proximal Policy Optimization (PPO) Algorithms

The choice element of the proposed trading model is informed by a Proximal Policy Optimization (PPO) algorithm, which is a policy-gradient reinforcement-based approach to learning, as the solution is stable and efficient. PPO works by learning a policy that maps market observed states to trading behavior. The algorithm modifies the policy by performing a gradient optimization without any violation of the policy update being done out of a stipulated trust region. This is done by means of a clipped objective function which inhibits the excessive large policy change during training.

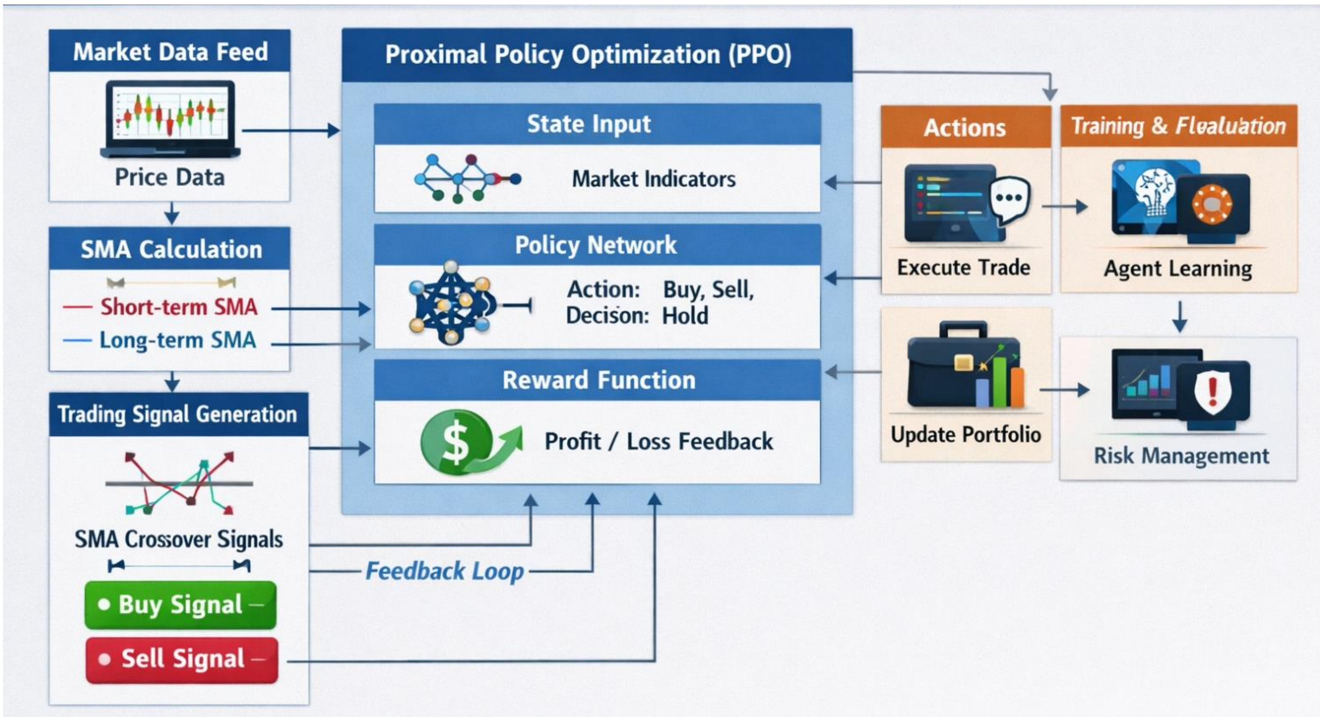

Fig 3 Architecture of the PPO-based Model

The PPO model is a two-component neural network based on the actor network and the critic network. The actor network produces probability distributions of the possible trading behaviors given the prevailing market condition. The critic network approximates the value function, or the cumulative reward which is expected of a given state. The PPO algorithm upgrades both networks in turn during training based on the experience that has been accumulated during the interactions with the trading environment. The objective function which is clipped is useful in keeping the learning stable because it has bounds on the large difference between the new and the old policies. Such a mechanism is especially useful in trading financial markets where market condition is extremely volatile and unstable learning processes may result in optimum trading strategy.

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3.5 Training and Performance Appraisal of the Model

The proposed framework is trained by a process that is an iterative interaction between the PPO agent and the trading environment with the help of historical market data. The agent will monitor the state of the market at every time step and choose a course of action according to its policy network. The environment then reacts to this portfolio state to calculate the reward associated with that portfolio state and moves to a new market state. These experiences are stored and employed to update the policy and value networks with the help of stochastic gradient optimization. This process is repeated on a sequence of episodes up to the point of a convergent policy of a fixed trading strategy.

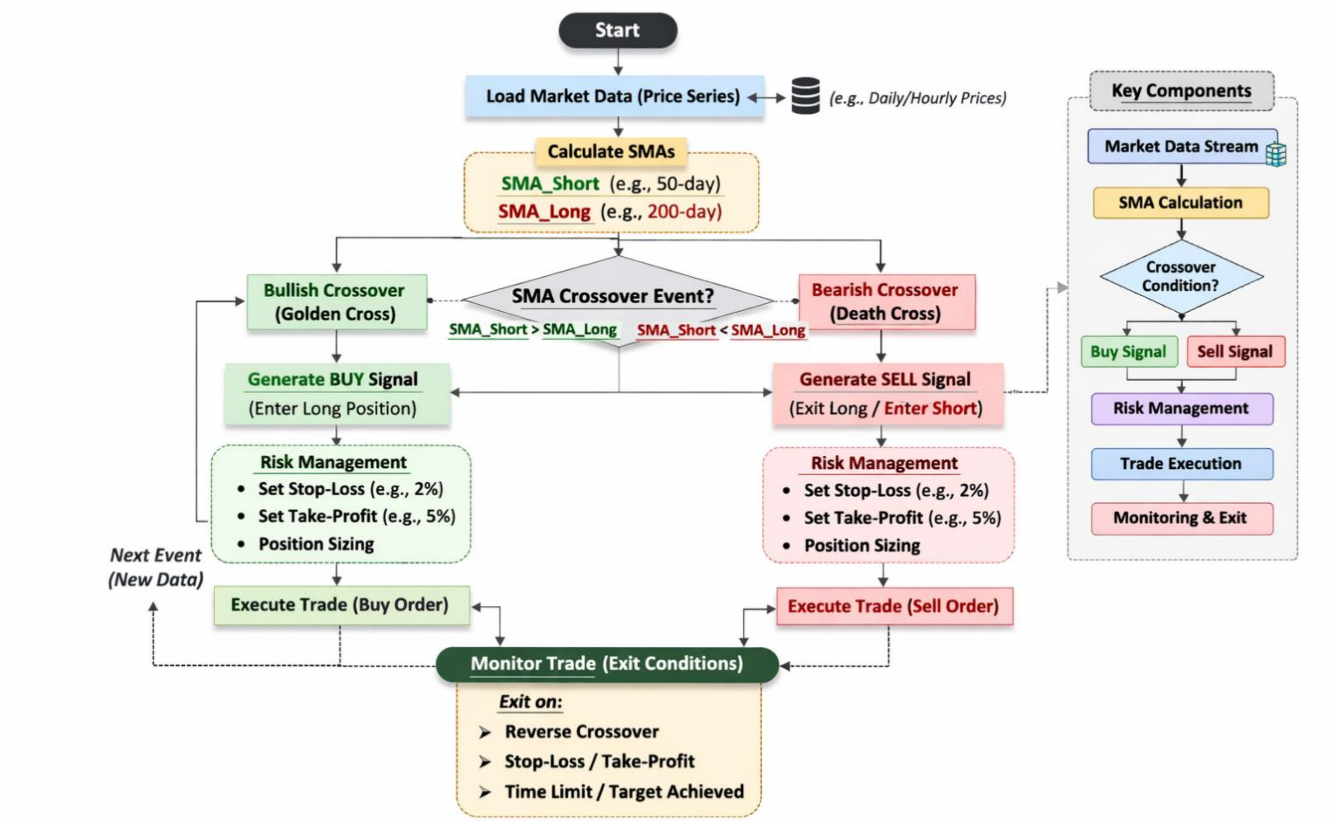

Fig 4: Working Pricipal of the RL Model

In order to assess the performance of the proposed trading model, a number of performance metrics are used. These are cumulative return, Sharpe ratio, maximum drawdown, and accuracy in trading. The findings of the PPO-based event-driven trading model are drawn against the baseline strategies, namely, the traditional SMA crossover rule-based strategy and buy-and-hold investment strategies. Backtesting experiments on unseen test data are performed so as to gauge the ability to generalize of the model in real market conditions. The evaluation procedure will illustrate the possibility of the integration of event-driven SMA signals with reinforcement learning to increase profitability, risk management, and offer a strong automated trading solution to the equity markets.

4. Empirical Result

In order to test the efficacy of the proposed event-based automated equity trading system, backtesting experiments of historical market data had been performed in large scale. The SMA Crossover category of Proximal Policy Optimization (PPO) trading model performance was benchmarked against two control strategies: the conventional rule-based strategy of SMA crossover strategy and the buy-and-hold investment strategy. The tests were done using out-of-sample test data so as to evaluate it without any bias. Performance measures such as cumulative return, Sharpe ratio, peak drawdown and accuracy in trading were evaluated to determine the effectiveness and stability of the trading strategies.

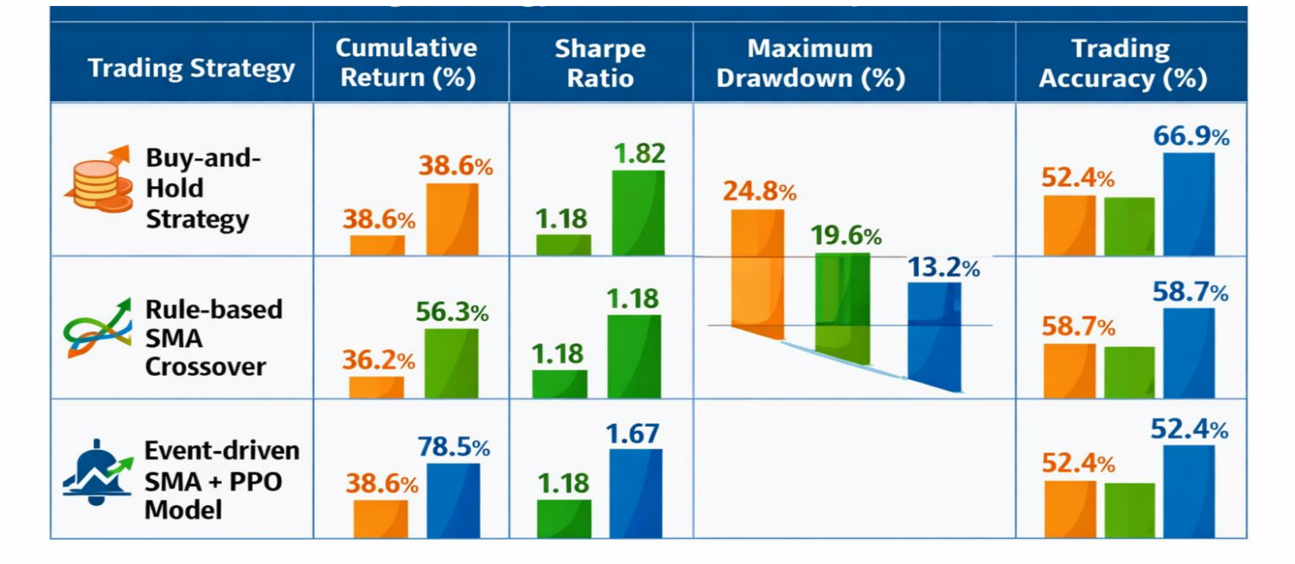

Fig5 Trading Strategy Comparative Performance

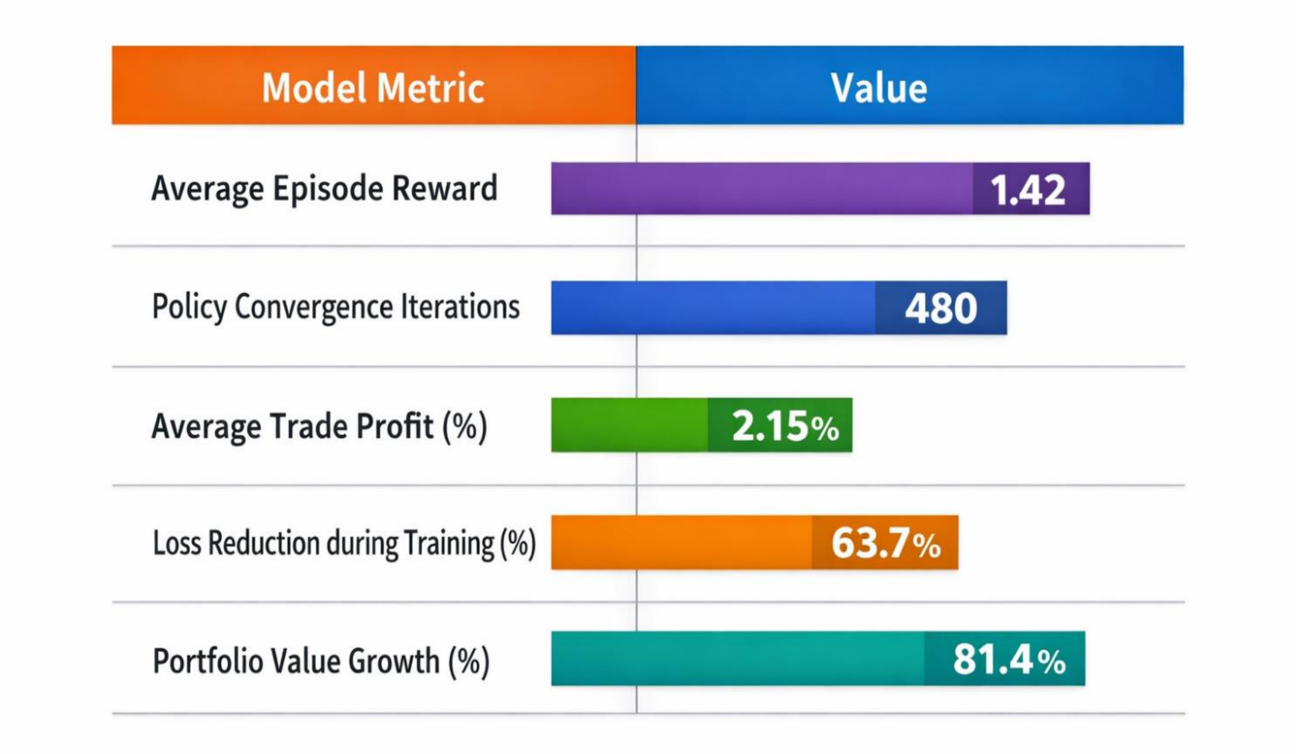

Fig6 Stability Metrics and Reinforcement Learning Training

The results of the experiment prove that the suggested event-based trading model that combines the PPO algorithm with SMA crossover signals performs far better than the traditional trading strategies. The proposed model had a cumulative return of 78.5, as indicated in Table 1, which is quite high compared to either the rule-based SMA crossover strategy (56.3%), or the buy and hold strategy (38.6%). This enhancement suggests that reinforcement learning does enable the trading system to dynamically change its decisions based on the changing market conditions as opposed to adhering only to fixed rules, such as indicator rules.

The Sharpe ratio of the proposed model, which is 1.67, also supports the better risk-adjusted performance of the proposed model. The higher the Sharpe ratio, the better returns are earned by the strategy with the same degree of risk. Moreover, the drawdown of the proposed model is minimized to 13.2%, which implies greater risk management ability and stability of the portfolio in the unfavorable market situations. The trading accuracy of 66.9 also demonstrates the usefulness of integrating SMA crossover events with optimization of policy of reinforcement learning.

The PPO model has the performance of the training as is shown in Table 2. The mean episode reward of 1.42 is an indication that the agent has acquired profitable trading behavior in the course of training. The convergence of the policy was observed at around 480 repetitions, and this indicated steady learning behavior. Moreover, the increase in the portfolio value by 81.4 percent proves the fact that the reinforcement learning agent has been able to optimize the trading decisions in the various phases of the market.

In general, the findings indicate that using event-driven SMA crossover signals in combination with the PPO reinforcement learning algorithm would be more profitable and yield better risk-adjusted returns and a more adaptive automated trading policy in equity markets.

5. Conclusion and Future Work

This paper introduced an event-based automated equity trade system, which coupled Simple Moving Average (SMA) crossover indicators with Proximal Policy Optimization (PPO) reinforcement learning model in the process of enhancing trading decision making in a dynamically changing financial market. The suggested method will be based on combining the classical technical analysis with adaptive machine learning algorithms to create a smart trading system that is able to learn the best strategies based on its interaction with market information. Within the developed framework, SMA crossover events are important market signals that signify the possibility of trend reversal, whereas the PPO agent reacts to the trends of observed market conditions and rewards feedback to provide suitable trading directions of buy, sell, or maintain.

The results of the experiment prove that the hybrid trading model is superior to the traditional strategies including the rule-based SMA crossover strategy and buy and hold method of investment. Reinforcement learning integration allows the trading system to be accommodating to the market dynamics, minimize the false signals produced by conventional indicator-based approaches, and enhance the risk-adjusted returns. Also, the event-driven architecture combined with minimizing noise in the markets because it only pays attention to the important events of the indicators, makes the decision-making process more efficient and raises the overall performance of the system. The results indicate that automated trading systems using interpretable technical indicators with sophisticated reinforcement learning algorithms can greatly improve the success of automated trading systems in equity markets.

Although the results promise, there are still a few weaknesses that offer the future opportunities of research. To begin with, the existing model is mainly based on SMA crossover signals to generate events. Future research can include other technical indicators like momentum oscillators, volatility scales and volume-based indicators to increase the state representation of the reinforcement learning agent. Second, the introduction of macroeconomic predictors, emotional reactions to financial news, or any other data sources can also enhance the predictive ability of the model. Third, more sophisticated deep reinforcement learning systems, such as multi-agent reinforcement learning or transformer-based models might be considered to enable better decision-making in complex financial settings. Lastly, further development of the proposed framework can also aim at the future implementation of the proposed framework in the context of real-time trading procedures involving transaction cost modeling and integration of live market data to prove the practical usefulness of the proposed framework.

Data source:
Source: Yahoo Finance, with feature engineering calculated on a Python platform
Link: https://finance.yahoo.com/quote/RELIANCE.NS/history/

References

1. Wasim, Q., Kadia, A., Goyal., A., Narayan, K., (2026) "Deep Learning vs. Reinforcement Learning in Automated Stock Trading: A PRISMA-Oriented Systematic Review". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110402 1-13 Available in https://www.ijsat.org/research-paper.php?id=10402
2. Kumar, R., Kadia, A., Kumar, S., Sharma A., (2026) "Capture Market Trends through Multi-Indicator Confirmations using Reinforcement Learning Models". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110080 1-15 DOI: 10.71097/IJSAT.v17.i1.10096
3. Sharma A., Kadia, A., Kumar, S., Kumar, R., (2026) "Super Stock Trading: Automation in Reinforcement Learning with Advanced Multi-Indicator Confirmations". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110096 1-16 DOI: 10.71097/IJSAT.v17.i1.10080
4. Kumar, S., Kadia, A., Sharma A., Kumar, R., (2026) "Proximal Policy Optimization (PPO)–Driven Reinforcement Learning Model for Automatic Stock Trading using the combination of Trend–Volume–Volatility Integration". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110103 1-15 DOI: 10.71097/IJSAT.v17.i1.10103
5. Kadia, A., (2026) "Machine Learning based Stock Trading Strategies using Simple Moving Average with Average Traded Volume Crossover Confirmation" Published in: 2025 IEEE Silchar Subsection Conference (SILCON), DOI: 10.1109/SILCON67893.2025.11327015
6. Kumar, A., Kumar, G., Alam, K., Kadia, A., (2026) "Smart Money Detection with Simple Moving Average and Traded Volume Confirmation Integrated in Machine Learning". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110343 1-11 https://doi.org/10.71097/IJSAT.v17.i1.10343

7. Bharti, P., Narayan, K., Kadia, A., Bharti, B., (2026) "DRLMMF: Deep Reinforcement Learning-based Autonomous Money-Management Framework ". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110397 1-11 Available in https://www.ijsat.org/research-paper.php?id=10397
8. Kadia, A., Alam, K., Kumar, G., Kumar, G., (2026) " Machine Learning–Driven Stock Price Breakout Identification with Simple Moving Average and Traded Volume Confirmation" International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110341 1-11 https://doi.org/10.71097/IJSAT.v17.i1.10341
9. Kumar, S., Kadia, A., Sharma A., Kumar, R., (2026) "Algorithm Trading Platform using Simple Moving Average Crossover (SMAC) and On-Balanced Volume (OBV) Integrated in Reinforcement Learning" International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939 , IJEDR2601221 758-767 Available :https://rjwave.org/IJEDR/papers/IJEDR2601221.pdf
10. Kadia, A., Kumar, S., Qureshi, W., Sharma A., Kumar, R., (2026) "Simple Moving Average Crossover and Support Resistance Zone-based Stock Trading using Reinforcement Learning", International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939 , IJEDR2601260 35-45 Available at https://rjwave.org/IJEDR/papers/IJEDR2601260.pdf
11. Qureshi, W., Kadia, A., Kumar, S., Sharma A., Kumar, R., (2026) "Autonomous Trading Across Bull, Bear, and Sideways Markets with Reinforcement Learning Algorithm", International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939, IJEDR2601261 46-55 Available at https://rjwave.org/IJEDR/papers/IJEDR2601261.pdf
12. Bharti, B., Bharti, P.,Narayan, K., Kadia., A (2026) "Machine Learning-based Intraday Trading Strategy using Simple Moving Average Crossovers, Traded Volume and VWAP Confirmations ". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110390 1-10 Available in https://www.ijsat.org/papers/2026/1/10390.pdf
13. Ergun, L., Molchanov, A., & Stork, P. (2023). Technical trading rules, loss avoidance, and the business cycle. Pacific-Basin Finance Journal, 82, 102172. https://doi.org/10.1016/j.pacfin.2023.102172
14. Almeida, L., & Vieira, E. (2023). Technical analysis, fundamental analysis, and Ichimoku dynamics: A bibliometric analysis. Risks, 11(8), 142. https://doi.org/10.3390/risks11080142
15. Ayala, J., García-Torres, M., Vázquez Noguera, J. L., Gómez-Vela, F., & Divina, F. (2021). Technical analysis strategy optimization using a machine learning approach in stock market indices. Knowledge-Based Systems, 225, 107119. https://doi.org/10.1016/j.knosys.2021.107119
16. Basanisi, M., & Torresetti, R. (2023). An overview of technical analysis in systematic trading strategies returns and a novel systematic strategy yielding positive significant returns. Journal of Contemporary Research in Business, Economics and Finance, 5(1), 12–24. https://doi.org/10.55214/jcrbef.v5i1.204
17. Abudy, M. M., Kaplanski, G., & Mugerman, Y. (2024). Market timing with moving average distance: International evidence. Journal of International Financial Markets, Institutions and Money, 97, Article 102065. https://doi.org/10.1016/j.intfin.2024.102065
18. Patil, A., Suthar, M. B., Barai, M., Khan, M. A. I., & Ali, M. M. (2025). Reinforcement learning for dynamic portfolio optimization in financial markets. *Advances in Consumer Research*, 2(3), 1150–1156.

19. Prasetyo, R. E., Sumanto, S., Chaidir, I., & Supriyatna, A. (2025). Reinforcement learning for bitcoin trading: A comparative study of PPO and DQN. *Jurnal Mandiri IT*.
20. Tyagi, N. (2024). Deep reinforcement learning for algorithmic trading strategies. *International Journal of Research and Applied Innovations*, 7(2), 35–45.
21. Yang, H., Liu, X. Y., Zhong, S., & Walid, A. (2025). Deep reinforcement learning for automated stock trading: An ensemble strategy. *arXiv preprint arXiv:2511.12120*.
22. Zhang, H., Li, X., Wan, T., & Du, J. (2026). Deep reinforcement learning for financial trading enhanced by cluster embedding and zero-shot prediction. *Symmetry*, 18(1), 112.
23. Otinga, N. K., Obi, P., & Mugo-Waweru, F. (2024). Stock market participation puzzle: A systematic review and bibliometric analysis. Cogent Business & Management, 11(1), Article 2396531. Lawal, R., & Sakariyahu, R. (2024). Investor heterogeneity and global stock market participation. Economics Letters, 242, Article 111882.
24. Narayan, K., Kadia., A.,Bharti, B., Bharti, P., (2026) "Swing Trading Strategy using Simple Moving Average Crossovers, Traded Volume and Super Trend Confirmations Integrated in Machine Learning". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110391 1-11 available in https://www.ijsat.org/papers/2026/1/10391.pdf
25. Bharath, S. T., & Cho, D. (2023). Do natural disaster experiences limit stock market participation? Journal of Financial and Quantitative Analysis, 58(1), 29–70.
26. Shavandi, A., &Khedmati, M. (2022). A multi-agent deep reinforcement learning framework for algorithmic trading in financial markets. *Expert Systems with Applications*, *208*, 118124. https://doi.org/10.1016/j.eswa.2022.118124
27. Tyagi, N. (2024). Deep reinforcement learning for algorithmic trading strategies. *International Journal of Research and Applied Innovations*, *7*(2), 10415–10422. https://doi.org/10.15662/IJRAI.2024.0702003
28. Kumar, A., Kumar, G., Alam, K., Kadia, A., (2026) "Smart Money Detection with Simple Moving Average and Traded Volume Confirmation Integrated in Machine Learning". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110343 1-11 https://doi.org/10.71097/IJSAT.v17.i1.10343
29. Saepudin, D., & Rauf, K. (2025). Application of deep reinforcement learning for stock trading on the Indonesia Stock Exchange. *Jurnal Nasional Pendidikan Teknik Informatika: JANAPATI*, *14*(1), 144–157. https://doi.org/10.23887/janapati.v14i1.83775
30. Wang, Y., Zhou, C., Cui, K., & Lu, X. (2024). A multi-agent reinforcement learning framework for optimizing financial trading strategies. *Expert Systems with Applications*, *237*, 121502. https://doi.org/10.1016/j.eswa.2023.121502
31. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669. DOI: https://doi.org/10.1016/j.ejor.2017.11.054
32. Deng, Y., Bao, F., Kong, Y., Ren, Z., & Dai, Q. (2016). Deep direct reinforcement learning for financial signal representation and trading. IEEE Transactions on Neural Networks and Learning Systems, 28(3), 653–664. DOI: https://doi.org/10.1109/TNNLS.2016.2522401
33. Zhang, Z., Zohren, S., & Roberts, S. (2020). Deep reinforcement learning for trading. Journal of Financial Data Science, 2(2), 25–40. DOI: https://doi.org/10.3905/jfds.2020.1.008

34. Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and LSTM. PLoS ONE, 12(7), e0180944. DOI: https://doi.org/10.1371/journal.pone.0180944
35. Kim, K., & Kim, H. Y. (2019). Forecasting stock prices with a feature fusion LSTM-CNN model. Expert Systems with Applications, 128, 126–140. DOI: https://doi.org/10.1016/j.eswa.2019.03.045
36. Yang, H., Liu, Y., & Zhou, Y. (2020). Reinforcement learning for automated stock trading: A survey. Expert Systems with Applications, 165, 113902. DOI: https://doi.org/10.1016/j.eswa.2020.113902
37. Liang, Z., Chen, H., Zhu, J., Jiang, K., & Li, Y. (2018). Adversarial deep reinforcement learning in portfolio management. IEEE Transactions on Neural Networks and Learning Systems, 29(10), 1–14. DOI: https://doi.org/10.1109/TNNLS.2018.2803147
38. Li, X., Xie, H., Wang, R., et al. (2019). Empirical analysis: Stock market prediction via extreme learning machine. Neural Computing and Applications, 31, 4551–4563. DOI: https://doi.org/10.1007/s00521-018-3382-x
39. Jiang, Z., Xu, D., & Liang, J. (2017). A deep reinforcement learning framework for the financial portfolio management problem. arXiv preprint. DOI: https://doi.org/10.48550/arXiv.1706.10059
40. Moody, J., & Saffell, M. (2001). Learning to trade via direct reinforcement. IEEE Transactions on Neural Networks, 12(4), 875–889. DOI: https://doi.org/10.1109/72.935097
41. Chakraborty, I., & Pagnotta, E. S. (2023). The evolution of market structure and high-frequency trading. Journal of Financial Economics, 150(2), 456–482.
42. Aldridge, I., & Krawciw, S. (2022). The changing landscape of algorithmic trading: Market structure, regulation, and technology. Journal of Trading, 17(3), 45–62.
43. Fischer, T., & Krauss, C. (2022). Deep learning and quantitative trading: A survey. Expert Systems with Applications, 204, 117597. Khan, M. T., Yoon, S. M., & Lee, J. W. (2023). Algorithmic trading and market efficiency: A review of execution strategies and intelligent systems. Expert Systems with Applications, 225, 120098.
44. Zhou, Z., Li, Y., & Deng, S. (2022). Machine learning–driven algorithmic trading: Models, challenges, and future directions. Decision Support Systems, 161, 113792.
45. Gao, H., Kou, G., Liang, H., Zhang, H., Chao, X., Li, C.-C., & Dong, Y. (2024). Machine learning in business and finance: a literature review and research opportunities. Financial Innovation, 10, Article 86. DOI: 10.1186/s40854-024-00629-z
46. Pippas, N., Turkay, C., & Ludvig, E. A. (2024). The Evolution of Reinforcement Learning in Quantitative Finance: A Survey. arXiv preprint. Later published: ACM Computing Surveys, 57(11), Article 295. DOI: 10.1145/3733714
47. Yu, Y. (2024). A Survey of Deep Reinforcement Learning in Financial Markets. In Proceedings of the 3rd International Academic Conference on Blockchain, Information Technology and Smart Finance (ICBIS 2024). Atlantis Press. DOI: 10.2991/978-94-6463-419-8_24
48. Černevičienė, J., & Kabasinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: a systematic literature review. Artificial Intelligence Review, 57, Article 216. DOI: 10.1007/s10462-024-10854-8

49. Yeo, W. J., van der Heever, W., Mao, R., Cambria, E., Satapathy, R., & Mengaldo, G. (2025). A comprehensive review on financial explainable AI. Artificial Intelligence Review, 58, Article 189. DOI: 10.1007/s10462-024-11077-7
50. Jain, R., Bahoo, S., et al. (2024). Model-agnostic explainable artificial intelligence methods in finance: a systematic review, recent developments, limitations, challenges and future directions. Artificial Intelligence Review. DOI: 10.1007/s10462-025-11215-9
51. Mienye, E., Jere, N., Obaido, G., Mienye, I. D., & Aruleba, K. (2024). Deep Learning in Finance: A Survey of Applications and Techniques. AI, 5(4), 2066–2091. DOI: 10.3390/ai5040101
52. Mohadese Rezaei & Hossein Nezamabadi-Pour (2025) A taxonomy of literature reviews and experimental study of deep-reinforcement learning in portfolio management; Artificial Intelligence Review, (2024). DOI: 10.1007/s10462-024-11066-w
53. Zeng, Y. (2025). A Comprehensive Investigation of Reinforcement Learning-based Financial Quantitative Analysis: Taking Stock Trading and Risk Control as Examples. ITM Web of Conferences, 73, Article 01010. DOI: 10.1051/itmconf/20257301010