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Smart Stock Trading using an Advanced Combination of Technical Indicators with Volume Confirmation Integrated in Reinforcement Learning

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Abstract

The study deals with a very important aspect of a country, the Stock Market (SM), which is the financial backbone of an economy. Nowadays, on average, 1/4th population is associated with the stock market, directly or indirectly, through mutual funds. The research integrates traditional technical analysis with cutting-edge reinforcement learning to improve the trading experiences of the traders and generate more returns. The proposed study is based on Simple Moving Average (SMA) crossover along with Average Traded Volume (ATV) and Relative Strength Index (RSI) confirmations of SMA crossover signals. SMA is the main signal generator that generates buy and sell signals during Golden Crossover (GC) and Death Crossover (DC), respectively. When this GC or DC appears with rising volume, ATV in the upwards direction confirms buy or sell signals. There is a very low probability of sustaining the GC and DC signals without high volume. Further, the signals are verified with RSI development to improve the market prediction level. These multi-indicator-based signals are executed through a Reinforcement Learning (RL) based algorithm to train the system in different market conditions to generate maximum profit. Back testing is done on 5 years of historical data of 10 large-cap stocks listed in the National Stock Exchange (NSE) in different time frames to compare the accuracy, Return on Investment (RoI), Sharpe ratio and Sortino ratio. The model was able to generate 85.00%, 78.35%,71.27 % accurate signals in daily, hourly and five-minute time frames with 260%,29%,4.92% RoI in 5 years, 1 year and 1 month, respectively. The study focuses on the integration of smart rule-based indicators with an advanced reinforcement learning algorithm for automation.

Keywords: Stock Market (SM), Simple Moving Average (SMA), Relative Strength Index (RSI), Reinforcement Learning (RL), Automated Trading, Average Traded Volume (ATV), National Stock Exchange (NSE)

1. Introduction

The stock market is the platform where companies raise funds from different types of investors from within the country or outside. Investors/traders are investing here for their profit, so that their invested company makes profit growth, and gets significant profit. But in reality, the scenario is different; there are several factors affecting the stock price. The stock market is a dynamic and very complex financial place, every moment there is generated huge amount of data described by Sudhakar et al. (2020) [1]. It is a very difficult job for investors or traders to analyze the data and predict the market trends. Traditionally there used number of indicators, technical and fundamental analysis to generate buy, sell or hold signals manually. Fundamental analysis described by Li et al. (2020) [2]. In this proposed research machine learning (ML) concept has been integrated with the analysis to develop a powerful automated signal generator to enhance decision-making power.

In the world of automation, stock market participants are very much interested in a system that can analyse a huge amount of data and help to take a machine-driven automated signal, which is more accurate and provides them high RoI. For this purpose, the proposed study will develop an automation system that can generate an accurate signal. The study combines a hybrid of largely used, more accurate technical analysis indicators, SMA crossover, along with ATV and RSI confirmations. To make the generator an automated rule based, and lean form of experience-based RL machine learning algorithm.

The SMA is a basic indicator to detect trends in stock. Its calculation of SMA is very simple. It is the average of historical closing prices in some time frame. For example, 10Days sum of closing price divided by 10 is 10D SMA. When two SMA lines of different frequencies cross each other called SMA crossover. Golden Crossover (GC) appears when the SMA line of low frequency crosses the higher frequency line on the upside, generating buy or bullish signals. Similarly sell signal or a bearish trend signal is generated during Death Crossover (DC), when the lower frequency SMA crosses the SMA with a higher frequency downside. SMA indicates trends of market behaviour, but SMA crossover generates a reversal point of trends. SMA is a very nice indicator to generate buy and sell signals. But it is too noisy. The indicators are not very effective during a sideways market. To increase the reliability, the study integrated SMA with stock volume analysis and relative strength index confirmation.

Traded volume is the amount of shares buy/sell or traded in a particular time frame. SMA crossover with rising volume or positive slope in the ATV line confirms the signals generated by SMA are not operator-driven, with very little possibility of being a fake signal. The second layer of confirmation is provided by RSI to generate more accuracy. If RSI is greater than 70 means overbought, buy signals should be avoided during that time, whereas RSI less than 30 means oversold. The sell signal should be avoided during that time.

To develop powerful decision-making by using patterns and dependencies in its market time series data, be imperceptible to investors or traders, as focused by Yang et al, (2024) [3]. Machine learning based trading strategies work on live historical data that is fetched from Yahoo Finance. The system-wide range of historical data, after filtering and analyzing feature and technical indicators, it passed to the ML model. The most important feature the system considers is Exponential Moving Average (EMA) crossovers described by Wagdi et al. (2023) [4]. Dey et al. (2024) proposed an automated trading strategy that is based on moving average (MA), Stochastic Relative Strength Index (SRSI)and price-volume actions, showing improved trading signal accuracy in the Indian and Malaysian share markets [5]. ML-based automated techniques analyse a huge volume of historical data and make decisions, which is very difficult in the traditional method. ML algorithms are integrated with technical indicators, moving average (MA) and Stochastic Relative Strength Index (SRSI), to generate buy and sell signals. ML-based automated trading techniques accelerate the momentum of trading capabilities of traders and investors largely due to the advancement of algo models, market data expansion and faster computations of ML models. Khuwaja et al., (2019) proposed that AI models show wonderful capabilities to analyze complex, dynamic and nonlinear market data [6]. Ali et al., (2025) and Rahman et al. (2025) proposed advanced ML models to enhance the performance of the model by considering temporal analysis and a hybrid combined technique have generated more accurate signals by using price and volume indicators [7], [8]. The basic algorithm Long Short-Term Memory (LSTM) deep learning-based network application showed a wonderful performance in capturing financial data and analyzing the dependencies of price movement, suggested by Fischer et al., (2018) [9].

Figure 1: Machine learning based automated trading strategies

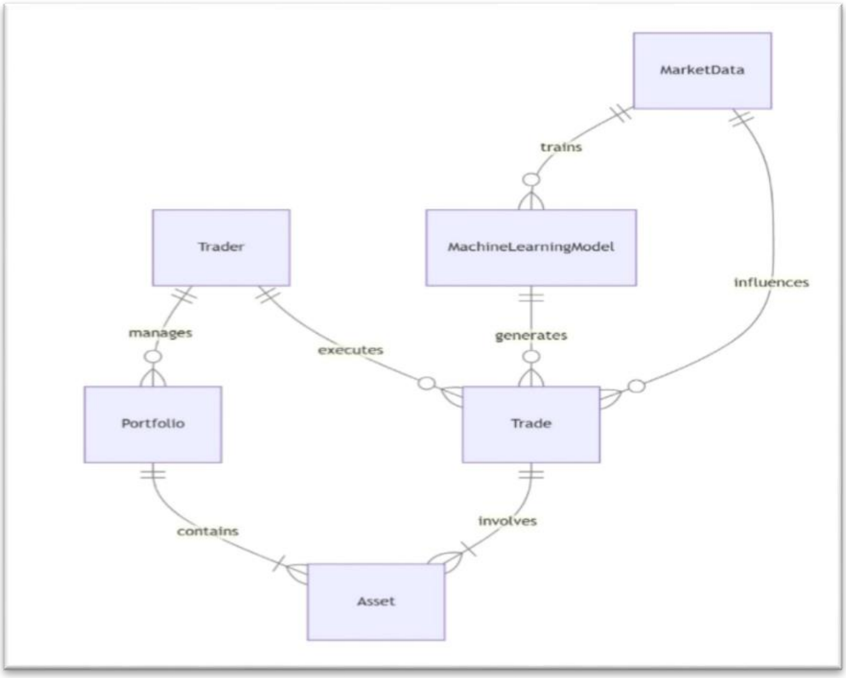


Figure 1 shows the execution process of market data collected from Yahoo Finance platform into trading decisions to manage a portfolio or take short-term trading and generate high RoI. The proposed study aims to develop an automated trading strategy to integrate an ML model with EMA crossover and volume confirmation. The objectives of the study are: (1) to develop a strong algorithmic strategy by integrating market participation metrics with technical indicators; (2) to train ML models which can produce trading signals for buy, sell and hold with high accuracy; and (3) validate the automated strategy by back testing it on historical financial data with Sharpe ratio, cumulative return. This study proposes an ML-based automated algorithmic trading strategy that integrates EMA crossover signals to generate buy, sell and hold signals, and it also confirms with traded volume trends to predict more accurate market movements. By integrating supervised machine learning into historical market data, the model focuses on developing outperforming traditional rule-based manual strategies in terms of high profitability and low risk-adjusted returns.

2. Literature review

2.1 Trading signal generation by SMA

Algorithmic trading is nowadays very popular among the traders and investors specially for anchor and those people dealing with large capital in financial market. Nowadays, these automated strategies are very effective due to the use of a machine learning approach. Machine learning learns the model with the historical data by calculating several technical indicators for buy, sell and hold signals. Licona-Luque et al. (2023) describe the performance of SMA before and after COVID-19 pre- and post-pandemic stock market in S&P 500 stocks [10]. Ferreira et al. (2019) show SMA performance in asset allocations [11]. Sharma et al. (2023) describe the entry and exit points using SMA crossover [12]. Nguyen et al., (2023) describe how Exponential Moving Average (EMA) crossover can detect the trend of price movements by finding the intersection of short-term EMA and long-term EMA [13]. Chen et al., (2025). Explains that due to the high volatility of market conditions and the dynamic live market, some situations may lack the moving average crossover. By integrating with EMA crossover and ML, it improves the trading experience and gives good results in not only back testing but also live market hours [14].

H1: SMA crossover generate a trading signal.

2.2 ATV and RSI integration with trading strategies

One quote is very popular among the traders: “traded volume does not lie”. The stock market may be manipulated, which can fail any model due to any major drivers of the market, i.e., also called big money. But that can be identified by the traded volume. Ali et al. (2025) explain that traded volume may increase the performance of the model multiple times by integrating traded volume analysis with the existing ML models significantly improves trading accuracy. He et al., (2020) describe the role of traded volume in stock price discovery [15]. Zhang et al. (2022) Traded Volume-based features and MA crossover logic give very accurate results in reinforcement learning oriented ML models. The AI model may incorporate with deep learning architecture and several technical indicators, such as volume and MA, for a high-frequency stock trading system [16]. The automated model performed better than other conventional algorithm trading systems in terms of accuracy, stability and profitability. In a study, Sun et al. (2023) established an ML technique to capture non-linear relations among different technical indicators and traded volume. That ML model also provides a very effective and accurate model for different market conditions. The model is more advanced due to the use of feedback-based reinforcement learning strategies [17]. Qureshi et al., (2023) integrated the RL model with several traditional indicators like moving averages, RSI and MACD [18]. Day et al., (2020) suggested in a study, stock trading signal generation using RSI in the US market [19]. Eggebrecht et al., (2023) develop a hybrid ML model that combines MA crossover, traded volume, and market sentiment data to increase the performance of trading [20].

H2: ATV and RSI confirms the trading signals.

2.3 RL-based ML model deployment

Kim et al., (2022) used an adaptive training-based machine learning algorithm to generate automated trading signals [21]. Agrawal et al., (2021) used a decision tree forest-based model to generate trading signals in the equity market [22]. Roy et al., (2021) developed a model for stock trading based on Fuzzy-Rough Set [23]. Support vector machine (SVM) based model using LSTM generated by Karthick et al., (2024). Kapoor et al.,(2022) developed a system based on Genetic Algorithms (GA) to predict stock movements [24], [25]. Pattanayak et al., developed a model to show the efficiency of Recurrent Neural Networks in stock market predictions [26]. İltüzer, Z. (2021) developed a model using machine learning based on financial ratios and shows 86% accuracy for classifications [27]. Ospina-Holguín et al., (2025) prepare a model based on RL algorithms and trained with moving average-based data [28]. Gated Recurrent Unit (GRU) and Convolutional Neural Networks (CNN) proposed by Chauhan et al., (2025) to analyze sentiment-based trading [29]. Li et al. (2023) analyse ML models for stock markets with the reinforcement learning (RL) (DQN, PPO) with popular technical indicators such as EMA, MACD and RSI and show significant Sharpe ratio gains over other traditional models [30]. Kim et al., (2024) proposed PPO and showed 28% higher Sharpe ratios by using volume features [31].

H3: RL-based ML model generates automated trading signals.

As a summary of the literature reviews, a suggestion is to conclude that nowadays, to generate effective and accurate ML-based automated trading strategies, combine the decisions from different technical indicators. It is very difficult to generate an accurate automated signal from single indicators. EMA crossover-based technical indicators are different from SMA or MA. EMA is more advanced and has a different weightage of different frequencies, making it a less lacking indicator. Traded volume analysis confirms the ML model for the generated buy, sell and hold signals. The proposed automated model is very simple and reliable in the financial stock market.

3. Data and variables

3.1 Overview

This proposed study focuses on developing and evaluating an ML-based automated stock market trading strategy by combining ML algorithms with conventional and very reliable technical indicators, SMA crossover with ATV and RSI confirmations. Experiment and simulation-based automated algorithmic method uses historical stock price OHLC (Open, High, Low, Close) Huang et al., (2022) and volume data to train the system and test in a controlled setting [32]. The Reinforcement Learning system generates the decision from live data fetched are categorizes it into the following steps:

3.2 Data Acquisition and Processing

The model fetches the stock market live and historical data from Yahoo Finance. Data can also be captured from any official websites of exchanges such as the National Stock Exchange (NSE), Bombay Stock Exchange (BSE), Nasdaq Composite (IXIC), Dow Jones Industrial Average (DJI), etc. The model accesses OHLC and Traded Volume (TV) data. OHLC is a combination of Open, High, Low and closing price of a certain counter; the counter may be individual equity stock, indices, commodities or currencies. For micro-cap, small-cap and some mid-cap stocks having large possibilities of manipulations in stock price, that’s why the model always suggests considering large-cap stocks, indices, commodities or currencies where liquidity is very high, such as NIFTY 50, HDFC Bank, Reliance, TCS, Bitcoin, Crude, etc. The model is trained and back tested in historical data of 5 years, 1 year and 1 month data are considered for long term, midterm and small term decision signals generation respectively in 10 large cap stocks of Nifty 50 index Reliance Industries, HDFC Bank, TCS, Infosys, ITC, ICICI bank, Sun pharma, Hindustan Unilever, Power Grid, Asian Paints.

3.3 Data Preprocessing and Cleaning

Security market holidays create major problems in continuous sequential data that are assigned null values for missing. To overcome this problem model is incorporated with the forward-filling (ffill) algorithm to ensure the continuity of data. To eliminate extra columns there use the adjusted price in the Adj Close column. For time-based data sequences, the OLHC data is converted into a date-time format.

4. Methodology and model specifications

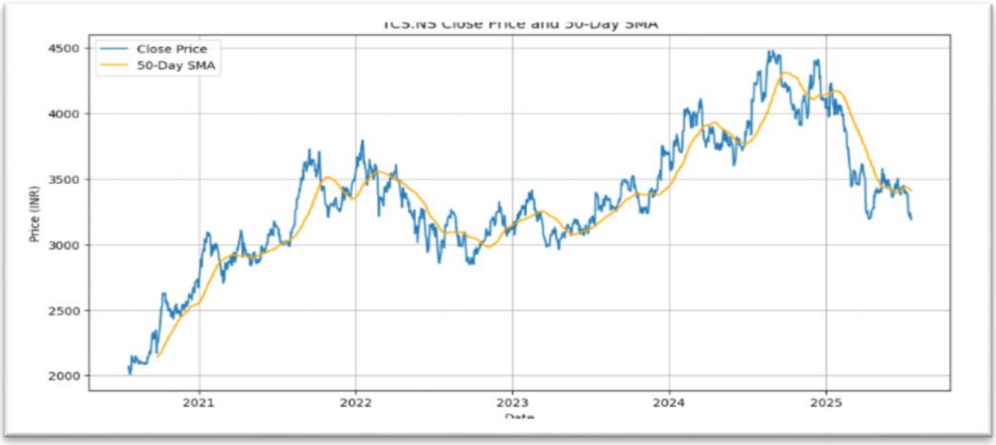
4.1. Feature Engineering

Simple Moving Averages (SMA): It is a very simple technical analysis indicator that is used to detect the price movement trends. SMA is simple mean of all historical closing price of a stock. The SMA helps overcome the problem that arises due to short-term volatility and results in very good predictions for the trend by averaging prices.

$$\mathrm{SMAt} = \frac{1}{\mathrm{N}} * \sum_{\mathrm{i}=0}^{\mathrm{N}-1} \mathrm{Pt} - \mathrm{i} \qquad 1$$

Where, Pt is the closing price in time t.
N is the number frequency (e.g., 10, 20, 50,100,200).
SMAt is the calculated SMA in time duration N.

Figure 2: 50 Days SMA of TCS (20/07/20 to 20/07/2025)



(Source: Author's compilation)

Figure 2 shows the 50-day simple moving average generated in the TCS price movement during the period from 20/07/2020 to 20/07/2025. The line nicely follows the price movements of stocks. Multiple SMA lines can be generated having different time frames in a single window.

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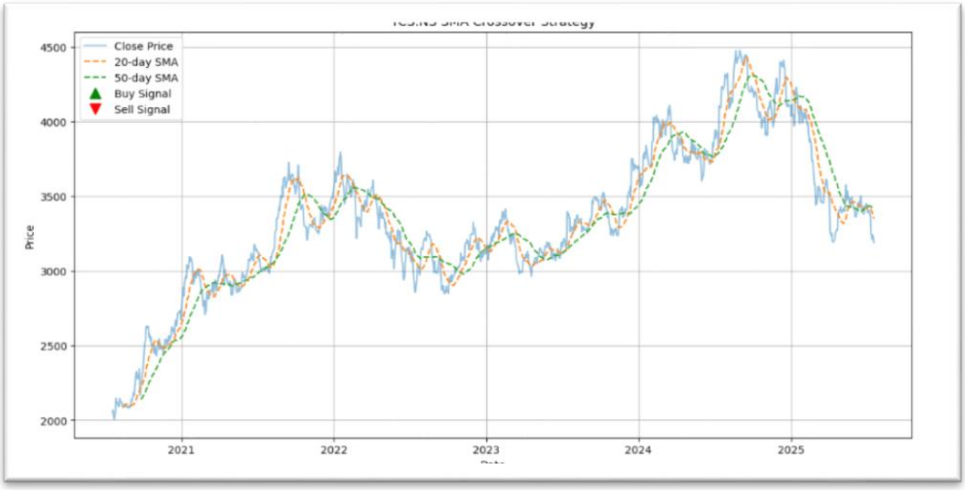
Crossover strategies: In both algorithmic and manual trading, SMA crossover strategies are frequently employed to determine entry and exit signals based on the correlation between two SMAs, usually slow and fast. Golden crossover, i.e., 20Days SMA crosses up to the long-term SMA, i.e., 50Days SMA. Whereas a death crossover or sell signal is generated when short-term SMA, i.e.20Days SMA, crosses down to long-term SMA, i.e., 50-day SMA, as shown in the figure below.

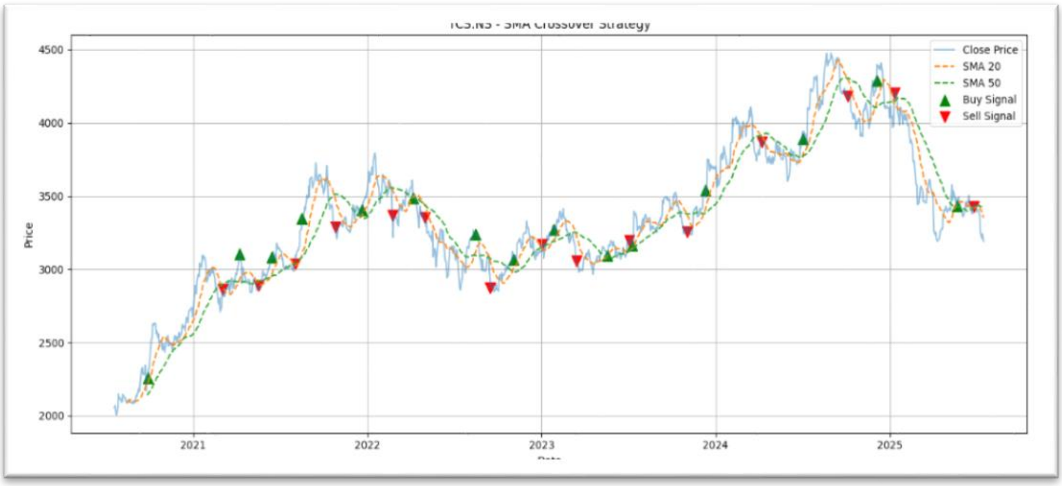
Figure 3: 20 Days and 50 Days SMA of TCS (20/07/20 to 20/07/2025)



(Source: Author’s compilation)

Figure 3 shows two SMA lines having frequencies of 20 days and 50 days during the same period and the same stock as mentioned earlier. The orange line is 20 days, and the green line is 50 days SMA. These SMA lines are drawn in the same frame in the figure. These lines cross each other several times. After some crossover price moments are upside, and after some downside shows and discussed in figure4.

Figure 4: 20 and 50 Days SMA crossovers in TCS with buy/sell (20/07/20 to 20/07/2025)



(Source: Author’s compilation)

Figure 4 is for 20 Days and 50 Days SMA crossovers (GC/DC) occur during 20/07/20 to 20/07/2025 5-year time period in TCS. When the low frequency SMA line (20 days) crosses the high frequency SMA line towards the upside, generated golden crossover or buy signal is generated. Similarly, sell signals or death crossovers are generated when low low-frequency SMA line (20 days) crosses high frequency SMA line (50 days) towards the downside in the figure represented by green and red triangles, respectively.

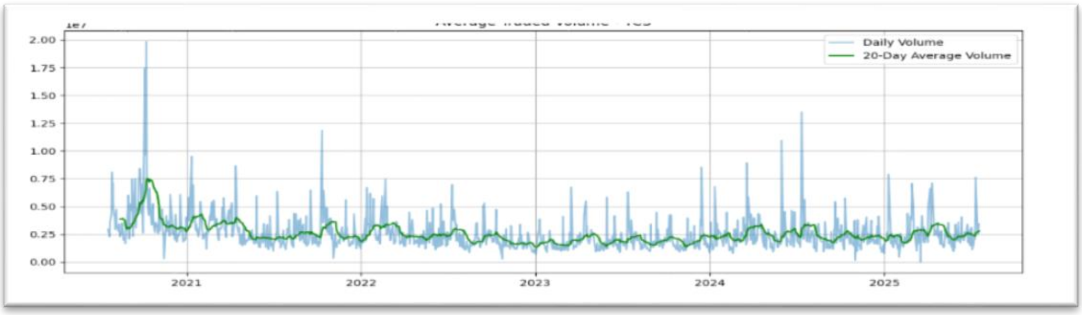
4.2. Average Traded Volume (ATV)

Traded volume is the number of shares changing hands of traders or investors at a certain moment. It indicates information about the liquidity of shares, investor participation on that counter and market activity.

$$\mathrm{ATVn} = \frac{1}{n}\sum_{i=0}^{n} \mathrm{Volumei} \qquad 2$$

ATV confirms or validates the signal generated from SMA's crossover. If a golden crossover or death crossover is generated and the ATV line is in uptrend, that is slope of ATV is positive, which confirms the signal generated from SMA, we can also say big money is entering or exiting from that counter. Whereas ATV line downward means big money does not have interest in that counter, so there are very

Figure 5: ATV and ATV moving average 20 days of TCS (20/07/20 to 20/07/2025)



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(Source: Author's compilation)

Figure 5 shows another important feature of engineering the ATV in the same duration (20/07/20 to 20/07/2025) in TCS. The line is a moving average line of 20 days of traded volumes. Any other time frame can also be considered. But it is ideal and mostly used by traders in traditional manual trading systems. When this moving average line on the upside i.e. slope, is positive, traders are showing interest in that stock, smart investors or big players are entering or exiting from that stock. There are high possibilities of big movements shortly. It does not generate trading signals, better to say it confirms the signals generated by SMA crossover.

4.3. Relative Strength Index (RSI)

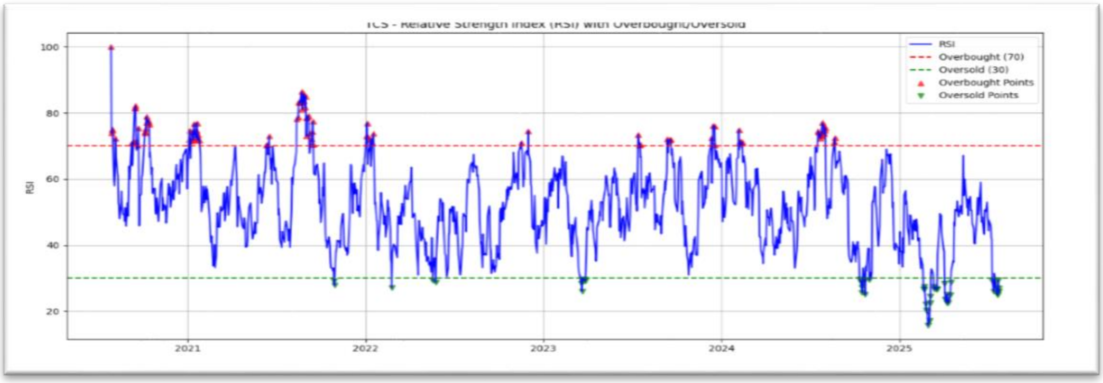
RSI is a momentum identifier. It is often use to find overbought (>70) and oversold (<30) conditions by traders.

$$\mathrm{RSI} = 100 - \left(\frac{100}{1+\mathrm{RS}}\right) \qquad 3$$

Were,

$$\mathrm{RS} = \frac{\text{Average Gain}}{\text{Average Loss}}$$

Figure 6: RSI of TCS (20/07/20 to 20/07/2025)



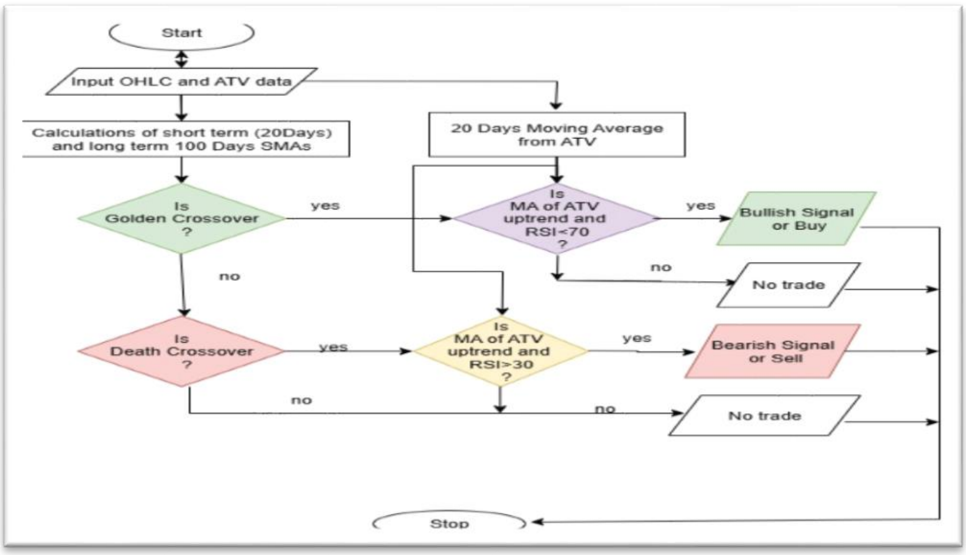
(Source: Author’s compilation)

Figure 6 shows another important feature engineering relative strength index or RSI in the same duration (20/07/20 to 20/07/2025) in TCS. In Figure two line is red (70) and another is green (30), representing overbought and oversold conditions, respectively. It does not confirm buy signals above 70 RSI, and it does not confirm sell signals below 30 RSI. So, it is also confirming buy and sell signals generated from the SMA crossover.

Table 1: ATV Matters in Trading

Use	Explanation
Liquidity Indicator	Higher ATV means big money having interest on buying or selling
Volatility Filter	Sudden ATV surges may indicate big movement possible near future
Signal Confirmation	It is not trading signal generator. It can confirm the signal.
Algorithmic Trading	It increases trading accuracy in multiple times.

Figure 7: Architecture of proposed model.



(Source: Author’s Design)

4.4. Reinforcement Learning Environment Design

Reinforcement Learning (RL) is the machine learning dynamic in nature. It learns from the environment with the best possible behaviour. It is very much useful for sequential and continuous decision-making environments because it places an emphasis on learning from the results of actions, in contrast to supervised learning, which depends on labelled datasets. Its state space considers SMAs crossover signal, ATV, price returns and action space consisting of buy, sell and no trade.

4.5. Reward Function

Basically, SMA crossovers identify the trend reversal of trend, that is where to take positions or exit from position. Bullish signals appear if shorter SMA crosses to the longer SMA, it identifies uptrends. Bearish signals or GC appears if the shorter-term SMA crosses below the longer-term SMA, it identifies the bearish down trends. To consider bullish and bearish signals into reward functions the actions of agent is aligned with these crossover indications as follows.

$$Rt = (Pt + 1 - Pt) + \alpha \cdot SMA_{Signalt} \qquad \textbf{4}$$

Where SMA_{Signal} is positive for golden crossover or up trend and negative for death crossover or down trends and α is a weighting vector.

4.6. Adjusting for Average Traded Volume

To adjust with ATV to the price movements significant trading volumes at the instance of SMA crossover is confirming the generated signals. To consider this as follows:

$$Rt = (Pt + 1 - Pt) \cdot (1 + \beta \cdot \frac{Vt - \bar{V}}{\bar{V}}) \qquad 5$$

Where, β adjusts the sensitivity for volume changes $\bar{V}$ ATV in given time frequency, Vt is ATV at instance. There ward function rewards more when profitable executions when ATV in up trends, that is slope is positive which indicates traders having interest on that security.

4.7. Model Training and Reinforcement Learning Selection

Proximal Policy Optimization (PPO) algorithms working on policy or policy gradient complex, continuous and hybrid action environments. It is robust and stable RL algorithm.

4.8. Training Strategy

The model is trained with 80 percent of historical data, validate the model by 10 percent and for testing 10 percent

5. Empirical results

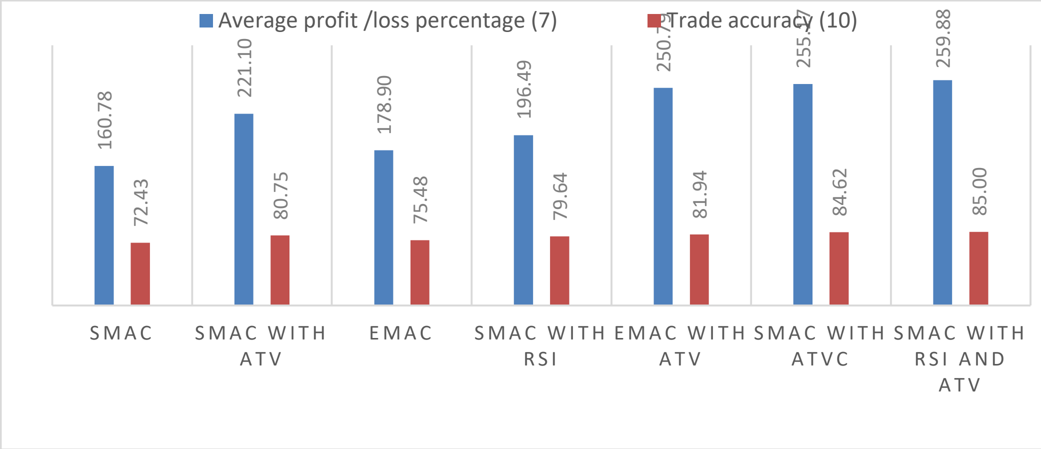
In the result analysis, there is a comparison of different popular trading strategies using RoI or profit loss, accuracy, Sharpe ratio, and Sortino ratio. The study considers three types of investment according to duration: long term considers five years; medium term considers one year; and short term considers one month duration and candle time frame, considering daily, hourly and five-minute frames respectively. The number of trades executed is the total number of trading buy sell signals generated by the models in 10 stocks mentioned below. The number of traded signals is classified into buy, sell and no trade signal categories. Trade accuracy is calculated by dividing the profitable trades executed by total trades executed. The average profit /loss percentage represents the total amount of profit or loss in all trades concerning investment. It is positive means profit, and negative means loss in percent. Sharpe ratio is calculated by the return produced from an investment in trading risk is measured. Sortino ratio is a calculation of risk-adjusted profit that indicates downside risk for investors who are risk-averse or worried about possible losses. It offers a more accurate evaluation of portfolio performance than the Sharpe ratio because it only takes into account negative deviations of returns from the mean. Trade accuracy is the ratio of no of profitable trades to the total trades that take place. Back testing is done on 10 large cap stocks of Nifty 50 index Reliance Industries, HDFC Bank, TCS, Infosys, ITC, ICICI bank, Sun pharma, Hindustan Unilever, Power Grid, Asian Paints and compares the total trading signal generated in these 10 stocks in 7 trading strategies in long term, medium term and short term of investment in table 2,3,4.

Table 2: Result analysis for different strategies in daily time frame for long term (5 years) in 10 stocks

Sl. No.	**Trading strategy (2)**	**Number of trades (3)**	**Buy signal (4)**	**Sell signal (5)**	**Profitable trade (6)**	**Average profit /loss percentage (7)**	**Sharpe ratio (8)**	**Sortino ratio (9)**	**Trade accuracy (10)**
1	SMAC	214	174	40	155	160.78	0.82	1.32	72.43
2	SMAC with ATV	161	132	29	130	221.10	1.46	1.62	80.75
3	EMAC	208	171	37	157	178.90	1.32	1.54	75.48
4	SMAC with RSI	167	136	31	133	196.49	1.62	1.73	79.64
5	EMAC with ATV	155	128	27	127	250.79	2.12	2.32	81.94
6	SMAC with ATVC	143	117	26	121	255.17	2.18	2.35	84.62
7	SMAC with RSI and ATV	140	114	26	119	259.88	2.27	2.52	85.00

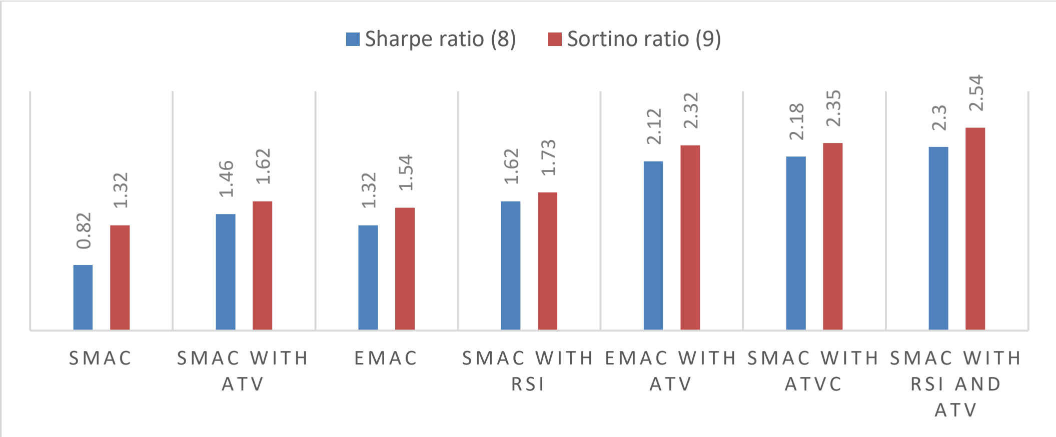
(Source: Author’s compilation)

Figure 8: Average profit/loss percentage and trade accuracy comparison in different strategies in daily time frame for long term (5 years) in 10 large cap stocks



(Source: Author's compilation)

Figure 9: Sharp ratio and Sortino ratio comparison in different strategies in daily time frame for long term (5 years) in in 10 large cap stocks



(Source: Author's compilation)

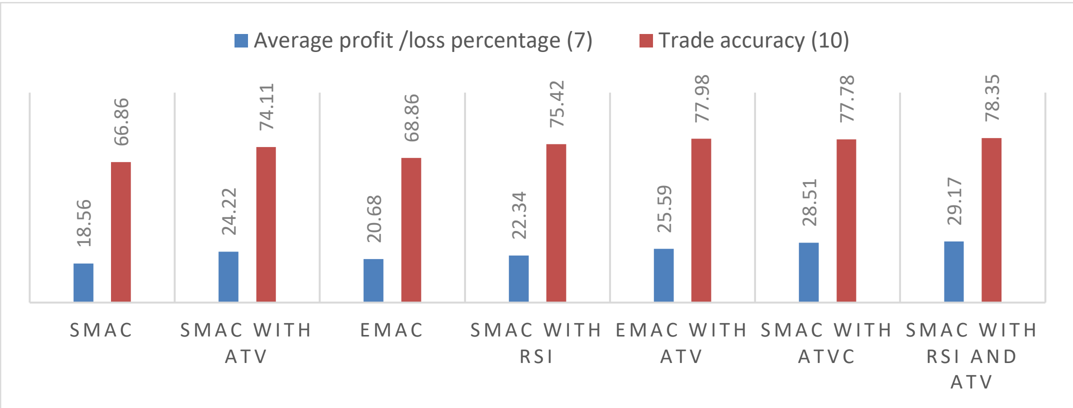
Table 2 compares the six most popular trading strategies using SMA crossover, SMA crossover with ATV, EMA crossover, SMA crossover with RSI, EMA crossover with ATV, SMA crossover with ATV crossover and lastly, with the model SMA crossover with RSI and ATV confirmations integrated with the RL algorithm. The number of trades is auto-generated buy-sell signals in 10 large-cap Nifty 50 stocks, Reliance Industries, HDFC Bank, TCS, Infosys, ITC, ICICI Bank, Sun Pharma, Hindustan Unilever, Power Grid, and Asian Paints listed in NSE in a 5-year duration and daily time frames. SMA crossover and EMA crossover generate a greater number of trading signals, by ATV and/or RSI confirmations, the rate of trade signal generation is minimized, as accuracy and profit percentage are largely affected. The above-mentioned six strategies provide 72.43%, 80.75%, 75.48%, 79.64%, 81.94%, and 84.62% accuracies with 160.78%, 221.10%, 178.90%, 196.49%, 250.79% and 255.17% returns in five years, respectively. Whereas the model provides 85.00% accuracy and a 259.88% return over 5 years, which is best in a long-term perspective. The model also provides the best Sharpe and Sortino ratios among these models. Figures 8 and 9 are the pictorial representations of profit percentage, trade accuracy, and Sharp ratio, Sortino ratio respectively as mentioned in table 2.

Table 3: Table: Result analysis for different strategies in hourly time frame for medium term (1Year) in 10 stocks

Sl. No.	Trading strategy (2)	Number of trades (3)	Buy signal (4)	Sell signal (5)	Profitable trade (6)	Average profit /loss percentage (7)	Sharpe ratio (8)	Sortino ratio (9)	Trade accuracy (10)
1	**SMAC**	172	141	31	115	18.56	0.74	1.24	66.86
2	**SMAC with ATV**	112	90	22	83	24.22	1.12	1.55	74.11
3	**EMAC**	167	138	29	115	20.68	1.06	1.43	68.86
4	**SMAC with RSI**	118	97	21	89	22.34	1.48	1.65	75.42
5	**EMAC with ATV**	109	89	20	85	25.59	1.98	2.25	77.98
6	**SMAC with ATVC**	99	83	16	77	28.51	2.12	2.18	77.78
7	**SMAC with RSI and ATV**	97	80	17	76	29.17	2.26	2.42	78.35

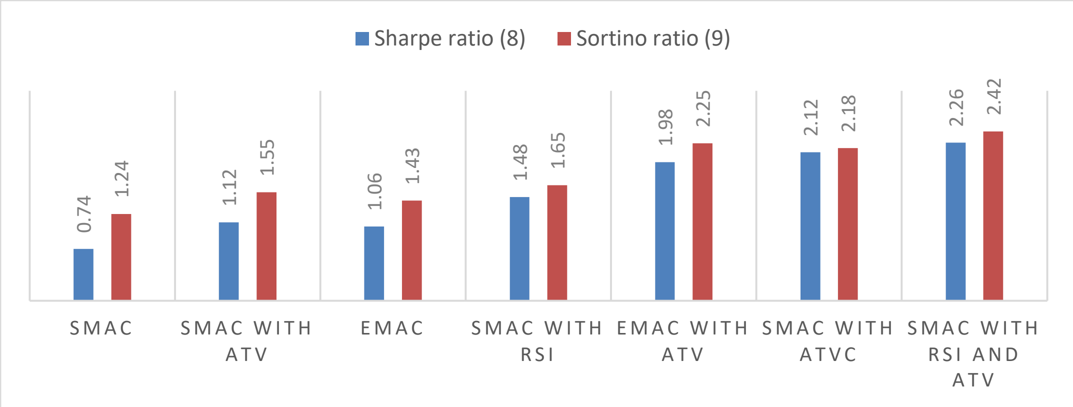
(Source: Author's compilation)

Figure 10: Average profit/loss percentage and trade accuracy comparison of different strategies in hourly time frame for medium term (1 year) 10 large cap stocks



(Source: Author's compilation)

Figure 11: Sharpe ratio and Sortino ratio comparison of different strategies in hourly time frame for medium term (1 year) 10 large cap stocks (Source: Author's compilation)



(Source: Author's compilation)

Table 3 compares the same mentioned strategies with the model SMA crossover with RSI and ATV implemented in the RL algorithm. The number of trades is auto-generated buy-sell signals in the same 10 large-cap Nifty 50 stocks as mentioned earlier in a daily time frame, in a 1-year duration, and hourly time frames. SMA crossover and EMA crossover generate a greater number of trading signals, by ATV and/or RSI confirmations, the rate of trade signal generation is minimized, as accuracy and profit percentage are largely affected. The above-mentioned six strategies provide 66.86%,74.11%,68.86%,75.42%,77.98% and 77.78% accuracies with 18.56%,24.22%,20.68%, 22.34%,25.59% and 28.51% returns in one year, respectively. Whereas the model provides 78.35% accuracy and a 29.17% return over one year, which is best in a medium-term perspective. The model also provides the best Sharpe and Sortino ratios among these models. Figures 10 and 11 are the pictorial representations of profit percentage, trade accuracy, and Sharpe ratio, Sortino ratio, respectively, as mentioned in Table 3.

Table 4: Table: Result analysis for different strategies in hourly time frame for short term (1 month) in 10 stocks

Sl. No.	Trading strategy (2)	Number of trades (3)	Buy signal (4)	Sell signal (5)	Profitable trade (6)	Average profit /loss percentage (7)	Sharpe ratio (8)	Sortino ratio (9)	Trade accuracy (10)
1	**SMAC**	1280	637	643	746	0.42	0.72	1.34	58.28
2	**SMAC with ATV**	822	407	415	546	1.45	1.82	2.12	66.42
3	**EMAC**	1256	621	635	756	0.69	1.12	1.57	60.19
4	**SMAC with RSI**	987	491	496	663	1.14	1.56	1.62	67.17

5	**EMAC with ATV**	794	378	416	569	1.62	2.08	2.38	71.66
6	**SMAC with ATVC**	724	357	367	511	1.62	2	2.23	70.58
7	**SMAC with RSI and ATV**	717	351	366	511	1.64	2.1	2.41	71.27

(Source: Author's compilation)

Figure 12: Average profit/loss percentage and trade accuracy comparison of different strategies in 5 minutes time frame for short term (1 month) 10 large cap stocks

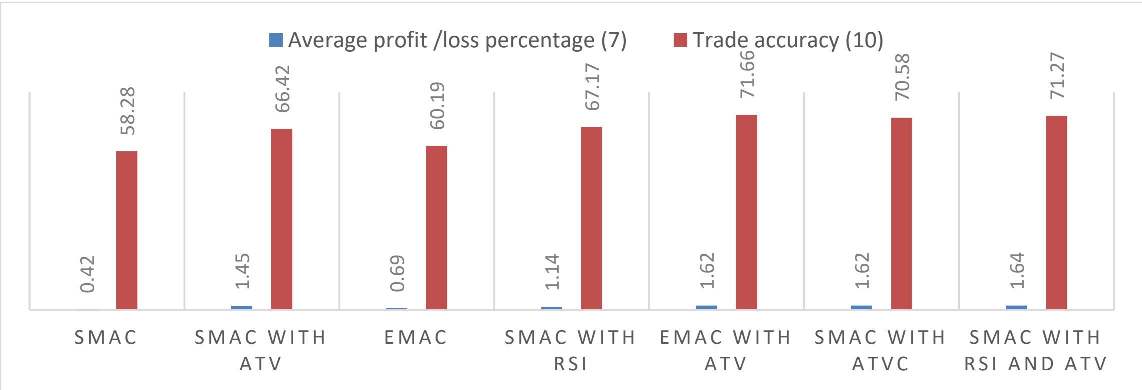


Figure 13: Sharpe ratio and Sortino ratio comparison of different strategies in in 5 minutes time frame for short term (1 month) 10 large cap stocks

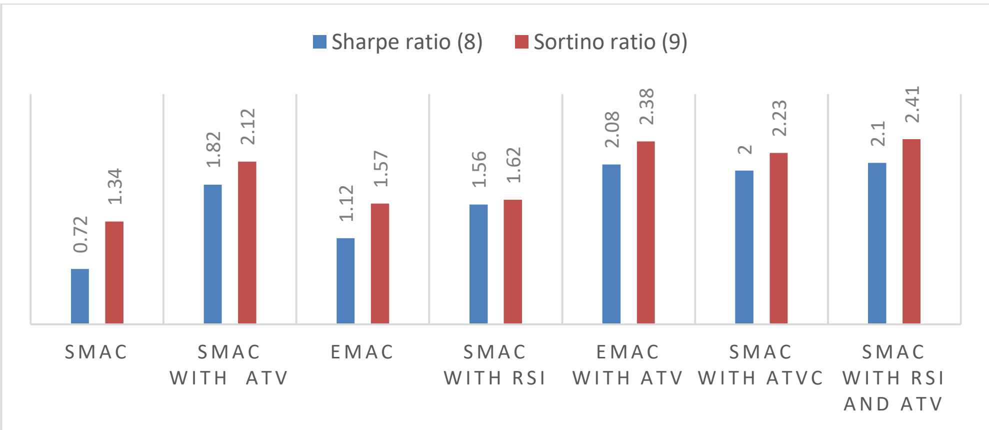


Table 4 is the resulting analysis in short-term or intraday trading. In the intraday scenario is a little bit different. Number of factors are there which affect the stock market directly and indirectly, such as news flow, data publication, quarterly results, etc. In Table 4, it is reflected. This table compares the six most popular trading strategies using SMA crossover, SMA crossover with ATV, EMA crossover, SMA crossover with RSI, EMA crossover with ATV, SMA crossover with ATV crossover and lastly, with the model SMA crossover with RSI and ATV confirmations integrated with the RL algorithm. The number of trades is auto-generated buy-sell signals in 10 large-cap Nifty 50 stocks, Reliance Industries, HDFC Bank, TCS, Infosys, ITC, ICICI Bank, Sun Pharma, Hindustan Unilever, Power Grid, and Asian Paints listed in NSE in a 1-month duration and 5-minute time frames. SMA crossover and EMA crossover generate a greater number of trading signals, by ATV and/or RSI confirmations, the rate of trade signal generation is minimized, as accuracy and profit percentage are largely affected. The above-mentioned six strategies provide 58.28%, 66.42%, 60.19%, 67.17%, 71.66% and 70.58% accuracies with 0.42%, 1.45%, 0.69%, 1.14%, 1.62% and 1.62% returns in five years, respectively. Whereas the model provides 71.27% accuracy and a 1.64% return over 1 month, which is almost the best in a short-term perspective, EMAC with ATV provides a little bit more accuracy than the model. The model also provides the best Sharpe and Sortino ratios among these models. Figures 12 and 13 are the pictorial representations of profit percentage, trade accuracy, and Sharpe ratio, Sortino ratio, respectively, as mentioned in Table 4.

From the above 3 types of trading result analysis in all cases, daily, hourly and 5-minute time frames, i.e., long-term, medium-term and short-term trading or investment strategies, ATV and RSI confirmation play a very important role. ATV largely affects profit percentage and trade accuracy, as well as it also improves the Sharpe ratio and Sortino ratio. But when even ATV is included, with SMA number of trade signals decreases. In a shorter time frame, a large number of trade signals can be used for frequent trading.

6. Conclusion

SMA is responsible for identifying trend of a stock bullish and bearish trend. Whereas SMA crossover is responsible for identifying trend reversals. GC represents the end of the bearish trend, and it is starting an upward journey. Similarly, DC represents the end of a bullish trend and it start correction. But it is very difficult for SMA crossover to find a sideways choppy market. That’s why SMA crossover has a poor accuracy rate. To overcome and filter out these SMA crossovers during a choppy market, ATV is introduced with a model that can work very nicely in sideways and choppy markets also and the results also show the same. Improving the ATV or slope of the ATV line is positive means traders are paying interest on that stock; there is a very high possibility of large volatility near future, whereas a low ATV suggests big money doesn’t have any interest in trading in that stock, so high possibility of sideways and choppy. To increase the accuracy of the model at the next level, the signal is verified by RSI to protect from overbought conditions during buy and oversold conditions during sell. The model is equally effective for equities, derivatives, indices and commodities. But for equities, it is suggested to choose the stocks having larger capitalizations, where traded volumes are significant. For small and microcap having a high possibility of manipulation. RL-based agents help to generate automated and optimal entry or exit points, considering SMA crossover signals with ATV and RSI confirmations, and they also minimize trades to reduce transaction costs and overfitting.

Authors' Biography

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Appendix

Table A1. OHLC and Volume data of TCS.NS during 20-06-2025 to 18-07-2025

Price	Close	High	Low	Open	Volume
Ticker	TCS.NS	TCS.NS	TCS.NS	TCS.NS	TCS.NS
Date					
20-06-2025	3424.0796	3434.6438	3399.363	3413.416	2351248
23-06-2025	3382.1223	3413.416	3358.602	3403.45	3123421
24-06-2025	3378.9329	3430.4582	3370.561	3422.984	3403048
25-06-2025	3433.1489	3438.3313	3388.5	3395.776	1757699
26-06-2025	3430.1592	3439.7266	3403.749	3433.149	2879106
27-06-2025	3429.4617	3454.6759	3419.396	3443.315	1778433
30-06-2025	3450.2908	3453.1809	3418.399	3428.265	1468351
01-07-2025	3418.1001	3473.2131	3401.955	3443.315	2375183
02-07-2025	3411.7217	3478.0963	3408.433	3475.405	3090585
03-07-2025	3389.2979	3423.6812	3386.109	3418.399	2531870
04-07-2025	3408.2336	3415.4092	3378.634	3396.474	1109320
07-07-2025	3400.1609	3414.5123	3396.872	3406.739	1639174
08-07-2025	3394.6794	3413.4159	3381.923	3393.484	2325242
09-07-2025	3372.3552	3402.453	3355.612	3398.467	2034938
10-07-2025	3370.5613	3387.5038	3344.649	3368.568	3035012
11-07-2025	3254.9536	3323.7202	3250.07	3288.739	7635550
14-07-2025	3211.8	3260.9334	3189.177	3254.954	3924009
15-07-2025	3241.3	3248.3759	3195.157	3195.157	2590889
16-07-2025	3233.1001	3244.8999	3220.6	3227	2540733
17-07-2025	3209.2	3242	3204.1	3224.1	2947640
18-07-2025	3189.8999	3228.8	3187	3225	3432645