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Synergizing quantitative finance models and market microstructure analysis for enhanced algorithmic trading strategies

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ABSTRACT

In today's complex financial markets, "Algorithmic Trading" has become very important. The study delves into the amalgamation of four pivotal indicators - Relative Strength Index (RSI), Exponential Moving Average (EMA), Volume-Weighted Average Price (VWAP), and Moving Average Convergence/Divergence (MACD) Relative Strength Index (RSI), Exponential Moving Average (EMA), Volume-Weighted Average Price (VWAP), and Moving Average Convergence/Divergence (MACD) to create and develop a potent trading strategy. Through intensive backtesting and parameter tuning, our study demonstrates 60.63 % profitable trades on the National Stock Exchange (NSE), India, surpassing the standalone indicators. The Weapon Candle Strategy created using the four indicators presents its efficiency as it was able to achieve a profit factor of 1.882. This suggests that when these four technical indicators combined to make a strategy, it can provide significantly more accurate and reliable trading signals compared to using a combination of two or three indicators. Algorithmic traders should use a multi-indicator approach to achieve a more comprehensive understanding of the market and make informed trading decisions.

1. Introduction

Trading in today's market is becoming more and more challenging due to the factors such as increase in the volatility, rapid information dissemination and the use of computer programs to automatically trade stocks or other financial assets. Manual trading strategies are not effective enough to keep up with the pace and ever-changing landscape. Algorithmic trading is gaining popularity as these are powered by complex algorithms and high speed computers. The algorithms can analyze vast amounts of data, execute trades with precision and respond fast to market conditions, giving a significant edge to those who are using algorithmic trading. Use of various machine learning and deep learning techniques are very common for stock market prediction (Shah et al., 2019, Zade et al., 2023) but algorithmic trading using technical indicators is gaining popularity due to its effectiveness. However, the current strategies available in the market fall short in terms of efficiency, highlighting the need for further improvement. Previous studies have predominantly focused on strategies utilizing a single indicator, without addressing how combining different indicators could enhance performance and reduce risks in trading (Cohen 2023b). Although numerous machine learning models and techniques have been developed for stock market prediction, there has been no significant implementation on the NIFTY 50 and BANKNIFTY indexes of the Indian stock market. Furthermore, there is a notable absence of algorithmic trading strategies that leverage a combination of indicators for these indexes. Stock markets in different countries work under varying regulatory frameworks, market dynamics, and economic conditions resulting in unique behaviors and responses to global. There are various technical indicators used in algorithmic trading including Relative Strength Index (RSI), Exponential Moving Average (EMA), Volume-Weighted Average Price (VWAP), and Moving Average Convergence/Divergence (MACD). RSI helps in identifying oversells & overbuys, EMA's provide trend following indications, VWAP gives an insight of Intra Day Liquidity Levels and MACD used to find out trend reversal signals. The study focuses on two Indexes NIFTY 50 and BANKNIFTY which comprises various stocks that are liquid and have a large market cap. The research aims to conduct a detailed investigation of the effect of individual and combined indicators in algorithmic trading. The proposed methodology,

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known as the weapon candle strategy, aims to enhance the performance of algorithmic trading using a combination of indicators. Major research contribution of the presented study is the combination of the indicators in achieving 60.63 % percentage profitable trades and a profit factor of 1.882 with a 1:1 profit to risk ratio which is balanced, optimal and best suited for various market conditions. The time period in which the trades have been executed is 15th April 2022–17 th April 2024 and the capital invested is 100000 INR. It has been found that the 15-minute time frame provides a structured approach towards minimizing exposure to risk and maximizing profits.

The paper is organized into several sections. Section 1 begins with a brief introduction to the purpose of research. Section 2 provides a comprehensive literature review. Section 3 explains the experimental design and the mathematical terminology used and also presents problem solving scripts. Section 4 is the findings and discussion. Finally, Section 5 summarizes the key results, outlines the contribution and practical applications and suggestions for the future.

2. Background study

2.1. Literature review strategy

In the current work, quantitative and qualitative analysis have been performed using advanced statistical methods and robust datasets. Through this, various hypotheses have tested and uncovered valuable insights that could enhance our understanding of the subject of investigation. For the study, three prominent databases are considered; ScienceDirect, Web of Science and Scopus. The dataset chosen consists of research articles published within the last five-year period, specifically focusing on the topic of algorithmic trading. The search on the dataset of ScienceDirect and Web of Science resulted in many papers that are titled "Algorithmic Trading" but they did not include technical indicators such as RSI, EMA, MACD and VWAP. So, upon further refining of queries to explore existing literature the technical indicators are included and further refined the query, which resulted in two papers, which were directed to the current study and research. By using the same query, Scopus dataset revealed 18 articles that were suggesting relevance to the study under consideration. This quantitative approach allowed pinpointing the specific subset of research papers that directly address the research interests. After removing duplicates and applying exclusion criteria, nine articles were aligned to the research under consideration. Qualitative analysis of these articles was done to gain valuable insights into the practical implementation and effectiveness of technical indicators in algorithmic trading strategies, contributing to the advancement of this evolving field.

2.2. Literature review

The study proposed by Anghel (2015) examines the stock market efficiency of stocks in 75 countries, using the MACD indicator. It conducts trading simulations to examine the MACD's consistency, however it generated abnormal returns, revealing that it often falls short, with the success of less than 50 %. The research also hints at the potential impact of financial crises on market efficiency, but clear evidence of a shift from the Efficient Market Hypothesis (EMH) to the Adaptive Market Hypothesis (AMH) remains elusive. This study neither uses any significant machine learning models or any combination of indicators in the algorithmic trading strategy which can be the reason for failing results and generation of abnormal results.

To improve the aspects of algorithmic trading the study done by Bajaj and Aghav (2016) cantered on crafting algorithmic trading methods customized for Nifty Index options, giving prime importance to the utilization of technical indicators like RSI, Moving Averages, and Average True Range. The main purpose is to enhance the trading parameter for optimal profit and minimize the risk through different well-defined entry and exit strategies. The effectiveness of utilizing technical analysis in Index option trading is highlighted showing stronger risk-adjusted return through diversified strategies. Profit factor to risk ratio is very high and in unstable market conditions it can lead to loss. The drawdown is more than the initial capital which could lead to debt in the unstable market conditions. However no significant results were observed here as well as it did not combine the indicators to improve on the results. The study worked on the individual indicators which can be considered as a reason for low accuracy.

The research presented by Vezeris et al. (2020) assessed three automated trading systems based on MACD, SMA, and PIVOT indicators using historical price data from FXTM from 2015 to mid-2017. A one-month verification period and backtesting over a range of historical eras (one to twelve months) were combined to implement weekly d-Backtest PS optimization. The systems' degrees of profitability varied, according to the results; AdMACD demonstrated a moderate level of profitability, while AdSMA and AdPIVOT demonstrated noticeably low levels. AdSMA, for example, continuously lost money during the one- to six-week verification periods; EURUSD, on the other hand, made −4054.69 and −3287.76 gains during the one- and six-week verifications, respectively. The study's shortcomings were the requirement for additional parameter tuning, the possibility of backtesting overfitting, and uneven profitability suggesting room for improvement.

The study proposed by Cohen (2020) tries to establish how RSI, MACD and Pivot Reversal (PR) are suitable for Bitcoin trading. The study uses the historical dataset of bitcoin from the period of April 2013 to October 2018. Authors explored different strategies through particle swarm optimization. The results demonstrated by the study shows that RSI produced poor results as compared to the buy and hold strategy and in contrast to that MACD and PR strategies outperformed the buy and hold strategy. Different setups devised by the researcher in order to execute the trades and from all of the setups only certain setups yielded good results. The results achieved by the optimum setup for different strategies were 1.53 for RSI, 2.74 for MACD and 7.39 for PR. The study shows how volatile the crypto market is and the strategies and setup devised are not tested on the stock market to validate its accuracy.

In the study presented by Salkar et al. (2021), the significance of different technical indicators that are MACD, RSI and On-Balance Volume was discussed. The authors focused on the US market for testing and implementation purposes. To verify, researchers carried out investigation and testing, they developed and tested a number of trading techniques using technical indicators. The researchers tried to achieve results combining the indicators two at a time such as MACD and Renko, MACD and RSI, MACD and OBV, OBV and Renko but were able to achieve only 12 % in the profit. It indicates that more research on combinations of various indicators is needed to improve the profit margin.

The research done by Ayala et al. (2021) includes the use of stock market data including indices like DJI, DAX, and IBEX that covers the period from January 1, 2011, to December 31, 2019. The proposed techniques includes data collection, model optimization with an emphasis on TEMA and MACD indicators, hybrid strategy formulation using optimized models, and backtesting on a test dataset. Performance evaluation is carried out on the basis of metrics such as MAE, RMSE, and sMAPE. The results showed different ranges for IBEX. Remarkably, for the DAX index, the hybrid MACD strategy (hMACD) beat the traditional MACD approach, obtaining a performance factor of 32.991 as opposed to 1.117 for the standard MACD. Nevertheless, despite the improved effectiveness of hybrid techniques, drawbacks were noted, such as higher prediction errors with longer horizons and possible overfitting because of model complexity.

The study done by Srivastava et al. (2021) examined on the dataset which includes normalized technical indicators and trading signals and covers daily historical prices from January 1st, 2013, to June 30th, 2020, for a total of 7.5 years and 1725 data points. The data set was split into two categories as training (1380 data points) and testing (345 data points). The Support Vector Machine (SVM), Random Forest, and

Gradient Boosting machine learning techniques were used. According to the results, Random Forest obtained 93.4 % accuracy, SVM obtained 86 % accuracy, and Gradient Boosting performed better than Random Forest. However, the trade-offs between computational complexity and accuracy: Random Forest's computational intensity, Gradient Boosting sensitivity to parameter adjustment, and SVM's fixed model complexity and potential overfitting are not addressed. Though the study focuses on the indexes and Indian stock market, it did not use any aspect of algorithmic trading and technical indicators and limited itself to prediction of the market.

The TI-SiSS trading algorithm is introduced by Frattini et al. (2022) which combines the technical indicator with Natural language Processing (NLP) based metrics from unconventional data sources such as social media and online news. Over the period of September 25, 2019, to February 18, 2022, 527 companies, the majority of which were Information Technology firms—had their daily market closing prices evaluated. Of these, 91 % were based in the USA. With a maximum return of 1.15 %, the TI-SiSS strategy outperformed single-threshold methods, more than tripling the top single-threshold strategy's return of 0.53 %. It also had the lowest average standard deviation (0.1638) and overall average maximum drawdown (0.02) while ranking highest in the Sharpe ratio across all tested currency pairs. However, the study's limitations include dependency on historical data which may not predict future performance accurately, potential overfitting to the specific dataset used, and the generalizability of the results to different market conditions or other types of assets.

The study presented by Agrawal et al. (2022) has provided work utilizing Stock Technical Indicators (STIs) on evolutionary deep learning models for stock market prediction. The model achieves an accuracy of 63.59 %, 56.25 %, and 57.95 % for HDFC, Yes Bank, and SBI, respectively. The research emphasizes the significance of STIs and deep learning methods in stock price forecasting and not the actual trade being executed. As predictions are limited to the historical data and not the recent data in the current scenario.

A trading strategy based on the Directional Changes (DC) in financial markets, is mentioned in the study presented by Adegboye et al. (2023). Using 200 datasets from 20 Forex currency pairings, the study used a genetic algorithm to optimize the weights of each directional change threshold in conjunction with a Multi-Threshold Directional Changes (MTDC) trading algorithm. When measured against benchmarks such as the buy-and-hold (BandH) strategy, this strategy performed better than Single-Threshold DC (STDC) techniques, demonstrating more profitability with an overall average return of 1.1577 %. In addition, MTDC had the lowest standard deviation and average maximum drawdown, all of which point to lower risk. Though it ranked first in this regard, it was unable to statistically surpass STDC methods in terms of standard deviation risk metrics. The study however identified certain shortcomings, including the absence of evidence about its effectiveness in other markets and the omission of testing using higher frequency data, such as tick or 1-minute data, which could have an influence on result robustness.

The research done in order to fit the polynomial auto regression model to intraday price data of four crypto currencies and convert the model into a real-time profitable automated trading was done where a PAR model was constructed to fit the cryptocurrencies (Cohen 2023a). They used ML models and trained on the minutes data for six months and then traded for six months. The result showed that 15.58 % net profit was achieved for Bitcoin using 67 min bars compared to −44.8 % for the Buy and Hold strategy, similarly for Ethereum 16.98 % net profit compared to −33.6 % buy and hold strategy. The author have not demonstrated the results using algorithmic trading, or combining the indicators for the trading. More research is needed to achieve a significant profit percentage and also to validate this model it needs to be tested on the Indian stock market.

The study presented, Prashanth et al. (2023) evaluated the performance of four technical indicators—Exponential Moving Average (EMA), Bollinger Bands (BB), Relative Strength Index (RSI), and Parabolic Stop and Reverse (PSAR)—using Bitcoin price data from Yahoo Finance for the period 2018–2022. The researchers devised four strategies: Multi-Indicator Based Hierarchical Strategy (MIHS) with EMA9, MIHS with EMA7, Multi-Indicator Based Hierarchical Constrained Strategy (MIHCS) with EMA9, and MIHCS with EMA7. Testing these strategies on five years of Bitcoin price data yielded impressive profit percentages of 154.45 %, 437.48 %, 256.31 %, and 701.77 %, respectively. These results highlight the volatile and erratic nature of the cryptocurrency market, generating high profit numbers that are unlikely to be replicated in the Indian Stock Exchange market using similar technical indicators. The study is limited to using indicators individually rather than in combination, suggesting a need for further exploration of combined indicator strategies in the market.

The study proposed by Sabri et al. (2023), the dataset includes yearly time series data for the period from year 1980 to year 2012, compiled from the World Economic Outlook Database of the IMF. The macroeconomic variables used for forecasting are Gross Domestic Product (GDP) and total investment. The methodologies include a combination of traditional time-series forecasting, decomposition methods, smoothing techniques, and Artificial Neural Networks (ANN). The Mean Absolute Percentage Error (MAPE) values indicate that the ANN model achieves higher accuracy, with a MAPE of 2.36 for GDP and 1.99 for total investment. In contrast, the exponential smoothing models have MAPE values of 5.77 for GDP and 3.85 for total investment. However, the study proposed limiting themselves to predicting the values.

The study done by Supsermpol et al. (2023), they tried to create predictive models for post-IPO financial performance, the study used a dataset that included financial data, including important financial indicators and IPO-related information, from 134 companies listed on the Stock Exchange of Thailand (SET) between 2002 and 2021. The results showed that using logistic regression the overall accuracy achieved is of 61.94 % and a test set accuracy of 55.55 %. With an accuracy rate of 72.14 % and an AUC of 0.8416, the random forest models performed even better, showing strong predictive power. However the study is limited to predicting the results only and more exploration is required in analyzing it in the real case scenario.

To understand the model evaluation process the work presented by Asanprakit and Kraiwanit (2023) is studied. Authors used route evaluation, confirmatory factor assessment to verify indicators, and the modelling of structural equations to create a Structural Equation Model (SEM) with pre-existing software for the causal factors. The study presented a variety of goodness-of-fit measures—statistical instruments used to evaluate how well a model fits the observed data. These metrics help researchers determine how the relationships between variables are accurately represented by their suggested framework or if there is a notable discrepancy between the predicted results and the actual data. Cano et al. (2023) suggested Smart Partial Least Square (PLS) version 4 program was utilized to carry out the suggested conceptual model since the PLS method may be employed to a complicated SEM with numerous constructs, can deal with reflecting and creative constructs, manage first- and second-order parameters simultaneously, and doesn't need normally distributed data as input. Latent variables, the associated observable variables, and the correlations between these variables might also be included by means of the program. By describing the indicators for every latent variable and the associations among those variables, SmartPLS 4 allowed for the specification of both the assessment model and the structural framework.

The study of the literature can be summarized as follows suggesting the potential gap:

- In previous studies, strategies using only a single indicator were presented. No one talks about how combining different indicators in situations can help in maximizing performance and reducing risks while trading.
- Many machine learning models and techniques have been developed and used for stock market prediction but no significant

implementation is done on the NIFTY 50 and BANKNIFTY of the Indian stock market.
- Also no algorithmic trading strategies using a combination of indicators is used on the indexes such as NIFTY 50 and BANKNIFTY.

3. Experimental design

3.1. Concept

The research employs a methodology centered on algorithmic trading, incorporating the Stock Market Tool, National Stock Exchange Open Interest API (NSE O/I API), Pine Script editor, indicators, back testing, and optimization. The concise integration of these elements forms the basis for a comprehensive analysis of algorithmic trading strategies, ensuring a precise examination of market dynamics and trading performance.

3.1.1. Gateway platform

The platform (TradingView Platform) shows different charts for different stocks and indexes, it also comprises different indicators inbuilt in the platform for analysing trends. For analysing technical indicators along with trading strategy creation, such graphical depiction is essential. Additionally, it is capable of being utilized to visualize the extent to which a trading approach is working. A domain-specific priming dialect termed Pine Script developed by 'TradingView' a Pine script editor, enables the development of a variety of unique markers and techniques (Dwivedi et al., 2022). The script editor mentioned above promotes the creation and evaluation of trading strategies that are tailored to individual specifications and unique technical indicators of trade. The TradingView Platform is an invaluable tool in helping users customize their strategies and gain an edge over competitors in the sector.

3.1.2. Indicators

Indicators are used to provide details about price movements and market returns. The VWAP, EMA, RSI, and MACD are among the indicators utilized to provide important inputs for trading strategy, assist in identifying valuable patterns and trends, as well as measure market sentiments. These indicators are important mathematical tools that are used to analyze stock market data. In the present day, a plenty of indicators are available, and the best indicator depends on the specific market and its intended use.

3.1.3. Trading rules

The trading algorithm is guided by a set of predefined criteria known as trading rules. These rules are generally based on technical and fundamental analysis of stock market data, risk management, management parameters, and specific entry and exit conditions that are tailored to the programmer's needs. Rules need to be well-defined and clear, ensuring consistency in trades and protecting against impulsive decisions. The rules provide a plan for deciding when to buy, sell, or hold a particular position and can be based on indicators, price action, or other factors. Trading algorithm are crucial for better performance and need to carefully construct and validate.

3.1.4. Algorithm

The algorithm combines all the parts to make crucial trading decisions. The program will evaluate every analytical marker, study actual time market information, and follow operating parameters determined before producing a buying or selling prediction. With the amount of information needed to process, the total performance of the strategy and financial gain are largely dependent on how accurate and efficient the software's algorithm is. This is where transactions will be executed, so the algorithm must be intricate and devoid of mistakes. It must be created efficiently since it must be accurate and capable of managing the number of details that will eventually be processed.

3.1.5. Retrospective evaluation in action (backtest)

The systematic way of employing previous market data to validate an approach. The outcome of the technique sheds light on the effectiveness of the trade plan and supports the functioning of technique. This procedure becomes important for verifying that the proposed methodology is resilient to diverse industry conditions as effectively as for quickening and certifying the transactions. It is a useful tool for crafting and evaluating trade algorithms while not requiring real money.

3.1.6. The process of performance improvement (optimize)

The process of creating an approach that seeks to reduce risks and enhance rewards is called effective enhancement. In this stage, a number of components, such as entry-exit requirements and risk-reduction policies have to be modified. In this step, the parameters are methodically optimized based on indicators plus historical performance data. It aims to enhance the robot's adaptability and usefulness. Using this recursive process, which steadily increases the robot's total revenues; we could ultimately balance rewards and risk. These variables can be optimized by the use of retrospective testing. It is important to be careful not to over fit on the historical data.

3.2. Work flow model

The gateway platform includes sophisticated charting features that facilitate the identification of possible locations of points to enter and exit as represented in Figure 1 which depicts the working of an algorithmic trading model. It can also be used as an application repository with stock value depicting tools. The model is a crucial tool for both designing trading methodologies and analyzing the information collected throughout the NSE O/I API. The programming language used to create trading algorithms is referred to as pine script, which is a potent and effective language that allows users to create intricate trading strategies while being relatively easy to learn and apply.

The trading strategy involves a multi-step process. Firstly, the algorithm focuses on observing the current trend using MACD, which has two lines - the MACD line and the signal line. A crossover between these two lines indicates a potential trend reversal, serving as the initial signal to buy or sell, making it the first confirmation point. The second conformation point involves analyzing the position of the previous candle relative to the EMA. If the candle is below the EMA, it suggests a bearish trend, providing further information. Volume analysis is used as the third confirmation point, looking for increasing volume compared to previous levels, which supports the anticipated trend direction, adding to the confidence in the trading signal. The fourth and final confirmation involves utilizing RSI to identify the overbought or oversold condition. If the RSI falls within a certain range (typically between 30 and 70), it confirms the signal generated by previous indicators. Once all these conditions are satisfied, the trade is executed. Additionally, the use of a weapon candle corresponds to the MACD crossover signal. The range measurement is done from the candle's high to the low of the other weapon candle when going for the long position, and the trade is taken on the next candle. The proposed strategy is termed as the weapon candle strategy.

Different time frames were tried and analyzed to figure out the best time frame for trading, which was found to be 15 min. Initially, there was an 8 period and 12 period MACD line, which on backtesting improved to 12 and 24, respectively. At the start, the average VWAP of 200 weapon candles was taken, which on backtesting improved to 75, resulting in improved accuracy. The EMA line was changed from 3 to 5 and then 9 subsequently to improve the accuracy of the algorithm, and the RSI ratio was changed from 60:40–70:30 (overbought: oversold) to improve the accuracy of the algorithm.

3.3. Mathematical terminologies used

RSI is widely used technical indicator. It analyses the pace and

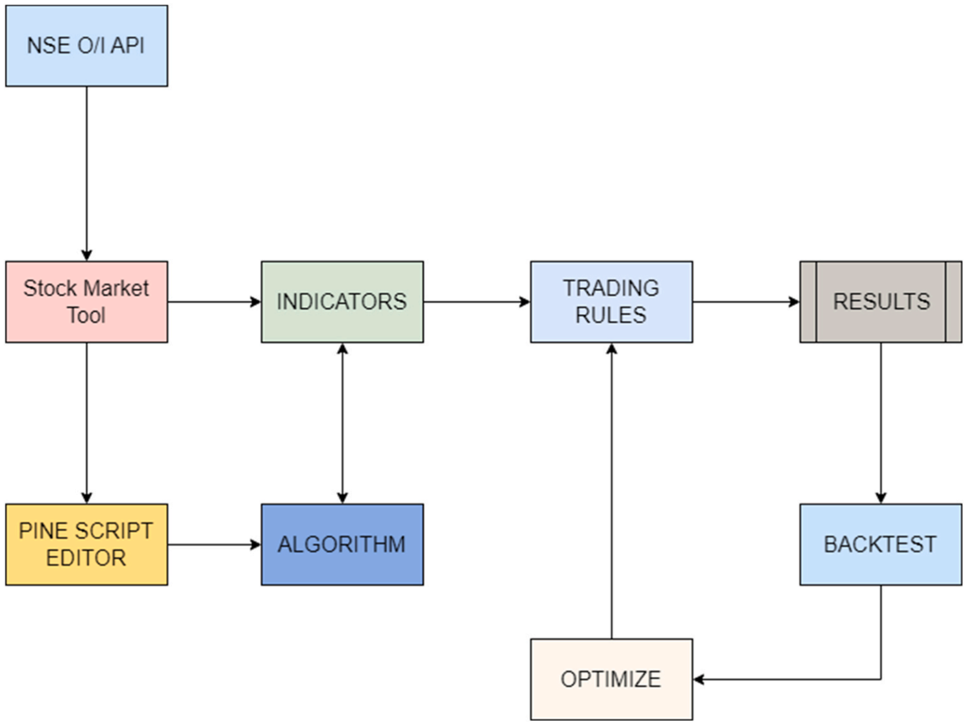

Fig. 1. The Work Flow Model.

degree of change of price movements. The expression for the calculation of RSI is as follows:

$$\text{RSI} = (100 - (100 / (1 + \text{RS}))) \tag{1}$$

&

$$\text{RS} = (\text{PA} / \text{PB}) \tag{2}$$

Where:

RS (Relative Strength) → average of up closes of ‘n days’ divided by the average of down closes of ’n’ days’.

Price of the Asset → closing price/any-relevant price of the asset.

Price of the Benchmark → closing price/any-relevant price of the benchmark (let us say an index or a different asset) that you compare it with.

Usually, the calculation of RSI is done over a period of 14 days, but the value of ’n’ can be taken according to the preference, as per the need of the study.

When RSI value normally is a number between 0 and 100. Values of RSI greater than 70 imply overbought scenarios, while less than 30 imply oversold scenarios.

VWAP is another useful trading indicator. The computation of VWAP is done using the following mathematical formula:

$$\text{VWAP} = (\Sigma\ (\text{Price} * \text{Volume})) / (\Sigma\ \text{Volume}) \tag{3}$$

Where:

Σ → addition over a given period

Price → price of the individual trade.

Volume → volume (no. of shares/contracts) of each trade.

VWAP provides a kind of average price that considers both how much a stock costs and how many shares are being traded. It’s a handy tool for traders and investors to get a sense of the overall market activity.

EMA is a type of moving average that gives more weight to recent prices, making it respond more quickly to changes in the price of an asset.

$$\text{EMA} = (\text{CP} - \text{EMA(PD)}) * (2 / (n + 1)) + \text{EMA(PD)} \tag{4}$$

Where:

CP → closing price of the asset for the present day.

EMA(PD) → EMA from the previous day.

’n’ → number of periods or days that are to be considered for calculating EMA. (Normally, 12 is a commonly used value for short-term EMAs, while 26 is for longer-term EMAs.

MACD comprises two lines: the MACD line and the Signal line.

i. Calculate the MACD Line:

$$\text{MACD Line} = \text{EMA(12pP)} - \text{EMA(26pP)} \tag{5}$$

Where:

EMA(12pP) → EMA of the asset’s price within 12 periods.

EMA(26pP) → EMA of the asset’s price within 26 periods.

ii. Calculate the Signal Line:

(typically, a 9-period EMA) based on the MACD Line:

$$\text{Signal Line} = (\text{EMA (MACD Line, 9 periods)}) \tag{6}$$

Where:

MACD Line illustrates the gap between the 12-period and 26-period EMAs of the asset’s price. The Signal Line is a 9-period EMA of the MACD Line. These lines and their crossovers are used by traders and investors in the making of multiple trading decisions.

3.4. Software application strategy

Problem Solving Script:

Step 1: Identify the Weapon Candle

Script:

isWeaponCandle()=>

The candle to the left of the weapon candle should have its close and open below 9EMA.

leftCandleCondition = close[1] < ema(close, 9) and open[1] < ema (close, 9)

The weapon candle should close above 9EMA and the MACD histogram should be above the baseline.

weaponCandleCondition = close > ema(close, 9) and histogram > 0 leftCandleCondition and weaponCandleCondition

Explanation:

This code defines a function called isWeaponCandle() to identify a specific candlestick pattern. This pattern requires:

1. The candle immediately preceding the candidate ("left candle") to have both its opening and closing prices below the 9-day Exponential Moving Average (EMA).
2. The candidate candle itself ("weapon candle") to close above the 9-day EMA and have a positive MACD histogram value. If both these conditions are met, the function will identify the candidate candle as a "weapon candle".

Step 2: Create a Long Position

Script:

```
var float entryPrice = na
var float stopLoss = na
var float targetPrice = na
if isWeaponCandle()
Set the entry price as the high of the weapon candle
entryPrice:= high
Set the stop loss as the low of the weapon candle
stopLoss:= low
Set the target price as the high of the weapon candle plus the number of ticks
targetPrice:= high + ticks
Enter a long position
strategy.entry("Buy", strategy.long)
```

Explanation:

The code presented defines the steps to enter a long position based on the "weapon candle" pattern which is identified in Step 1. It performs the following:

1. Variable Declaration:

- Stores the entry price for the long position.
- Stores the stop-loss price for the long position.
- Stores the target price for the long position.

2. Checks for the weapon candle:

- If the function returns, then it means the current candle is a "weapon candle".

3. Sets entry, stop-loss, and target prices:

- If the weapon candle is identified, then the entry price is set to the high price of the candle.
- The stop-loss price is set to the low price of the candle.
- The target price calculation is done by adding the number of ticks to the high price of the candle.

4. Enters a long position:

- If all conditions are met, then the code enters a long position using the function.
- The first argument specifies the entry type as "Buy".
- The second argument specifies the position type as "long".

In summary, the presented code snippet implements a trading strategy that enters a long position when a "weapon candle" pattern is identified and sets the entry, stop-loss, and target prices accordingly.

Step 3: Monitor the Trade

Script:

```
if not na(entryPrice)
// If the closing price is less than or equal to the stop loss, then close the position
if close <= stopLoss
then strategy.close("Buy")
entryPrice:= na
If the closing price is greater than or equal to the target price, then close the position
if close >= targetPrice
then strategy.close("Buy")
entryPrice:= na
If the MACD histogram is less than or equal to 0, then close the position
if histogram <= 0
then strategy.close("Buy")
entryPrice:= na
```

Explanation:

The presented code snippet describes how to manage an open long trade based on specific conditions:

1. Check for an active trade: It first checks if is not 'na', implying there's an open long position.
2. Stop-loss check: If the current closing price () is less than or equal to the stop-loss price (), then the trade is closed using, and is reset to 'na' to indicate no active trade.
3. Target price check: If the current closing price is greater than or equal to the target price (), then the trade is closed, and is reset.
4. MACD histogram check: If the MACD histogram is less than or equal to zero, then it suggest a potential trend reversal, the trade is closed, and is reset.

In summary, this code snippet actively monitors an open long trade and closes it if any of the specified exit conditions (stop-loss, target price, or MACD histogram) are met.

Step 4: Calculate and plot the risk-to-reward ratio

Script:

```
risk = entryPrice - stopLoss
reward = targetPrice - entryPrice
riskRewardRatio = risk / reward
Plot the risk-reward ratio
plot(riskRewardRatio, title="Risk-Reward Ratio", color=color.blue)
```

Explanation:

This code segment calculates and visualizes the risk-to-reward ratio for a given trade. Here's a breakdown:

Calculations:

- risk: The potential loss if the trade is unsuccessful, calculated as the difference between the entry price and the stop-loss price.
- reward: The potential profit if the trade is successful, calculated as the difference between the target price and the entry price.
- riskRewardRatio: The ratio of potential risk to potential reward, calculated by dividing risk by reward. This metric helps assess the trade's potential profitability relative to its risk.

Plotting:

- The calculated riskRewardRatio is plotted using the function.
- The plot is titled "Risk-Reward Ratio" for clarity.
- The plot's line color is set to blue for visual distinction.

Indicators used - MACD, 9EMA, RSI, VWAP

Position in the market if the conditions are met - Long position

Weapon candle parameters -

i. The candle to the left of the weapon candle should have its close and open below 9EMA.
ii. The weapon candle should close above 9EMA.

iii. The MACD corresponding to the weapon candle should be positive, i.e. the histogram should be above the MACD baseline.

Ticks (Definition):
Ticks = Entry price - exit price
Experimental Setup -
Step 1 - Identify the weapon candle, given on the parameters above.
Step 2 - create a long position on the candle immediately on the right of the weapon candle. The entry price is given by the high of the weapon candle.
Step 3 - The exit price is determined by the number low point of the weapon candle. This is known the stoploss.
Step 4 - the target price is given by entry price + Ticks. Thus we can see that the risk to reward ratio is 1:1.

4. Results and analysis

4.1. Standalone indicator performance

The study reveals that each standalone indicator exhibits unique strengths and weaknesses in generating profits. The individual profit percentages for each indicator are recorded and compared.

RSI, as shown in Figure 2, excels in identifying overbought and oversold conditions, according to which trades are taken. It can be observed that RSI standalone doesn't perform well in the Indian stock market.

A strategy made on VWAP as shown in Figure 3 provides the above results. The entry and exit positions are based on volume based action. It can be observed that VWAP standalone doesn't perform well in the Indian stock market.

A strategy based on EMA is represented in Figure 4 where a threshold is set and it captures short term momentum in the market depending on the buy or sell signal. If the EMA value is below the threshold then sell and if the value of EMA is above the threshold then buy. This indicator shows a positive PnL but has less profitability.

A trading strategy based on MACD is illustrated in Figure 4, which identifies potential trend reversals, on which buy and sell signals are generated based on the crossover of two lines - signal line and MACD line. It indicates a better profit compared to other indicators with this indicators, but it has a higher drawdown.

4.2. Proposed combining 4 indicators

In order to optimize trading efficiency and enhance profit generation, the power of four prominent technical indicators (RSI, VWAP, EMA, and MACD) is amalgamated to create the weapon candle strategy. This strategy is carefully crafted to initiate trades exclusively when all four indicators converge to signal a synchronized buy or sell opportunity, as explained in Section 3.2 and scripts are explained in Section 3.4. All the combined indicators are fine-tuned with reinforcement learning. By doing so, we mitigate the impact of false signals and elevate the overall precision and reliability of our trading approach as shown in Figure 6.

The weapon candle strategy is built on the integration of RSI, VWAP, EMA, and MACD has yielded compelling outcomes, demonstrating a marked enhancement over the stand-alone applications of these technical indicators shown in Table 1. It is observed from the Table 1 that standalone indicators do not perform well in the market conditions, as evidenced by the profit factor being less than 1.1 when compared. Along with that it demonstrates both a high drawdown and lower profitability percentage. By combining several technical indicators, backtesting and fine tuning it, we are able to achieve a profit factor of 1.882 as shown in Table 2. A significant increase in percentage profitability of 48.63 % and 18.19 % has been observed when comparing the current study with those conducted by Salkar et al. (2021) and Bajaj and Aghav (2016), respectively. It should be noted that the current study proposes various other key performance factors, such as drawdown and profit factor, which were not mentioned in the studies compared. This outstanding performance highlights the power of synergy amongst technical tools when compared with the existing literature. When used together, these indicators provided complementary insights, leading to superior trading outcomes and demonstrating the potential benefits of a multi-indicator approach in algorithmic trading as shown in Figure 7. The results suggest that the combination of the selected indicators is a highly effective choice, as evidenced by the impressive outcomes achieved.

5. Conclusion

Algorithmic trading has become a feature of today's complex and constantly evolving financial markets. By combining indicators like RSI, EMA, VWAP, and MACD, backtesting and fine tuning the strategies, algorithmic trading techniques can surpass individual indicators and reach exceptional results for the Indian stock market. This research

Fig. 2. RSI Result.

Fig. 3. VWAP Result.

Fig. 4. EMA Result.

displays the possibility of combining indicators to provide more accurate and dependable trading signals, resulting in an amazing profit factor of 1.882. To get knowledgeable about the market while making well-informed decisions, algorithmic traders have to employ a variety of metrics. Additionally, by carefully choosing while balancing the indications used, combination indicator tactics can be improved. To find the best and most successful algorithmic trading methods, it is crucial to optimize and test backwards the techniques before going live. Although the algorithm performs well in the uptrend market, the performance gets affected by stable market conditions, but still performs significantly well in contrast to the other methods. Overall, the research clarifies how integrating indicators in algorithmic trading can assist the traders to maximize profits while lowering risks. As we continue to delve into this field, the potential for improved financial outcomes and risk management becomes increasingly apparent. The study on algorithmic trading can be improved in future by combining various other indicators and devising different strategies to improve the accuracy and the efficiency of algorithmic trading.

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No conflict of Interest

Hereby all authors declare no conflict of interest.

Ethical Statement

Not applicable because the paper does not involve research on animals or human subjects under the Bioethics Act, it has not induced or influenced the psychological or social behavior of the respondents.

CRediT authorship contribution statement

Om Mengshetti: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Nilima Zade:** Writing – review

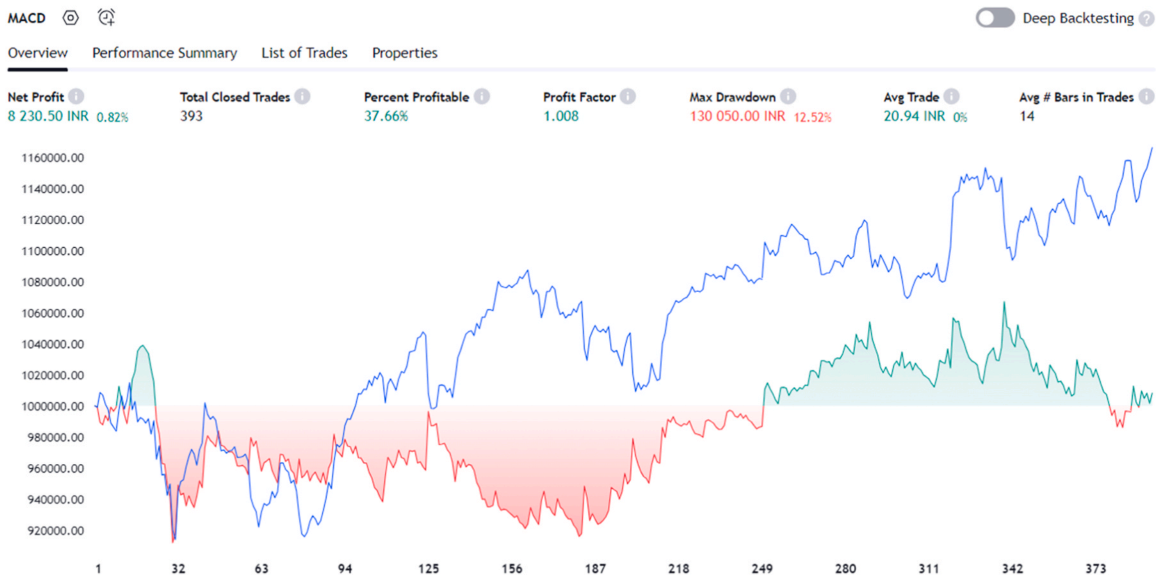

Fig. 5. MACD Result.

Fig. 6. Weapon candle strategy.

Table 1
Standalone Indicator Strategy Result.

Standalone Indicator strategy results							
Name	**Net Profit (INR)**	**Gross Loss (INR)**	**Gross Profit (INR)**	**Percentage Profitable**	**Max Draw Down (INR)**	**Max Draw Down (%)**	**Profit Factor**
EMA	3035.35	91,101.75	94,137.00	23.89 %	24,231.75	2.39	1.033
MACD	8230.50	1084,061.25	1092,291.75	37.66 %	130,050.00	12.52	1.008
RSI	-36,851.25	118,553.25	81,702.00	4.53 %	65,831.25	6.47	0.689
VWAP	-7914.00	150,431.25	129,558.75	12.61 %	56,555.25	47.77	0.973

Table 2
Combined Indicator Strategy Result.

Combined Indicator strategy results								
Ref. No.	**Name**	**Net Profit (INR)**	**Gross Loss (INR)**	**Gross Profit (INR)**	**Percentage Profitable**	**Max Draw Down (INR)**	**Max Draw Down (%)**	**Profit Factor**
Salkar et al. (2021)	MACD +RSI	NOT GIVEN	NOT GIVEN	NOT GIVEN	12.00 %	NOT GIVEN	NOT GIVEN	NOT GIVEN
Bajaj and Aghav (2016)	Combined(Moving Average + Channel+ ATR)	9,75,933	NOT GIVEN	NOT GIVEN	42.44 %	103,917	NOT GIVEN	NOT GIVEN
Proposed Work	Weapon Candle strategy	104,017.50	35,184.75	139,202.25	60.63 %	24,738.75	2.42	1.882

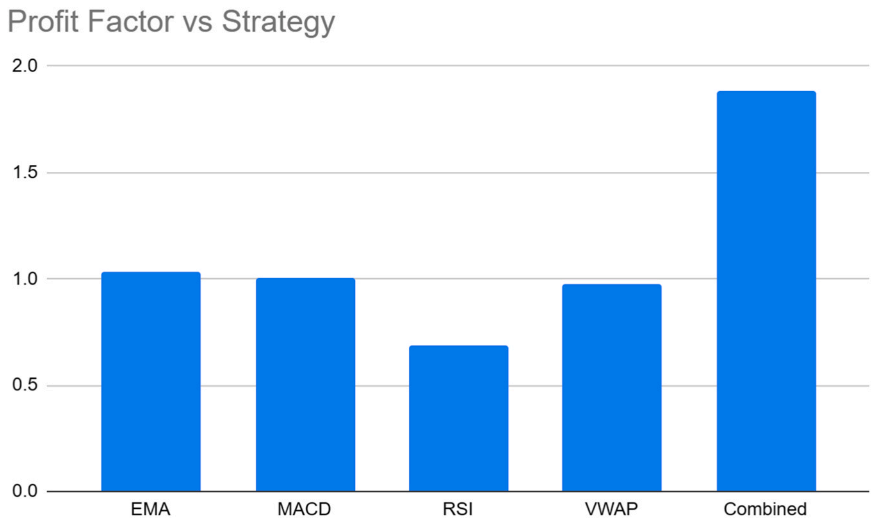

Fig. 7. Profit factor visualization.

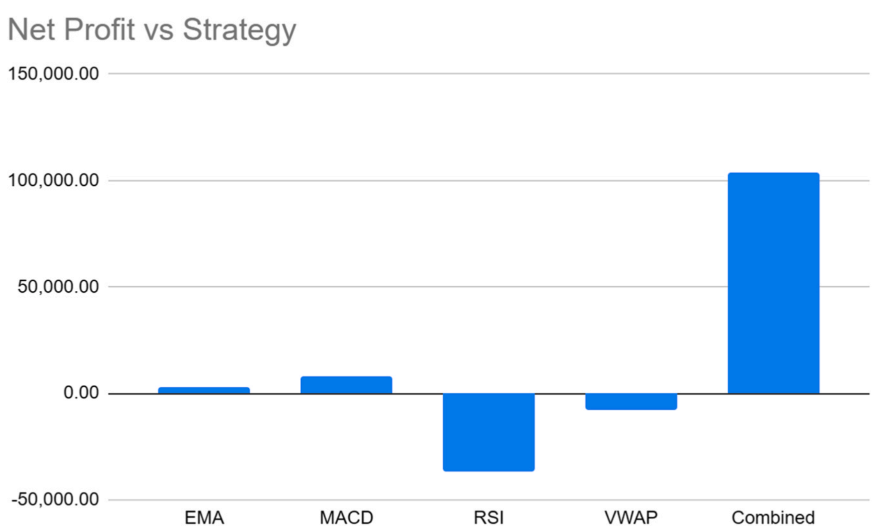

Fig. 8. Net profit per strategy visualization.

& editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Dr Ketan Kotecha:** Writing – review & editing, Supervision, Resources, Project administration. **Kanishk Gupta:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Gayatri Joshi:** Visualization, Validation, Investigation, Data curation. **Siddhanth Mutha:** Visualization, Validation, Data curation.

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