IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 17 October 2024, accepted 9 December 2024, date of publication 12 December 2024, date of current version 20 December 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3516053

RESEARCH ARTICLE

An Algorithmic Trading Approach Merging Machine Learning With Multi-Indicator Strategies for Optimal Performance

NARONGSAK SUKMA[1] **AND CHAKKRIT SNAE NAMAHOOT**[1,2]
[1]Faculty of Science, Naresuan University, Phitsanulok 65000, Thailand
[2]Center of Excellence in Nonlinear Analysis and Optimization, Faculty of Science, Naresuan University, Phitsanulok 65000, Thailand

Corresponding author: Chakkrit Snae Namahoot (chakkrits@nu.ac.th)

This work was supported in part by the Faculty of Science, Naresuan University, and in part by the Faculty of Science, Naresuan University.

ABSTRACT This study investigates the integration of machine learning techniques with multi-indicator strategies in algorithmic trading to overcome the limitations of traditional trading methods. As financial markets become increasingly complex and volatile, innovative approaches are essential to improve predictive accuracy and adaptability. This research aims to develop an algorithmic trading framework that dynamically selects relevant indicators to optimize trading performance. Researchers propose a flexible and computationally efficient model that takes advantage of advanced machine learning algorithms alongside multiple technical indicators, designed to adapt to changing market conditions. An empirical analysis evaluates the effectiveness of this approach against traditional trading indicators. The results demonstrate that the proposed algorithm achieved an impressive total return of 901%, significantly outperforming traditional indicators such as Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, On-Balance Volume (OBV), and Ichimoku. Furthermore, the model maintained a high win rate during the backtesting, showcasing its robustness under various market conditions. These findings highlight the potential of hybrid strategies that combine machine learning with technical analysis. This research emphasizes the need for adaptive trading models that can respond to the dynamic nature of financial markets. The integration of machine learning with multi-indicator strategies is shown to enhance trading performance. Future work should focus on improving the interpretability of the model and exploring diverse datasets to further enhance the effectiveness of algorithmic trading methodologies.

INDEX TERMS Undervalued stocks, algorithmic approaches, machine learning, predictive modeling, financial markets.

I. INTRODUCTION

In the complex realm of investment strategies, the quest to maximize returns while mitigating risks has perpetually preoccupied institutional investors. Central to this pursuit is the identification of undervalued stocks, a pursuit fraught with complexities and challenges, but offering tantalizing prospects of outperforming market benchmarks and delivering superior returns over the long term. Traditional approaches to the valuation of stocks, grounded in fundamental analysis and market sentiment, have long served as the basis for investment decision-making processes [1], [2], [3]. However, the dynamic and multifaceted nature of financial markets, characterized by volatility, uncertainty, and information asymmetry, requires a more nuanced and data-driven approach to identifying undervalued stocks. It is within this evolving landscape that the convergence of machine learning (ML) methodologies and investment strategies presents a compelling narrative of innovation and opportunity [4], [5], [6]. Historically, investment decisions have been guided by human intuition and analytical frameworks based on historical data and financial metrics [7]. Although these approaches have been successful, they are inherently limited by the biases and cognitive constraints inherent in human decision-making

The associate editor coordinating the review of this manuscript and approving it for publication was Yiqi Liu.

processes. In contrast, ML algorithms offer the promise of transcending these limitations by systematically analyzing vast amounts of data, identifying patterns and trends [8], and generating predictive models capable of making informed autonomous decisions [9]. Financial markets have experienced profound changes in recent years, largely driven by rapid technological advancements and the proliferation of data. As a result, traders and investors are increasingly faced with the challenge of navigating a complex and volatile environment. Traditional trading strategies, which often rely on fundamental and technical analysis, may struggle to adapt to the fast-paced dynamics of modern markets. This has led to a growing interest in algorithmic trading, a method that utilizes computer algorithms to execute trades based on predefined criteria. In this context, the integration of sophisticated analytical tools becomes essential to improve trading performance and decision-making. also, Algorithmic trading has gained traction due to its ability to process vast amounts of data and execute trades at high speeds, thereby democratizing market access. However, despite its advantages, many algorithmic trading models face limitations in predictive accuracy and adaptability. This raises critical questions about the effectiveness of existing strategies and the potential for improvement through innovative approaches. Consequently, this research aims to explore the integration of machine learning techniques with multi-indicator strategies to address these challenges. Additionally, to frame this exploration, the study poses two primary research questions:

RQ1: How can the integration of machine learning with multi-indicator strategies enhance the predictive accuracy and performance of algorithmic trading models?

RQ2: What impact does the use of a multi-indicator approach have on the interpretability and decision-making processes of traders using algorithmic trading systems?

These questions are crucial to understanding the potential benefits of combining traditional technical analysis with modern computational techniques. To answer these questions, the research sets two key objectives. First, it aims to develop and evaluate a comprehensive framework that merges machine learning techniques with multi-indicator strategies, thereby improving the predictive accuracy and overall performance of algorithmic trading models. This objective is based on the recognition that traditional indicators, when enhanced through machine learning, can provide deeper insight into market trends and dynamics. Second, the study seeks to assess the interpretability of the proposed multi-indicator approach in algorithmic trading, offering insights that enhance traders' understanding of model predictions and decision-making processes. This objective is particularly important as it addresses the often-criticized nature of machine learning models, which can hinder their adoption among practitioners.

The significance of this research lies in its potential to contribute to the existing body of knowledge on algorithmic trading. By leveraging a multi-indicator approach, the study aims to provide valuable insights for both individual and institutional investors, ultimately enhancing the effectiveness of their trading strategies. Furthermore, the findings will offer a solid foundation for future research in the field, driving innovation in algorithmic trading methodologies.

As the financial landscape continues to evolve, the need for adaptable and resilient trading strategies becomes increasingly critical. Integration of machine learning with traditional technical indicators represents a promising way to achieve this goal. By addressing the identified gaps in the existing literature and leveraging multi-indicator analysis, this research has the potential to drive significant advancements in algorithmic trading practices.

The remainder of this paper is structured as follows. Section II provides a literature review on algorithmic trading, machine learning applications, and multi-indicator strategies. Section III describes the research methodology, including data collection, model development, and evaluation metrics. Section IV presents the results of the empirical analysis, highlighting the performance of the proposed framework. Section V discusses the implications of the findings for traders and investors, while Section VI concludes the article and suggests avenues for future research.

II. RELATED WORK

A. TECHNICAL ANALYSIS

The existing body of research on algorithmic trading has made significant progress in integrating machine learning techniques with technical indicators, but several key gaps remain. Reinforcement Learning (RL) and BiLSTM models have demonstrated improved predictive precision, but these approaches often rely on a limited set of technical indicators, which can result in model complexity and potential overfitting [10], [11]. Furthermore, deep learning models, while effective, require significant computational resources, making their application in real-time trading systems challenging [12], [13]. Hybrid models that combine technical and fundamental analysis [14] or sentiment analysis [15] show promise, but their validation is often limited to specific markets or asset classes, restricting their broader applicability. Furthermore, studies indicate that high predictive accuracy does not always lead to high profitability, particularly in models that use sentiment and numerical data. There is a clear need for models that optimize profitability while maintaining accuracy. Furthermore, existing models, such as RL integrated with technical or sentiment analysis [16], often lack adaptability to rapidly changing market dynamics, a crucial aspect for real-world trading applications. Although some research explores hybrid approaches [17], there is untapped potential in combining various machine learning techniques and multiple indicators to create more robust and dynamic models. Addressing these gaps, the research proposed in this article aims to develop a more adaptive, computationally feasible, and profitable trading system, leveraging the strengths of multiple models and indicators to improve both prediction accuracy and profitability.

B. MULTI-INDICATOR APPROACHES

The current literature on algorithmic trading with machine learning and multi-indicator strategies highlights both advancements and limitations across various studies. A framework combining multi-indicator feature selection (MICFS) with Convolutional Neural Networks (CNN) has been shown to enhance prediction accuracy and trading returns by selecting relevant indicators and reducing data complexity [18]. While the MICFS-CNN approach shows promising 60.02% accuracy and 31.07% returns, the reliance on fixed indicators limits its adaptability to different stock indices and market conditions. This flexibility gap is critical, as different market environments may require dynamic indicator selection methods for optimal results. Furthermore, algorithms that use multiple indicators, such as RSI, EMA, MACD and VWAP, have also been investigated, showing that the combination of various indicators improves performance and reduces risks [19].

However, most of these studies limit their exploration of machine learning models, which could further enhance the effectiveness of these strategies in different contexts. For example, while Python script can make a strategy development, a deeper exploration of the integration of machine learning with traditional indicators is necessary to optimize results, especially in volatile markets [20]. Furthermore, a novel approach in the blockchain space has introduced a method to improve notary node participation and resource allocation, although this research is not specific to algorithmic trading [21]. However, its credit evaluation algorithm presents a useful parallel for resource allocation, a concept that could inspire similar advances in cross-chain asset trading models or even trading indicators in stock markets. Furthermore, another important area of research focuses on multi-indicator trend analysis, which demonstrates how technical indicators such as RSI, EMAs, MACD, and Bollinger Bands can improve trading profitability and forecast accuracy [22]. Although this study addresses the need for systematic strategies, it points out that risks of overfitting and potential data biases still challenge reliable long-term predictions. Machine learning methods could mitigate some of these issues by improving the feature selection process and adapting to diverse data sources, but these techniques remain underexplored in conjunction with traditional financial indicators.

Furthermore, the introduction of multiparametric models that incorporate factors such as energy (E) and entropy (S) into trading decision variables has also been shown to reduce noise and improve reliability in market analysis [23]. Although this approach emphasizes market behavior and dynamic decision-making, it lacks comprehensive empirical validation, and the complexity of integrating multiple indicators can lead to false signals. More research is needed to empirically validate how such models perform under different market conditions. However, a more recent study proposes using multi-indicator CNNs for trading signal predictions, outperforming traditional models in terms of accuracy [24]. The findings suggest that the combination of machine learning techniques with multiple indicators has significant potential to improve trading efficiency.

However, the complexity requires extensive computational resources and its adaptability under different market conditions requires further exploration [25], [26], [27], [28]. In addition, a study using SPA tests and in-sample and out-of-sample tests in ten technical trading rules from futures markets found that the best-performing rules could outperform buy-and-hold strategies under certain conditions [29].

This research highlights the profitability of technical analysis, yet its generalizability across different markets and conditions is limited, emphasizing the need for more adaptable and machine learning-based methods. While significant progress has been made in algorithmic trading by combining technical indicators and machine learning techniques, key gaps remain. Current approaches are often constrained by fixed indicator selection, computational complexity, and limited adaptability in diverse market environments. This proposed research aims to address these gaps by developing a flexible and computationally efficient model that dynamically selects the most relevant indicators. This model will aim to optimize performance under different market conditions, thus contributing to the advancement of algorithmic trading research.

C. MACHINE LEARNING IN FINANCE

The application of machine learning (ML) and algorithmic trading strategies has garnered significant attention, with numerous studies exploring various approaches to improve predictive accuracy and decision-making in financial markets. However, key gaps remain in optimizing multi-indicator strategies, integrating diverse financial data sources, and ensuring scalability across different market conditions. For example, hybrid approaches that combine machine learning with network analysis have shown promise in predicting financial distress by leveraging company correlation networks [30]. However, challenges related to the complexity of network construction and limited sector applicability persist. In the realm of green finance, ML models have indicated that digital finance can promote sustainable development [31], but the mechanisms through which this occurs remain underexplored, limiting the generalizability across various industries. Several studies have investigated the potential of combining machine learning techniques with financial fraud detection [32], cybersecurity [33], and portfolio management [27], [34], [35]. Supervised ML approaches have proven to be effective in identifying financial fraud [32], while knowledge distillation frameworks have been proposed to defend against membership inference attacks [33].

However, these models often rely on specific datasets, which may not capture the dynamics of the broader financial ecosystem. Furthermore, in portfolio management, deep reinforcement learning combined with quantum finance principles [36], [37] has shown potential in optimizing trading strategies. However, the complexity of implementation and overfitting issues suggest that further research is needed to enhance the adaptability and robustness of the model under different market conditions. Furthermore, explainable AI (XAI) techniques have been proposed to improve transparency in financial decision making [38], but comprehensive studies on their applications in algorithmic trading are lacking. Although various ML algorithms have been used to improve trading predictions [39], the focus on traditional methods limits the exploration of advanced techniques such as deep learning, which could improve predictive accuracy. In particular, neural networks have outperformed traditional models in the pricing of real estate derivatives [40] and statistical arbitrage strategies [41], but there are still gaps in addressing prediction noise and improving feature selection. Bayesian optimization and support vector regression have been applied to portfolio returns [42], but the exclusion of endogeneity issues underscores the need for more robust models capable of handling complex financial data. In addition, incorporating natural language processing (NLP) techniques into algorithmic trading is another promising avenue. One study successfully used NLP to analyze the temporal dimension of financial news, achieving high precision and recall [43].

However, reliance on labeled data sets limits the applicability to other contexts without similar data. Machine learning techniques have also been used to detect risk factors in rural financial environments [44] and identify arbitrage opportunities in quantitative finance [41]. However, both studies highlight the need for comprehensive datasets and feature engineering to capture the complexities of the financial market. This proposed research seeks to address these existing gaps by integrating various ML techniques and trading indicators to optimize performance under various market conditions. Unlike prior studies that focus on single methodologies or limited datasets, this research aims to provide a comprehensive framework for optimizing algorithmic trading performance through the integration of ML with multi-indicator strategies.

D. INTEGRATION OF MACHINE LEARNING AND TECHNICAL ANALYSIS

The intersection of machine learning (ML) and technical analysis in algorithmic trading represents a transformative frontier within the financial industry, yet the existing literature reveals several critical gaps that underscore the need for further research. Studies show that ML algorithms, such as logistic regression, support vector machines, and neural networks, significantly improve stock selection capabilities compared to traditional models [45], [46], [47]. For example, empirical analyses utilizing historical data from major stock indices illustrate that while these models achieve commendable predictive accuracy, their long-term viability in diverse market conditions remains unexplored [48], [49]. This gap is particularly concerning given the dynamic nature of financial markets, which are influenced by a variety of factors, including macroeconomic trends and investor sentiment [11], [50]. Furthermore, research incorporating sentiment analysis into predictive models shows promise in improving accuracy, but the scalability and robustness of these methods in different asset classes warrant further investigation [51], [52]. Although approaches utilizing long-short-term memory (LSTM) networks have demonstrated impressive performance, their application to individual stock movements remains largely unaddressed, indicating a crucial need for user-friendly systems that enhance interpretability and real-world applicability [53], [54]. Furthermore, studies that integrate reinforcement learning (RL) with sentiment analysis highlight its potential to optimize trading decisions but suggest the need to explore various sentiment tools for broader applicability [55], [56]. Additionally, the effectiveness of Belief Rule Based Expert Systems (BRBES) in stock price prediction outperforms traditional techniques, but there is a lack of clarity on the influence of varying market conditions, which requires comparative analyzes to validate their efficacy [57]. Furthermore, the promising results obtained from combining LSTM models with traditional trading strategies emphasize the need for continuous refinement and deeper exploration of macroeconomic impacts [58], [59]. Heuristic search strategies combined with classification algorithms also indicate success in identifying relevant indicators for stock returns, but the need for innovative predictors to enhance future models persists [60].

However, many studies do not address how model complexity and market anomalies affect the performance of trading strategies [61]. By merging machine learning with multi-indicator strategies, this research seeks to fill these gaps, providing a comprehensive framework that not only optimizes trading performance, but also enhances understanding of model behavior in fluctuating market conditions. Thus, the proposed research is crucial to advance algorithmic trading methodologies, address identified shortcomings and pave the way for more effective trading strategies in the financial sector.

III. PRELIMINARY

A. STEP 1: DATA ACQUISITION

In Step 1, focus on data acquisition, which is crucial to build a robust algorithmic trading strategy. This step involves collecting historical and real-time data to create a comprehensive data frame, specifically targeting the S&P 500 Index [62]. The quality and precision of these data significantly influence the performance of subsequent analytical steps, including feature engineering and model training. By Objectives of Data Acquisition are first, Historical Data: To analyze past performance and identify trends or patterns that can inform future trading strategies. Second, Real-Time Data: To make timely trading decisions based on the latest market conditions. Lastly, Comprehensive Dataset to ensure a well-rounded dataset that includes various attributes, such as price, volume, and market conditions that the format has present in Table 1.

TABLE 1. Description of data.

Feature	Description
Date	The specific day on which the market data were collected.
Open	The price at which the financial asset began trading at the beginning of the session.
High	The maximum price that the financial asset achieved during the session.
Low	The lowest recorded price for the financial asset throughout the session.
Close	The final price of the financial asset when the session ended.
Adj Close	The closing price was adjusted for factors such as dividends, stock splits, and other corporate actions.
Volume	The total amount of shares or contracts traded reflecting the level of activity in the market during the session.

a) Data Acquisition Process
   i) Define the Stock Universe
      (1) Identify the stocks that are part of the S&P 500 index.

$SP500 = \{sp1, sp2, sp3, \ldots, sp_n\}$

sp_i represents an individual stock in the S&P 500.

   ii) Historical Data Retrieval
      (1) Use the Yahoo Finance API to obtain historical stock price data for each stock in the S&P 500.
      (2) This includes daily price data over a specific period (for example, the last 10 years, 2010-2023).
   iii) Data fields to Retrieve:
      (1) Open Price: The price at the start of the trading day.
      (2) Close Price: The price at the end of the trading day.
      (3) High Price: The maximum price during the trading day.
      (4) Low Price: The minimum price during the trading day.
      (5) Volume: The number of shares traded during the day.
   iv) Data Structuring:
      (1) Combine historical and real-time data into a structured format, such as a data frame.
      (2) This data frame will serve as the foundation for subsequent steps in the trading strategy. The structure of the data frame may include the following:

$$DataFrame = \{Date, Stock, Open, High, Low, Close, Volume\}$$

B. STEP 2: INITIATE NOVEL FEATURE ENGINEERING WITH UNDERVALUED STOCKS CALCULATION

In this enhanced step of feature engineering, the goal is to identify undervalued stocks using a combination of technical indicators and financial ratios. The process ensures that the stock meets both value-investment principles and technical analysis criteria before passing on as undervalued.

a) Formula for Undervalued Stocks (US):

$$US = \begin{cases} if > S\frac{1}{150}\sum_{i=1}^{150} a_i > \frac{1}{200}\sum_{i=1}^{200} a_i \\ \wedge\frac{1}{200}\sum_{i=1}^{200} a_i \text{ is trending up for at least } 1 \text{ month} \\ \wedge S > \frac{1}{50}\sum_{i=1}^{50} a_i > \frac{1}{150}\sum_{i=1}^{150} a_i \wedge S > \frac{1}{50}\sum_{i=1}^{50} a_i \\ \wedge S > L_{52Low} X 1.3 \wedge S > H_{52high} X 0.75 \\ \wedge passes\ based\ on\ financial\ ratios\ and\ principles \end{cases}$$

where:
S = current price of the stock
a_i = stock price for respective day i
L_{52Low} = 52-week low price of the stock
H_{52high} = 52-week high price of the stock

b) Financial Ratios and Principles Check for each stock in the **a),** apply financial ratio checks: If the stock passes the following criteria:
   i) $PE_{ratio} > MinPE$
   ii) $PB_{ratio} < MaxPB$
   iii) Dividend Yield > Min Dividend Yield
   iv) Earnings Growth > min earnings growth
   v) Earnings Growth > min earnings growth
   vi) Earnings Growth > min earnings growth
   vii) Debt to Equity < max debt-to-equity
   viii) Price to Sales < max price-to-sales
   ix) Return on Equity > Min Return on Equity
   x) Return on Equity > Min Return on Equity
   xi) Price to Cash Flow > min price-to-cash-flow
   xii) Price to Cash Flow > min price-to-cash-flow
   xiii) Current ratio > Min current ratio
   xiv) Quick ratio > min quick ratio
   xv) Then move the stock to the final list of undervalued stocks.
   xvi) Otherwise, drop the stock.

Output: The final list of selected undervalued stocks that meet both technical and financial criteria.

C. STEP 4: MODEL TRAINING AND EVALUATION

In this step, we focus on training the selected machine learning model using the identified indicators and the target variable, which represents the investment opportunities (e.g., undervalued stocks). The model learns to recognize patterns and relationships within the data to make predictions. Following the training process, we evaluate the model performance using various metrics, including accuracy, precision, recall, F1 score, and error measures such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics provide insights into the model's effectiveness in generating reliable trading signals and its ability to generalize to unseen data, ultimately guiding investment decisions.

a) Model Training:
   i) The model is trained using the selected indicators and the target variable (e.g., undervalued stocks).
   ii) Let X be the matrix of selected indicators and y be the target variable.

iii) The model can be represented as: $y - f(X; \theta)$ where f is the function that represents the model (eg, linear regression, decision tree) and are the parameters of the model.

b) Model Evaluation Metrics:

i) Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$

ii) Precision $= \frac{TP}{TP+FP}$

iii) Recall (Sensitivity) $= \frac{TP}{TP+FN}$

iv) F1 Score $= 2.\frac{Precision \cdot Recall}{Precision+Recall}$

where:

True positives (TP) = the number of correct positive predictions.

True Negatives (TN) = The number of correct negative predictions.

False positives (FP) = the number of incorrect positive predictions.

False Negatives (FN) = The number of incorrect negative predictions.

IV. PROPOSED METHODS

A. INITIATE FEATURE ENGINEERING WITH UNDERVALUED STOCKS

This algorithm merges real-time data, historical stock prices, and financial metrics to identify undervalued stocks in the S&P 500 for algorithmic trading. The process begins by gathering historical data, such as open, closed, high, low prices, and volume, for individual S&P 500 stocks, using the Yahoo Finance API. The data are structured into a comprehensive data set for further analysis. The next step applies novel feature engineering by calculating "Undervalued Stocks" (US) using a formula based on key technical indicators and stock price trends. Additional financial checks are performed to evaluate ratios such as PE, PB, dividend yield, and debt-to-equity to ensure that stocks meet sound financial principles. Stocks passing both the technical and financial criteria are moved to a final "BUY" list, providing a solid foundation for trading decisions based on undervalued stock opportunities. This systematic approach optimizes performance and minimizes risk in trading, as shown in Algorithm 1.

B. DATA PREPARATION

This research performs a quantitative analysis of the S&P 500 using data obtained from the Yahoo Finance API [63]. The methodology used aligns with Algorithm 1 and Figure. 1, which begins by acquiring historical and real-time data to construct a data frame comprising SP500 stocks. Subsequently, the algorithm goes through a series of condition checks. First, it evaluates each stock against value investing criteria, considering parameters such as the Price-to-Earnings (PE) ratio and the Price-to-Book (PB) ratio in comparison to industry standards. Stocks that meet these criteria advance to the next stage, where technical analysis templates are applied, assessing metrics such as stock price trends and 52-week highs and lows. Those who pass this stage undergo scrutiny based on financial ratios and principles, including dividend yield, earnings growth, and debt-to-equity ratio. Stocks that meet all the conditions emerge as the final list of selected stocks. This comprehensive approach integrates fundamental

Algorithm 1 Identify Undervalued Stocks

Input: Real-time data, volume, market data, Fact Sheet (i.e., book value, dividend yield)

Step 1: Data Acquisition Process
1. Define the stock universe.
SP500 = {sp1, sp2, sp3, ..., sp_n} // Individual stocks in the S&P 500

2. Historical Data Retrieval
For each stock in SP500:
a. Use the Yahoo Finance API to fetch historical stock price data for the last 10 years (2010-2023).
b. Retrieve the following data fields:
- Open Price
- Close price
- High price
- Low Price
Volume

3. Data Structuring
Combine historical and real-time data into a structured format:
DataFrame = {Date, Stock, Open, High, Low, Close, Volume}

Step 2: Initiate Novel Feature Engineering with Undervalued Stocks Calculation
1. For each stock in DataFrame:
a. Calculate Undervalued Stocks (US)

2. Financial Ratios and Principles Check
For each stock:
a. Check the following financial ratios:
- PE_ratio > Min PE
- PB_ratio < Max PB
- Dividend Yield > min dividend yield
- Earnings growth > min earnings growth
- Debt to Equity < max debt-to-equity
- Price to Sales < max price-to-sales
- Return on equity > min return on equity
- Price-to-Cash Flow > Min Price-to-Cash Flow
- Current ratio > min current ratio
- Quick ratio > min quick ratio

3. Final selection
If the stock passes both technical and financial criteria:
Move the stock to the final list of undervalued stocks.
- Set the 'BUY' list of undervalued stocks.
Else:
- Reduce the stock.

Output:
The final 'BUY' list of selected undervalued stocks that meet both technical and financial criteria.

analysis with technical indicators, improving the robustness of stock selection. Research collects data over a decade, from 2010 to 2023, ensuring a comprehensive analysis of market trends and stock performance. During this period, information is collected for approximately 500 companies listed on the S&P 500 index, offering a broad representation of the US stock market as presented in Table 2.

Moreover, in the realm of quantitative analysis for stock selection, data preparation plays a crucial role in ensuring the robustness and reliability of the subsequent machine learning (ML) model [64] s. Algorithm 1, a crucial component of this process, sets the stage for identifying undervalued stocks based on predefined criteria. However, a common challenge in this context arises when the output of Algorithm 1 produces a relatively small number of selected stocks compared to the total pool, resulting in unbalanced sample sizes [65]. This imbalance can significantly affect the performance of ML models, particularly in cases where the minority group (i.e. undervalued stocks) is underrepresented.

To address this issue, the synthetic minority sampling technique (SMOTE) has emerged as a widely used sampling technique [66]. SMOTE is specifically designed to enhance the sample size of the minority group by generating synthetic instances that resemble existing minority class observations. By synthesizing new data points within the feature space, SMOTE effectively mitigates the imbalance and ensures adequate representation of undervalued stocks in the data set. Incorporating SMOTE into the data preparation pipeline for Algorithm 1 not only facilitates a more balanced distribution of samples, but also enhances the model's ability to discern patterns and make accurate predictions. Therefore, by using SMOTE as a preprocessing step, researchers can improve the efficacy and reliability of ML models to identify undervalued stocks, ultimately contributing to more informed investment decisions.

C. ADDITIONAL TECHNICAL INDICATOR FOR FEATURE SELECTION USING CORRELATION ANALYSIS

Researchers refine the list of technical indicators by applying feature selection. This involves reducing a larger set of trading indicators, as shown in Table 3, to a smaller and more relevant set of relevant indicators. When dealing with a large set of technical indicators, some indicators may provide overlapping information or may not contribute significantly to the predictive ability of the model. This redundancy can lead to overfitting, where the model performs well on training data but fails to generalize to unseen data. Feature selection helps us to retain only the most informative and diverse indicators, which in turn enhances the accuracy and interpretability of the model.

1) CORRELATION FORMULA

The correlation between two trading indicators I_i and J_i is calculated using the Pearson correlation coefficient.

$$C_{ij} = \frac{CoV(I_i, I_j)}{\sigma\ (I_i)\ .\sigma(I_j)}$$

TABLE 2. Data description to build ML model.

Feature	Description
US_Score	A metric used to assess the financial distress of Undervalued Stocks
Total_Trend	Overall trend analysis based on various factors.
Debt_to_Equity_Ratio	Ratio that compares the debt of a company with its equity.
Current_Ratio	The ratio indicates a company's ability to pay short-term obligations with short-term assets.
Quick_Ratio	Measure of a company's ability to meet its short-term obligations with its most liquid assets.
Return_on_Equity	Measure of a company's profitability in relation to shareholder equity.
Book_Value_per_Share	Measure of the company's total equity value on a per-share basis.
Leverage_Ratio	Ratio that indicates the proportion of debt to equity in a company.
Net_Asset_Ratio	Ratio comparing a company's net assets with its total assets.
Investment_Intensity	Degree in which a company invests in its operations, assets, or projects.
Equity_Multiplication_Factor	Factor by which equity is multiplied in certain calculations.
Non_Current_Asset_Ratio	Ratio that compares the noncurrent assets of a company with its total assets.
Liability_Proportion	Proportion of assets of a company that are financed by liabilities.
Adjusted_Capital_Value	Value of a company's capital after adjustments.
Equity_Composition	Composition and structure of a company's equity.
Non_Current_Liability_Share	Proportion of non-current liabilities of a company.
EPS	Earnings per share, indicating a company's profitability.
Gross_Profit_Margin	Measure of a company's profitability, showing the percentage of revenue remaining after deducting the cost of goods sold.
Operating_Margin	Measure of a company's profitability showing the percentage of revenue remaining after deducting operating expenses.
Net_Profit_Margin	Measure of the profitability of a company, showing the percentage of revenue remaining after deducting all expenses.
EBITDA	Earnings before interest, taxes, depreciation, and amortization.
Operating_Cash_Flow	Measure of a company's ability to generate cash from its core operations.

TABLE 2. ***(Continued.)*** **Data description to build ML model.**

Feature	Description
Free_Cash_Flow	Measure of a company's ability to generate cash after accounting for capital expenditures.
Cash_Conversion_Cycle	Measure of the time it takes for a company to convert its investments in inventory and other resources into cash flows.

TABLE 3. **Technical indicators.**

Trading Strategy	Methods	Operation	Parameter	Source
RSI	Momentum	Calculation of Average Gains and Losses	Time period	[67]
Stochastic oscillator %K	Momentum	Calculation of the highest and lowest prices	Period, %D length	[68]
CCI	Momentum	Calculation of typical price, moving average and standard deviation	Time period	[69]
CMO	Momentum	Calculation of the rate of change in price	Time period	[70]
COPP	Momentum	Calculation of the Weighted Moving Average of the Rate of Change of Price	Time period	[71]
PPO	Momentum	Calculation of the percentage difference between two moving averages	Fast and Slow	[72]
MACD	The Trend Following	Calculation of Moving Averages	Fast and Slow Longue, Signal Longue	[73]
EMA	The Trend Following	Calculation of Moving Averages	Time period	[74]
KAMA	The Trend Following	Calculation of Moving Averages	Fast and Slow	[75]
SMA	The Trend Following	Calculation of Moving Averages	Time period	[34]
VAMA	The Trend Following	Calculation of Moving Averages Weighted by Volume	Time period	[76]
TRIMA	The Trend Following	Calculation of the Triangular Moving Average	Time period	[77]
Ichimoku	The Trend Following	Calculation of Moving Averages and Cloud Area	Time period	[78]
Bollinger Bands	Volatility	Calculation of Moving Averages and Standard Deviations	Period, standard deviation	[79]
KC	Volatility	Calculation of Moving Averages and Average True Range	Period, ATR multiplier	[80]
UI	Volatility	Calculation of Drawdowns	Time period	[81]
VWAP	Volume	Calculation of the Average Price Weighted by Volume	Time period	[82]
OBV	Volume	Calculation of the cumulative volume based on price movements	Time period	[83]
MFI	Volume	Calculation of typical price and money flow	Period	[84]

where:

- C_{ij} is the correlation coefficient between indicators I_i and J_i
- $CoV(I_i, I_j)$ is the covariance between I_i and J_i
- $\sigma\,(I_i)\,and\,\sigma(I_j)$ are the standard deviations I_i and J_i, respectively.

The correlation coefficient C_{ij} ranges from -1 to 1:

- $C_{ij} = 1$ indicates perfect positive correlation (the indicators move together),
- $C_{ij} = -1$ indicates perfect negative correlation (the indicators move in opposite directions),
- $C_{ij} = 0$ indicates no linear correlation.

2) FEATURE SELECTION PROCESS

i) Start with 20 Trading Indicators:

(1) Initially, we consider a broad set of 20 technical trading indicators.

$$I_1, I_2, I_3, I_4, I_5, \ldots, I_{20}$$

ii) Calculate Pairwise Correlations

We compute the pairwise correlation between each pair of indicators I_i and J_i. This results in a correlation matrix, which shows the correlation coefficients for every pair of indicators

iii) Set a correlation threshold:

We define a correlation threshold, typically threshold = 0.75. If the correlation coefficient between two indicators $C_{ij} > 0.75$, they are highly correlated, and one of the indicators is deemed redundant.

iv) Select the final indicators:

After applying the correlation analysis, we are left with a smaller subset of small indicators that are not correlated and provide the most relevant information to predict stock movements.

v) The final set of selected indicators:

$I_1, I_5, I_6, I_{10}, I_{15}, I_{18}$ = Moving Averages, Relative Strength Index (RSI), Moving Average Convergence Divergence, Bollinger Bands, On-Balance Volume (OBV), Ichimoku Cloud

These indicators are diverse and capture different aspects of the behavior of the stock price, ensuring that the model has a well-rounded set of training features. Combining the MA20_MA50, RSI, MACD, Bollinger bands, OBV, and Ichimoku indicators provides a well-rounded trading strategy by leveraging the strengths of each tool as outlined in Table 4. MA20_MA50 shows the direction of the trend, RSI identifies overbought/oversold conditions, and MACD highlights momentum. Bollinger bands track volatility, OBV confirms trends through volume, and Ichimoku reveals support, resistance, and trend direction. Together, they offer a comprehensive market analysis for more informed trading decisions.

(1) Moving Averages:

(a) Simple Moving Average (SMA): $= \frac{1}{n}\sum_{i=1}^{n} Close_i$

(b) Exponential Moving Average (EMA): $= \alpha.Close_t + (1-\alpha).EMA_{t-1}, where\ \alpha = \frac{2}{n+1}$

(2) Relative Strength Index (RSI):

(a) $\Delta_i = Close_i - Close_{i-1}$

(b) $Gain_i = max(\Delta_i, 0)$

(c) $Loss_i = max(-\Delta_i, 0)$

(d) RS $= \frac{average(Gain_n)}{average(Loss_n)}$

(e) RSI $= 100 - \frac{100}{1+RS}$

TABLE 4. Pros and cons of the selected trading strategy.

Trading Strategy	Methods	Operation	Pros	Cons
Relative Strength Index (RSI)	Momentum indicator	Identifies overbought and oversold conditions	Provides timely entry/exit	False signals in range
Moving Average Convergence Divergence (MACD)	Momentum indicator	Identifies the direction of the trend direction and momentum strength	Clear buy/sell signals	Lagging indicator
Ichimoku	Trend-following indicator	Identifies trend direction and support/resistance	Capture multiple aspects of trend	Complex for beginners
Moving Average 20/50 (MA20_MA50)	Trend-following indicator	Identifies the short-term and long-term trend direction	Smooths out price fluctuations	Delayed signals
Bollinger Bands	Volatility indicator	Measures price volatility and potential reversals	Identifies extreme conditions	False signals in range
On Balance Volume (OBV)	Volume-based indicator	Correlates volume with price movements	Confirms price trends	Inconsistent in choppy

(3) Moving Average Convergence Divergence (MACD) Oscillator:
  (a) MACD line: $MACD = EMA_{12} - EMA_{26}$
  (b) Signal line: $Signal = EMA_{MACD,signalperiod}$
  (c) MACD histogram: $Histogram = MACD - signal$

(4) Bollinger Bands:
  (a) Middle Band (SMA): $Middle\ Band = SMA_n$
  (b) Upper Band: Upper Band $= Middle\ Band + \kappa.StdDev$
  (c) Lower Band: Lower Band $= Middle\ Band - \kappa.StdDev$

(5) On-Balance Volume (OBV):
  (a) $OBV_i = OBV_{i-1} + Volume_i\ if\ Close_i > Close_{i-1}$
  (b) $OBV_i = OBV_{i-1} - Volume_i\ if\ Close_i < Close_{i-1}$

(6) Ichimoku Cloud:
  (a) Conversion Line: Conversion Line $= \frac{maxhigh_n + minlow_n}{2}$
  (b) Base Line: Base Line $= \frac{maxhigh_m + minlow_m}{2}$
  (c) Leading Span A: LeadingSpanA $= \frac{ConversionLine + BaseLine}{2}$
  (d) Leading Span B: LeadingSpanB $= \frac{maxhigh_z + minlow_z}{2}$
  (e) Leading Span: LeadingSpan $= Close_{-y}$

D. MACHINE LEARNING MODEL ASSORTMENT ALGORITHM

Algorithm 2, This algorithm presents an integrated approach to stock price prediction using an assortment of machine learning models. It systematically applies various models: Gradient Boosting Machines (GBM), Support Vector Machines (SVM), Random Forest, Logistic Regression, Neural Networks (NN), Decision Tree, K-Nearest Neighbors (KNN) and Gaussian Naive Bayes—to historical and real-time stock data. Each model is trained on a subset of the data, evaluated using key performance metrics (Accuracy, Precision, Recall, and F1-Score), and compared to identify the optimal model for accurate stock predictions. By leveraging multiple machine learning techniques, this algorithm improves predictive performance and adapts to the complex dynamics of financial markets.

Algorithm 2 Machine Learning Model Assortment

Input:
- Historical and real-time stock data X, Labels Y
- Machine learning models: GBM, SVM, Random Forest, Logistic Regression, Neural Networks, Decision Tree, KNN, Gaussian Naive Bayes

1: **for** each model in {GBM, SVM, Random Forest, Logistic Regression, NN, Decision Tree, KNN, Gaussian Naive Bayes} **do**
2: **for** each stock $i = 1$ to m **do**
3: Prepare training data X_{train}, test data X_{test}, label sets Y_{train}, X_{test}
4: Train the model on X_{train}, Y_{train}
5: Use the trained model to predict stock labels Y = model.predict (X_{test})
6: Evaluate performance metrics: Accuracy, Precision, Recall, F1-Score
7: Store the performance results for the model
8: end for
9: end
10: Select the model with the best performance based on evaluation metrics.

Output:
- Trained models, evaluated performance metrics (Accuracy, Precision, Recall, F1-Score)
- Output the trading signals for stocks Si where $Si \in \{1$ (Buy), -1 (Sell), 0 (Hold)$\}$

E. BACKTESTING

Backtesting is essential to assess the effectiveness of a trading strategy by applying it to historical data [85], [86], [87]. In this process, portfolio performance is assessed by measuring the gains or losses of each trade over time. The equity curve tracks the growth of the portfolio by updating with each calculated return. Key performance metrics, such as total return, maximum drawdown, and the Sharpe ratio, help gauge the strategy's profitability, risk management, and consistency. This approach allows traders to fine-tune strategies before deploying them in real-world trading environments.

- Portfolio Backtesting:
  - Portfolio Performance: $Returns_t = Position_t.(Close_t - Close_{t-1})$
  - Equity Curve: $EquityCurve_t = (1 + Returns_t).EquityCurve_{t-1}$
- Performance Metrics:
  - Total Return: $TotalReturn = EquityCurve_n 1$
  - Maximum Drawdown: $MaxDrawdown = min\left(\frac{EquityCurve}{EquityCurve_{cummax}}\right) - 1$
  - Sharpe Ratio: $SharpeRatio = \sqrt{252}.\frac{mean(Returns)}{std(Returns)}$

V. EXPERIMENTS

The experiments in this study start by identifying undervalued stocks through both forward and backward testing methods. Backward testing uses historical data to simulate how the trading strategy would have performed in the past, while forward testing applies the strategy to a period outside the backtesting to ensure its predictive power in unseen data. This approach helps to validate the reliability of the feature engineering process in selecting undervalued stocks. Once the undervalued stocks are identified, the study proceeds to compare the performance of multiple machine learning models. Gradient Boosting Machines (GBM), Support Vector Machines (SVM), Random Forest, Neural Networks, and other algorithms are applied to determine the most effective model to predict stock performance. Models are trained and evaluated on the basis of their accuracy, precision, recall, and other relevant metrics.

Finally, the performance of each model is presented using portfolio backtesting, where key performance indicators such as total returns, maximum drawdown, and Sharpe ratio are calculated. Additionally, performance metrics such as accuracy, precision, recall, and F1 score are evaluated to assess the predictive capacity of each model. This comprehensive evaluation helps determine the best machine learning model for optimizing trading strategies, offering robust portfolio performance in both past and future market conditions.

A. BACKWARD TEST AND FORWARD TEST

First, the backward test period, evaluated from January 1, 2022, to December 31, 2022, assesses the model's performance on historical data. Second, the forward test period, tracked from January 1, 2023, to December 31, 2023, monitors its performance on new data. Within the forward test period lies the test date of January 2023, allowing comparison of the model's performance on January 2023 data to its historical performance. The table shows the performance of three stock indices, the S&P 500, the NASDAQ 100, and the Dow Jones, showing the number of components, components selected by the model, win / loss / neutral ratios, and cumulative returns for both the backward and forward test periods. The win/loss/neutral ratio signifies how often the model selections surpassed, lagged or matched the benchmark return, while the cumulative return reflects the total return of the model selections during the test periods, as shown in Table 5 and shows the forward test since Jan 2020 – June 2024 by DCA performance and recommended stocks overview in Table 6.

B. IDENTIFYING UNDERVALUED STOCKS APPROACH TO A FEATURE ENGINEERING

First, the S&P 500 was selected, which is one of the most important economic indexes in the United States. Comprising the 500 largest companies by market capitalization, the S&P 500 accounts for around 80% of the total value of the US stock market. Developed by Standard & Poor's, a subsidiary of McGraw-Hill, in 1957, the S&P 500 is widely used as an indicator of the state of the American economy [88]. Our system filtered 503 stocks in the S&P 500 according to the

TABLE 5. Backward test and forward test.

Index	Total	Hit	Backward test [2022/01/01 - 2022/12/31] WIN: Neutral: LOSS	Backward test [2022/01/01 - 2022/12/31] Cumulative Return	Forward test [2023/01/01 - 2023/12/31] WIN: Neutral: LOSS	Forward test [2023/01/01 - 2023/12/31] Cumulative Return
S&P 500	503	4	4: 0: 0	10.94%	4: 0: 0	13.72%
Nasdaq100	100	5	5: 0: 0	15.60%	4: 1: 0	10.21%
Dow jones	30	3	2: 1: 0	4.62%	2: 1: 0	2.36%

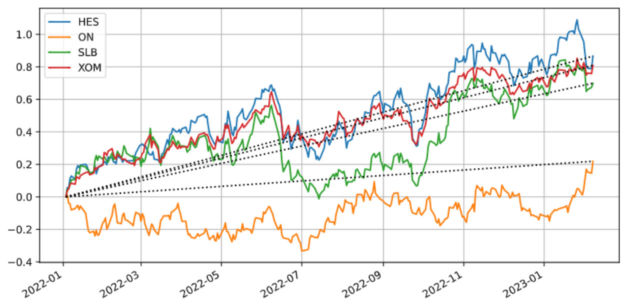

FIGURE 1. S&P 500.

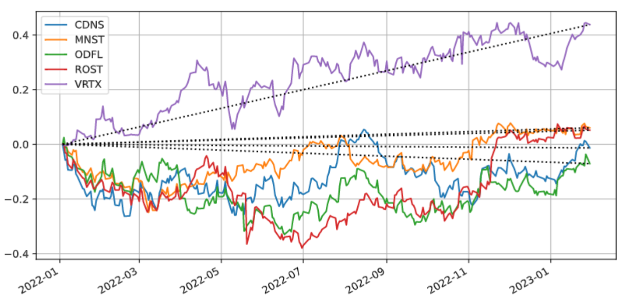

FIGURE 2. NASDAQ100.

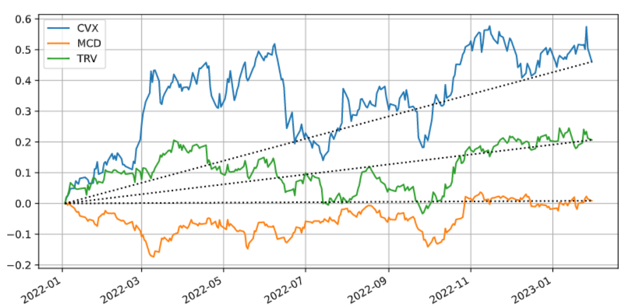

FIGURE 3. Dow Jones.

TABLE 6. DCA performance and recommended stock overview.

No	DCA date	Total	Recommend Stock	Return (%) on Dec 2021	Return (%) on Dec 2022	Return (%) on Dec 2023	Return (%) on June 2024
1	1-Jan-20	3	['AAPL', 'AMD', 'TSLA']	399.13	92.54	308.01	266.62
2	1-Feb-20	3	['AMD', 'NVDA', 'TSLA']	438.85	97.75	446.72	786.49
3	1-Mar-20	0	[]				
4	1-Apr-20	3	['AMD', 'MRNA', 'NVDA']	306.18	128.05	283.99	658.29
5	1-May-20	4	['AMD', 'MRNA', 'NVDA', 'TSLA']	346.56	104.04	283.15	494.96
6	1-Jun-20	2	['NVDA', 'TSLA']	216.06	52.67	171.54	307.78
7	1-Jul-20	6	['AAPL', 'AMD', 'MRNA', 'NVDA', 'PYPL', 'TSLA']	151.16	23.66	121.95	246.97
8	1-Aug-20	6	['AAPL', 'AMD', 'NOW', 'NVDA', 'PYPL', 'TSLA']	72.88	-21.51	75.57	172.08
9	1-Sep-20	2	['NVDA', 'TSLA']	148.56	-6.98	182.66	454.78
10	1-Oct-20	5	['AAPL', 'CRM', 'NVDA', 'PYPL', 'TSLA']	76.97	-20.06	80.54	194.03
11	1-Nov-20	7	['AAPL', 'AMD', 'CRM', 'MRNA', 'NVDA', 'QCOM', 'TSLA']	62.15	-16.28	57.18	144.18
12	1-Dec-20	10	['AAPL', 'AMD', 'AVGO', 'CRWD', 'MRNA', 'NKE', 'PYPL', 'QCOM', 'TSLA', 'UBER']	34.95	-21.67	21.34	43.49
13	1-Jan-21	11	['AAPL', 'DD', 'ETSY', 'F', 'GM', 'GS', 'MU', 'PYPL', 'QCOM', 'TSLA', 'UBER']	20.57	-28.81	-4.58	8.44
14	1-Feb-21	11	['DIS', 'GM', 'GOOG', 'GOOGL', 'LRCX', 'MRNA', 'MU', 'NVDA', 'PYPL', 'TSLA', 'UBER']	25.01	-33.73	16.38	86.03
15	1-Mar-21	19	['AAL', 'AMAT', 'AVGO', 'BA', 'BAC', 'C', 'CAT', 'CCL', 'CZR', 'DIS', 'F', 'GE', 'GM', 'GNRC', 'GS', 'MU', 'NXPI', 'PARA', 'UAL']	4.09	-30.97	-4.42	14.15
16	1-Apr-21	9	['AMAT', 'BA', 'MRNA', 'MU', 'NVDA', 'PYPL', 'TSLA', 'UBER', 'WFC']	18.53	-32.53	18.52	84.71
17	1-May-21	2	['FCX', 'WFC']	1.34	-10.57	3.36	18.91
18	1-Jun-21	4	['F', 'GM', 'MRNA', 'NVDA']	25.64	-29.21	9.20	111.60
19	1-Jul-21	1	['MRNA']	-29.33	-48.42	-71.16	-64.95
20	1-Aug-21	1	['WFC']	0.74	-15.22	1.90	17.76
21	1-Sep-21	6	['AMAT', 'GOOG', 'GOOGL', 'GS', 'MRNA', 'WFC']	1.69	-29.21	-6.15	19.88
22	1-Oct-21	4	['F', 'GS', 'MS', 'WFC']	2.46	-22.06	-11.60	-3.19
23	1-Nov-21	5	['AMD', 'F', 'NVDA', 'TSLA', 'WFC']	-2.16	-49.88	-5.88	41.07
24	1-Dec-21	3	['EPAM', 'F', 'NVDA']	10.21	-46.77	-3.23	82.56

TABLE 6. *(Continued.)* DCA performance and recommended stock overview.

No	DCA date	Total	Recommend Stock	Return (%) on Dec 2021	Return (%) on Dec 2022	Return (%) on Dec 2023	Return (%) on June 2024
25	1-Jan-22	1	['F']		-48.27	-42.77	-44.06
26	1-Feb-22	0	[]				
27	1-Mar-22	2	['DVN', 'OXY']		4.23	-12.17	-10.41
28	1-Apr-22	1	['OXY']		17.13	11.14	14.48
29	1-May-22	1	['OXY']		-7.19	-11.93	-9.29
30	1-Jun-22	1	['OXY']		4.25	-1.09	1.88
31	1-Jul-22	0	[]				
32	1-Aug-22	1	['OXY']		-14.52	-18.89	-16.46
33	1-Sep-22	2	['ENPH', 'OXY']		-0.66	-27.10	-31.20
34	1-Oct-22	0	[]				
35	1-Nov-22	1	['OXY']		-5.72	-10.54	-7.86
36	1-Dec-22	1	['ENPH']		-12.57	-56.81	-67.21
37	1-Jan-23	0	[]				
38	1-Feb-23	0	[]				
39	1-Mar-23	0	[]				
40	1-Apr-23	2	['NFLX', 'NVDA']			58.96	223.29
41	1-May-23	1	['NVDA']			70.93	337.22
42	1-Jun-23	4	['AMD', 'META', 'NFLX', 'NVDA']			24.94	101.51
43	1-Jul-23	5	[AMD', 'CCL', 'META', 'NFLX', 'NVDA']			15.39	72.77
44	1-Aug-23	4	['AVGO', 'META', 'NFLX', 'NVDA']			12.92	89.58
45	1-Sep-23	5	['ADBE', 'META', 'NFLX', 'NVDA', 'ORCL']			5.57	59.19
46	1-Oct-23	2	['META', 'TSLA']			10.27	22.64
47	1-Nov-23	2	['META', 'NVDA']			15.75	131.59
48	1-Dec-23	2	['META', 'NVDA']			7.92	114.13
DCA Total Return Year to Date (%)				**101.40**	**-0.89**	**49.45**	**126.06**

algorithm and produced four results. After conducting a year-long test, it was found that the system had a 100% win rate. The cumulative return was calculated to be 50%. Furthermore, a forward test was performed, and it was discovered that the cumulative return was 13.72% if these four stocks were purchased on January 1, 2023, compared to their prices on January 31, 2023 as shown in Figure 1.

Second, the researchers screened the NASDAQ 100, a large US growth stock index determined by market capitalization. The index reflects the profits of the leading U.S. corporations and is considered one of the world's most important stock indices. The system filtered 100 stocks using the NASDAQ 100 algorithm and produced five results, as shown in the figure. 2. A 100% win rate was found if these five stocks were purchased in January 2022 and compared to their prices in December 2022. The cumulative return was calculated to be 15.60%. A forward test was also performed, resulting in a cumulative return of 10.21%. The wind ratio was determined to be 4:1, or 80%. As shown in Figure. 3. Third, the researchers screened the Dow Jones, the oldest stock market index in the United States. The index is calculated using the prices of stable-performing companies and is considered a nationally recognized industry leader. Our system filtered 30 stocks using the Dow Jones algorithm and produced three results. A 66% win rate, 33% draw rate, and 0% loss rate were found if these three stocks were purchased in January 2022 and compared to their prices in December 2022. A forward test was performed, and the win rate was found to be 66%, the draw rate was 33%, and the loss rate was 0%. The cumulative return was calculated to be Dow Jones 4.62% and 2.36% for the test and the forward test, respectively.

C. ASSORTMENT OF MACHINE LEARNING

This research explores a variety of machine learning (ML) models to improve the identification of undervalued stocks, presenting readers with a comprehensive evaluation of their efficacy and practical utility. By scrutinizing multiple models, each characterized by unique strengths and limitations, this study offers crucial insights for judicious model selection tailored to specific requirements. Gradient Boosting Machines (GBM) emerge as a standout performer, showcasing impressive metrics across the board, with an accuracy of 0.731, precision of 0.74, recall of 0.73, and F1-score of 0.72. The GBM ensemble approach and the ability to handle complex relationships make it a robust choice for predictive modeling. Support Vector Machines (SVM) and Random Forest display comparable accuracy, with SVM demonstrating superior precision, while slightly lag in recall and F1 score compared to Random Forest. SVM achieved an accuracy of 0.687, a precision of 0.71, a recall of 0.69, and an F1 score of 0.67, while Random Forest achieved an accuracy of 0.687, a precision of 0.68, a recall of 0.69, and an F1 score of 0.66. This underscores the nuanced trade-offs inherent in classification accuracy optimization. Logistic regression strikes a balance between simplicity and performance, achieving an accuracy of 0.678, with precision, recall, and F1 score hovering around 0.68 and 0.67 respectively. Neural networks (NN) offer flexibility in the capture of intricate relationships, albeit with a slightly reduced accuracy rate of 0.662. Decision trees offer interpretability, but may be prone to overfitting, with an accuracy of 0.638, and a balanced precision, recall, and F1 score of approximately 0.64 and 0.63, respectively. K-Nearest Neighbors (KNN) exhibit decreased accuracy and performance due to their reliance on proximity-based classification, with an accuracy of 0.463, a precision of 0.42, recall of 0.46, and an F1 score of 0.43. Gaussian naive Bayes, despite its computational efficiency, demonstrates limited precision and efficacy in this context, with an accuracy of 0.065 and very low recall and F1 score metrics. By elucidating the strengths and limitations of each model, this research equips the reader with the knowledge necessary to make informed decisions regarding model selection, thus improving the efficacy and efficiency of undervalued stock identification processes in financial markets, as shown in Table 7 and Figure 4.

TABLE 7. Machine learning test performance details.

Model	Accuracy	precision	recall	f1-score
Gradient Boosting Machines (GBM)	0.731	0.74	0.73	0.72
Support Vector Machine	0.687	0.71	0.69	0.67
Random Forest	0.687	0.68	0.69	0.66
Logistic Regression	0.678	0.68	0.68	0.67
Neural Networks (NN)	0.662	0.66	0.66	0.66
Decision Tree	0.638	0.64	0.64	0.63
K-Nearest Neighbors (KNN)	0.463	0.42	0.46	0.43
Gaussian Naive Bayes	0.065	0.62	0.07	0.06

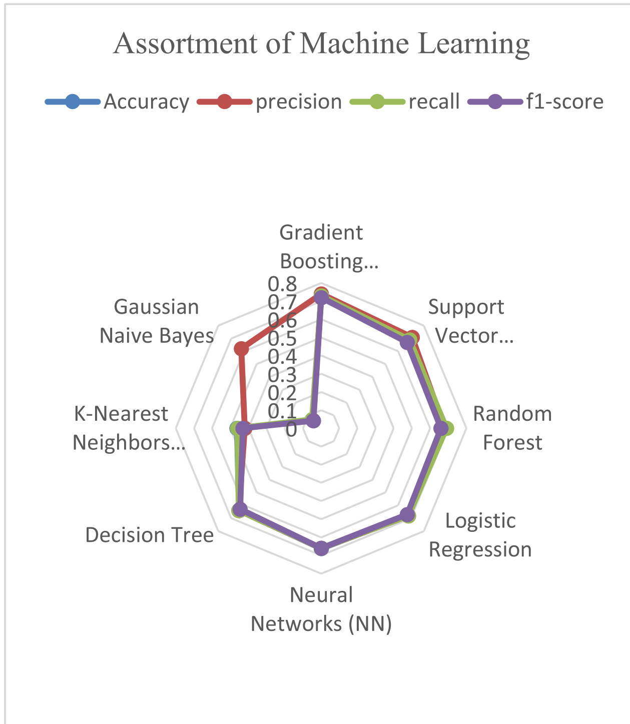

FIGURE 4. Analyze the radar graph of machine learning test performance.

D. COMPARISON BETWEEN APPROACHED ALGORITHM TRADING AND THE TRADITIONAL TRADING INDICATOR

In this section, we present a comprehensive evaluation of the performance of our proposed algorithmic trading approach in comparison to six widely recognized traditional trading indicators: Moving Average (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, On-Balance Volume (OBV) and Ichimoku. The analysis uses data from Apple's stock, drawn from the largest S&P 500 index, covering the period from January 2, 2014, to October 14, 2024. To facilitate a clear comparison, we based our evaluation on the total returns generated from an initial investment of $10,000. This approach allows us to quantify the effectiveness of each trading strategy in terms of profitability over the specified time frame. The results, summarized in Table 8 and illustrated in Figures 5-11, reveal significant disparities in performance among the various methods. The findings indicate that the algorithmic trading approach achieved a remarkable total return of 901%, substantially exceeding the returns generated by all traditional indicators. For example, MACD, which emerged as the top-performing traditional indicator with the highest performance, yielded a total return of 598%. Other indicators, such as the RSI and Ichimoku, produced returns of 329% and 529%, respectively. These results highlight the algorithm's superior ability to capitalize on market opportunities and navigate the complexities of stock price movements. Consistent performance of the

TABLE 8. Comparison of the total return between the approach to algorithm trading and the traditional trading indicator.

Subject	MA	RSI	MACD	Bollinger	OBV	Ichimoku	Approached Algorithm
Start	2014-01-02	2014-01-02	2014-01-02	2014-01-02	2014-01-02	2014-01-02	2014-01-02
End	2024-10-14	2024-10-14	2024-10-14	2024-10-14	2024-10-14	2024-10-14	2024-10-14
Start Value USD	10,000	10,000	10,000	10,000	10,000	10,000	10,000
End value USD	42,984	20,848	69,810	29,698	25,549	62,906	**100,149**
Total Return	329 %	108 %	598 %	196 %	155 %	529 %	**901 %**

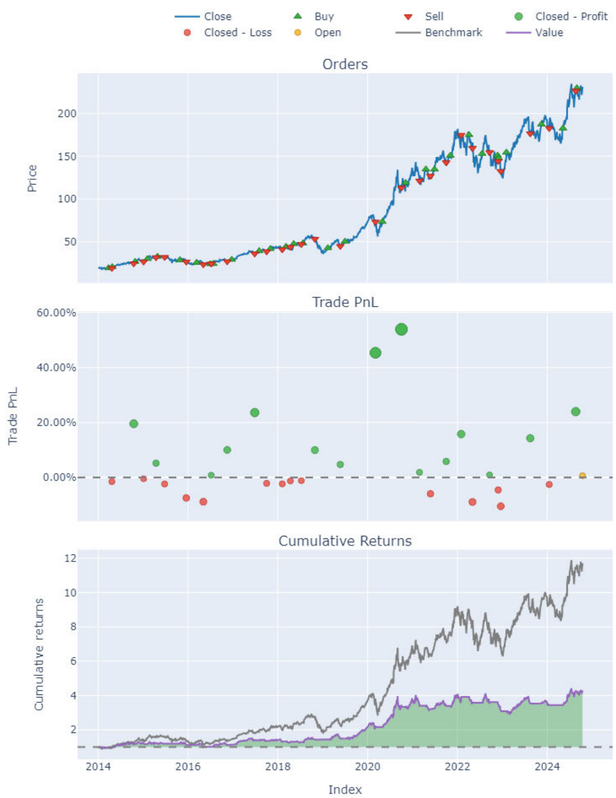

FIGURE 5. MA20_MA50.

algorithmic approach underscores its potential to leverage advanced computational techniques and complex pattern recognition, which are often beyond the capabilities of traditional indicators. Although traditional trading strategies rely primarily on historical price and volume data, our algorithm incorporates a wider range of data inputs and employs sophisticated machine learning techniques to identify and exploit market trends. This capability allows for a more dynamic and responsive trading strategy, which is particularly valuable in the context of rapidly changing financial markets.

Furthermore, comparative analysis emphasizes the growing importance of algorithmic trading methodologies in the financial sector. As markets become increasingly complex and volatile, traders are seeking more effective tools to enhance their investment strategies. The results of this study suggest that the adoption of advanced algorithms can significantly improve overall profitability and provide a competitive edge in trading.

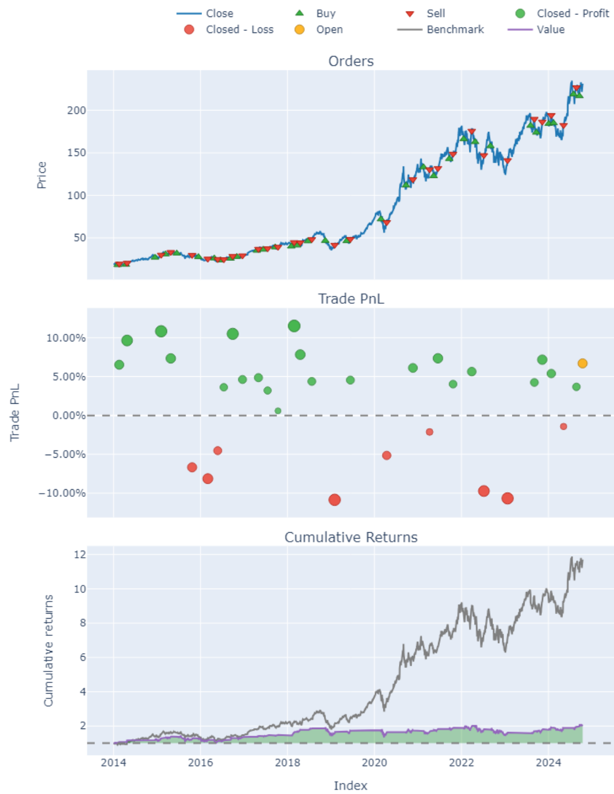

FIGURE 6. Relative Strength Index (RSI).

The result of this analysis not only demonstrates the effectiveness of our algorithmic trading approach, but also reinforces the need for traders to embrace innovative methodologies that can adapt to the evolving landscape of financial markets. By integrating advanced algorithms into their trading strategies, investors can optimize their decision-making processes and achieve superior investment outcomes.

E. KEY FINDINGS

The results of this comparative analysis clearly indicate that the algorithmic trading approach offers significant advantages over traditional trading indicators when applied to Tesla's stock over the specified period. The data reveal several key findings that highlight the superiority in various aspects.

First, the algorithmic trading strategy achieved a remarkable total return of 901%, substantially outpacing all traditional indicators. In comparison, the Moving Average Convergence Divergence (MACD), which was the top-performing traditional indicator, yielded a total return of 598%, showcasing the algorithm's effectiveness in capitalizing on market opportunities. Furthermore, the algorithm maintained a consistently higher level of profitability throughout the testing period. Although other indicators, such

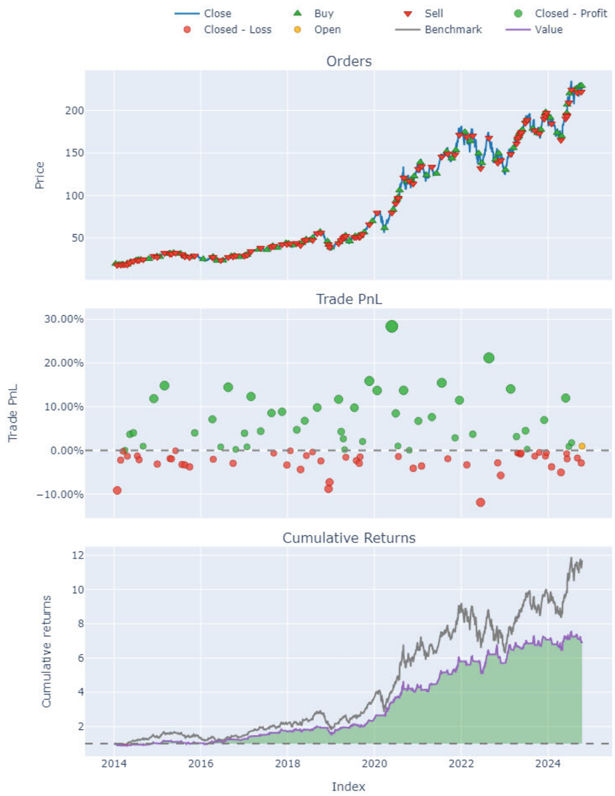

FIGURE 7. Moving Average Convergence Divergence (MACD).

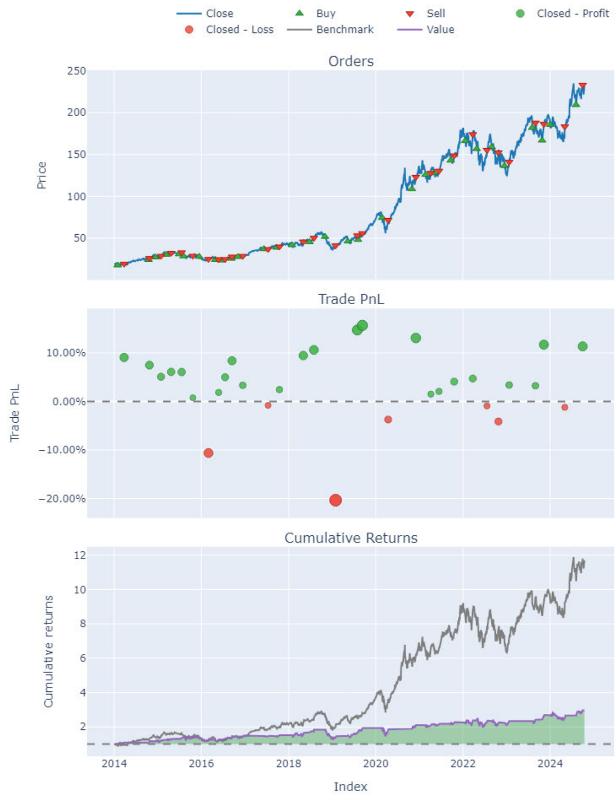

FIGURE 8. Bollinger bands.

as the relative strength index (RSI) and Ichimoku, also performed well with returns of 329% and 529%, respectively, they ultimately fell short of the algorithm's sustained performance. In addition to profitability, the algorithmic approach integrated robust risk management strategies, mitigating potential losses, and, thereby, enhancing its effectiveness. This comprehensive focus on risk is particularly valuable in volatile market conditions, which often pose significant challenges to traditional trading strategies.

Second, the algorithm demonstrated a remarkable ability to adapt to changing market conditions during the study period. This adaptability is critical for long-term investment success, especially in a dynamic environment such as the stock market, where conditions can change rapidly. Lastly, the algorithm uses large data sets and intricate patterns, enabling a more nuanced understanding of market movements. On the contrary, traditional indicators rely primarily on historical price and volume data, which can limit their effectiveness in rapidly changing market environments.

The results in this chapter indicate that these findings underscore the potential for algorithmic trading approaches to revolutionize investment strategies, providing traders with advanced tools that improve decision-making and optimize performance. As the financial landscape continues to evolve, adopting these innovative trading algorithms may become essential to achieve superior investment outcomes. This research not only contributes valuable information on the effectiveness of algorithmic trading compared to traditional methods but also encourages further exploration and application of these strategies in real-world trading scenarios.

VI. DISCUSSION

The integration of machine learning techniques with multi-indicator strategies in algorithmic trading represents a significant advancement in the field, as evidenced by the findings of this research. Empirical results demonstrate that the proposed framework not only enhances predictive accuracy but also optimizes trading performance under various market conditions. This dual benefit underscores the potential of hybrid models that leverage the strengths of traditional technical analysis and modern computational methods. One of the key insights from this study is the dynamic selection of indicators, which allows for a more nuanced understanding of market trends. Traditional trading strategies often rely on fixed sets of indicators, which can limit their effectiveness in rapidly changing environments. On the contrary, our approach adapts to market conditions, enabling traders to respond more effectively to fluctuations and anomalies. This adaptability is crucial in the volatile financial landscape, where the ability to pivot quickly can significantly affect investment outcomes. Moreover, the positive impact of the multi-indicator approach on interpretability and decision-making processes cannot be overstated. The nature of many machine learning models has been a barrier to their

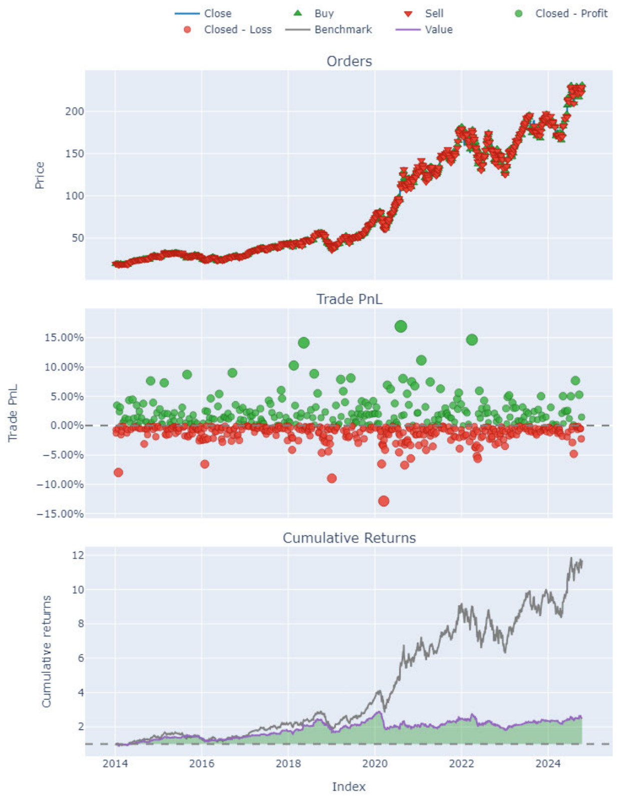

FIGURE 9. On-Balance Volume (OBV).

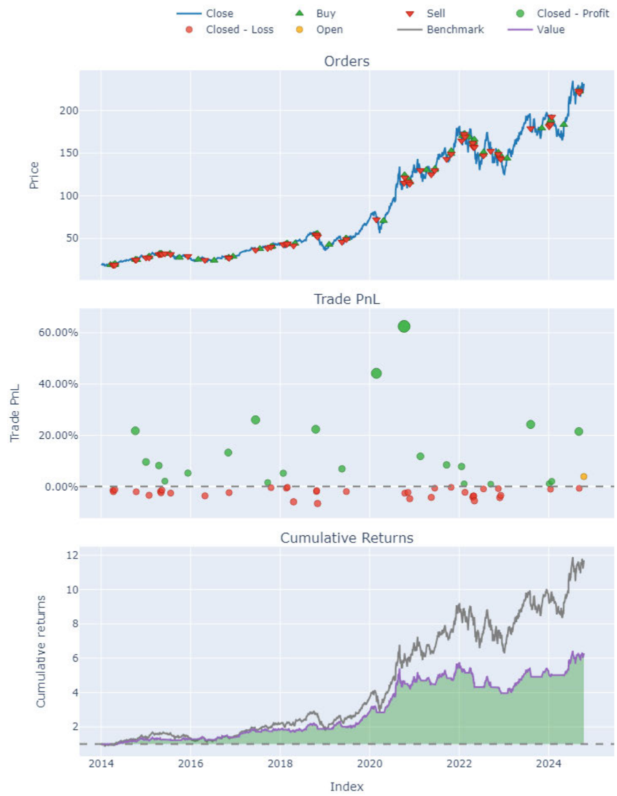

FIGURE 10. On-Balance Volume (OBV).

widespread adoption among practitioners [89], [90]. By providing clearer insights into the predictions of the model, our framework fosters greater trust and confidence among traders, which is essential for the successful implementation of algorithmic trading strategies. This aspect of our research highlights the importance of not only developing sophisticated models, but also ensuring that they are accessible and understandable to users.

In contrast, the application of long- and short-term memory (LSTM) networks in algorithmic trading has shown mixed results in previous studies [10], [61], [91]. For example, while LSTMs are designed to capture temporal dependencies in sequential data, this research demonstrated that LSTMs often struggle with overfitting, particularly when trained on limited datasets [92], [93], [94]. Their findings indicated that while LSTMs could achieve high accuracy in predicting stock price movements, the models frequently failed to translate this accuracy into profitable trading strategies due to their complexity and the need for extensive hyperparameter tuning. Furthermore, LSTMs can be computationally intensive, making them less suitable for real-time trading applications [95], [96], [97], [98]. In contrast, our proposed multi-indicator framework emphasizes computational efficiency and flexibility, allowing for quicker adaptations to market changes without the extensive resource requirements associated with LSTM models [99]. This is particularly relevant in high-frequency trading environments, where speed and adaptability are paramount. Another limitation of LSTMs highlighted in the literature is their interpretability. Although they can model complex relationships in data, the lack of transparency in how LSTMs arrive at their predictions can hinder their practical application in trading [100], [101]. In our research, the multi-indicator approach not only improves predictive accuracy but also enhances interpretability, providing traders with insights into the rationale behind model predictions. This transparency is crucial to fostering trust and facilitating informed decision-making among traders. In addition, this paper integrates machine learning with traditional valuation metrics like PE and PB ratios to identify undervalued stocks, contrasting with [102] focus on the UMO factor, which captures mispricing through corporate financing actions. While the current research emphasizes quantitative analysis, the UMO studies highlight behavioral finance's role in market dynamics and [103] provides a deeper exploration of behavioral factors influencing market mispricing. Both approaches aim to enhance predictive power and investment strategies, suggesting that a hybrid model combining machine learning techniques with insights from behavioral finance could lead to superior stock selection and performance outcomes, addressing the complexities of market behavior and misevaluation.

Overall, this research contributes valuable insights to the field of algorithmic trading by proposing a flexible and computationally efficient model that optimizes trading

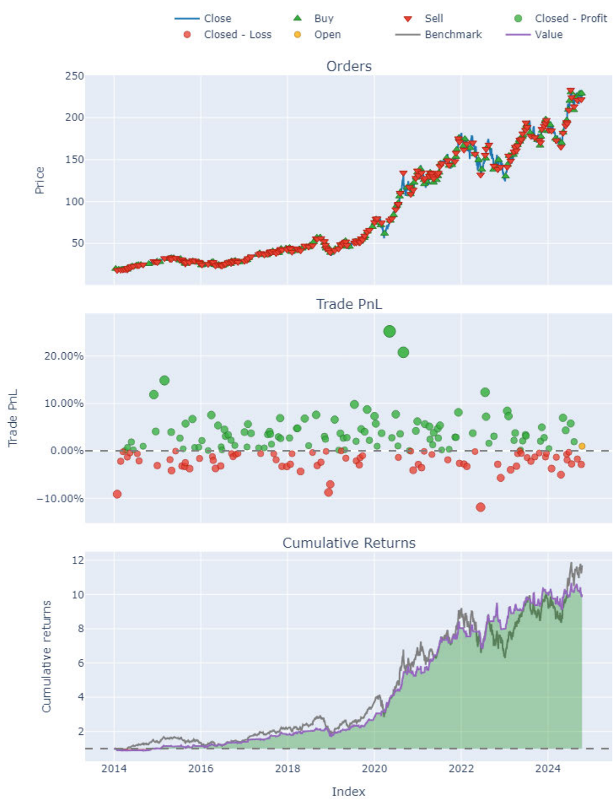

FIGURE 11. Approached algorithm trading.

performance while enhancing the understanding of market dynamics. As the financial landscape continues to evolve, the adoption of innovative trading algorithms that leverage machine learning and multi-indicator strategies will be essential for achieving superior investment outcomes. We encourage further exploration and validation of these methodologies to drive advances in algorithmic trading practices, ultimately benefiting both individual and institutional investors.

VII. CONCLUSION

This research paper presents a comprehensive exploration of integrating machine learning with multi-indicator strategies in algorithmic trading. The findings indicate that while traditional trading methods have made significant strides, they often struggle to maintain predictive accuracy and adaptability in rapidly changing market dynamics. Using advanced machine learning algorithms, the proposed framework shows marked improvements in predicting stock movements and optimizing trading strategies under various market conditions.

In addressing the research questions, we found that integrating machine learning with multi-indicator strategies significantly enhances the predictive accuracy and overall performance of algorithmic trading models. This improvement is attributed to the dynamic selection of indicators, which allows a nuanced understanding of market trends and mitigates the limitations associated with fixed indicator sets. Furthermore, the multi-indicator approach positively impacts the interpretability and decision-making processes of traders. By providing deeper insights into model predictions, this approach helps demystify the ‘‘black box’’ nature of machine learning, fostering greater trust and confidence among practitioners.

Despite these promising results, the study acknowledges certain limitations, such as reliance on specific datasets and the need for broader validation across different asset classes. Future research should focus on refining these models, enhancing their scalability, and exploring the integration of explainable AI techniques to improve transparency in decision-making processes.

In conclusion, this research contributes valuable information to the field of algorithmic trading by proposing a flexible and computationally efficient model that optimizes trading performance and enhances understanding of market dynamics. As the financial landscape continues to evolve, adopting innovative trading algorithms that leverage machine learning and multi-indicator strategies will be essential for achieving superior investment outcomes. We encourage further exploration and validation of these methodologies to drive advances in algorithmic trading practices.

LIMITATIONS AND FURTHER RESEARCH

This research advances the integration of machine learning with multi-indicator strategies in algorithmic trading, yet several limitations exist. Reliance on specific data sets may restrict the generalizability of the findings in different markets. Additionally, the computational complexity of advanced algorithms can hinder the application in real time. Overfitting remains a concern, as models may not generalize well to unseen data. To address these issues, future research should explore diverse datasets, optimize models for real-time use, and incorporate explainable AI techniques to enhance interpretability. Longitudinal studies and the inclusion of external factors could further improve predictive capabilities and model robustness.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationship that could be construed as a potential conflict of interest.

DATA AVAILABILITY STATEMENT

Original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

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NARONGSAK SUKMA received the first Ph.D. degree in information technology management from Mahidol University. He is currently pursuing the second Ph.D. degree in computer science with Naresuan University. He is also a Researcher at Naresuan University. With over 20 years of experience in information technology management, he has worked across diverse industries, including financial, banking, logistics, and telecommunications. He is a results-driven leader known for his expertise in IT governance, risk management, compliance, and the strategic application of advanced technologies. He is passionate about driving organizational transformation, improving decision-making, and enhancing operational efficiency. His innovative approaches enable businesses to harness the power of AI and big data, aligning technology solutions with strategic objectives to gain a competitive edge in a rapidly evolving digital landscape.

CHAKKRIT SNAE NAMAHOOT received the Ph.D. degree in computer science from the University of Liverpool. He is currently an Associate Professor and the Chairperson of the Ph.D. Program in computer science at Naresuan University. He is a distinguished academic and researcher renowned for his significant contributions to computer science and information technology. His expertise spans artificial intelligence (AI), smart systems, data analytics, and innovative software development, with a focus on industrial applications. His research interests include AI, smart systems, the Semantic Web, ontologies, web and mobile applications, data and web mining, the IoT, big data, and digital transformation.