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TRADING STRATEGIES DEVELOPMENT USING COMBINED ENHANCED VOTER-METHOD WITH TECHNICAL INDICATORS AND MACHINE LEARNING

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Abstract. *The financial landscape has significantly transformed recently, primarily driven by technological advances. This research addresses the complex challenges traders and investors face in today's volatile financial markets. Traditional trading strategies rooted in fundamental and technical analysis often struggle to adapt quickly to market dynamics. This study advocates for seamlessly integrating time-honored technical indicators into a unified framework, enhancing their predictive capacity and adaptability using advanced data analysis and machine learning techniques. Algorithmic trading, facilitated by machine learning models, democratizes market access, and offers unparalleled adaptability. This research presents a comprehensive framework that amalgamates the enhanced voter method with traditional technical indicators and advanced machine-learning models, shedding light on the efficacy of this integrated approach. The results demonstrate substantial improvements in key evaluation metrics, with performance indicators as follows: Accuracy = 0.698725, ROC AUC = 0.678409, PR AUC = 0.893218, Precision = 0.885099, Recall = 0.543486, and F1 score = 0.588353. This research offers a robust and adaptable framework for day trading, which benefits traders, investors, and those interested in the stock market, promoting increased adaptability, precision, and resilience in the dynamic financial landscape.*

Keywords: Algorithmic trading, Enhanced voter method, Machine learning, Technical indicators, Financial markets

1. **Introduction.** The financial landscape has been profoundly transformed in recent years, driven by relentless technological advancements. Machine learning and artificial intelligence (AI) have become the cornerstones of algorithmic trading, a pivotal force in the evolution of financial markets [1]. This research addresses the complex challenges facing traders and investors navigating the volatile markets [2-4]. Traditional trading strategies, rooted in fundamental and technical analysis, often struggle to adapt quickly to market dynamics. In response, our research aims to craft trading strategies by seamlessly integrating the enhanced method [5,6] with conventional technical indicators and advanced machine learning models. This integration seeks to enhance predictive accuracy and the strategy's overall performance. Algorithmic trading, also known as algo trading, executes orders through computer programs, and its widespread adoption, fueled by machine learning models, has democratized market access, and introduced a new era of adaptability [7,8]. The ability to analyze data, make optimal decisions, and execute trades swiftly has made algorithmic trading pivotal in modern finance. Machine learning models in algorithmic trading recognize and respond to changing market dynamics, making

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financial markets more accessible, cost-effective, and liquid [9,10]. However, traditional trading strategies face limitations in fast-paced markets. Fundamental analysis excels in long-term decisions but falters in short-term adaptations. Technical analysis, which relies on historical data, struggles with algorithmic and high-frequency trading. Our research distinguishes itself by advocating for integrating time-honored technical indicators into a unified framework. This integration, coupled with advanced data analysis and machine learning, aims to enhance predictive capacity and adaptability to modern financial markets. Machine learning, a branch of artificial intelligence, has revolutionized various industries by enabling informed, data-driven decisions based on large datasets. In trading, machine learning excels at uncovering hidden patterns and adapting to market conditions, providing a competitive edge. Its utility in algorithmic trading for predictive modelling, signal identification, and strategy optimization is evident.

Contrary to prevailing trends, our research delves into the methodology of integrating the enhanced voter method with traditional indicators and advanced machine learning models. We navigate data collection, preprocessing, model development, and evaluation, providing a rigorous analysis grounded in real-world data and empirical experiments. This research guides traders and investors in contemporary financial markets, promising increased adaptability, precision, and resilience.

This system, developed by researchers, offers guidance to investors for better decision-making. Its ability to provide reliable trading signals helps make wiser investment decisions, reduce risk, and maximize financial returns. Therefore, exploring stock investing opportunities becomes crucial to navigating an ageing society's challenges. Trading strategies are essential for informed decision-making in buying and selling financial assets [11]. Fundamental analysis relies on economic, financial, and qualitative factors to determine an asset's intrinsic value, aiming to capitalize on market inefficiencies. However, it has limitations, such as reliance on data accuracy and information lag. Technical analysis examines price and volume data to identify patterns and trends but may struggle to adapt to new market conditions. The efficient market hypothesis posits that markets promptly incorporate all available information, challenging traders looking for inefficiencies. Behavioural finance theory emphasizes psychological biases that impact decision-making and can potentially increase market volatility. Machine learning has gained popularity in financial trading, allowing computers to learn from data and make intelligent decisions [12]. Different algorithms offer various approaches, including classification, regression, clustering, and reinforcement learning. Challenges include data quality, overfitting, and interpretability. Despite their potential benefits, complex machine learning models pose interpretation challenges. The enhanced voter method, which reduces false signals, complements multiple indicators when selected judiciously selected [13].

In conclusion, while trading strategies evolve with machine learning, understanding their challenges and limitations is crucial to making informed decisions in the complex financial landscape.

2. **Framework and Algorithms.** The research framework, as shown in Figure 1, offers an illuminating snapshot of the systematic workflow governing trading strategy development. This comprehensive framework seamlessly integrates various elements, commencing with the amalgamation of S&P 500 index data and culminating in evaluating a machine learning model's performance. In particular, this model uses the robust capabilities of the Random Forest algorithm, chosen for its ability to handle time-series data prevalent in stock markets. Figure 1 acts as a visual roadmap, setting the stage for a data-driven approach guided by technical analysis and machine learning. In parallel, Algorithm 1 serves as the keystone in this journey, describing the fundamental steps that lead to the creation of informed trading strategies. The process starts with ingesting historical stock data and defining vital features essential for analysis. A pivotal phase follows, where each

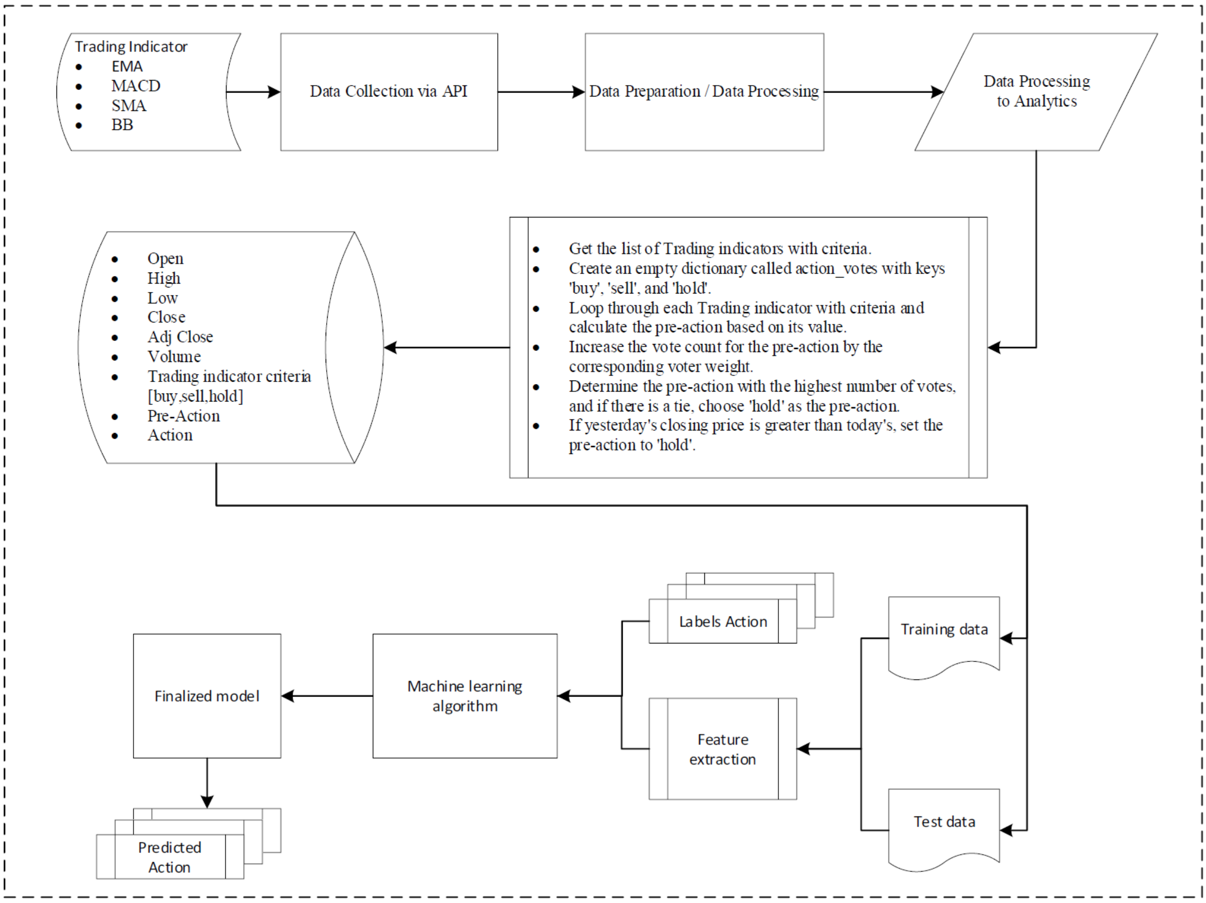

FIGURE 1. The research framework

trading indicator's pre-action conditions are meticulously defined. This encompasses the establishment of buy and sell thresholds, accompanied by assigning voter weights to these indicators, a crucial foundation that underpins prudent decision-making in the world of trading. Algorithm 1 further solidifies its alignment with the tenets of machine learning by adopting the Random Forest algorithm, chosen for its innate suitability in deciphering intricate patterns and trends within time series data. The algorithm then unfurls the process of pre-action calculation for each data point, leaning on the collective judgment of the technical indicators. This step plays a pivotal role in determining a crucial element in the final trading strategy, considering various factors, including the relative strength of each indicator and the prevailing market conditions. Subsequently, the final action is derived, thoughtfully factoring in the action, the closing price of the previous trading day, and predefined buy/sell criteria. This meticulous process ensures the execution of well-informed trading decisions, meticulously harmonizing technical analysis with the immense capabilities of the Random Forest machine learning model. In its entirety, Algorithm 1 stands as a key navigational tool to navigate the intricacies of modern financial markets, offering a robust and data-driven approach to trading strategies.

3. **Experiment Process.** The experimental process, highlighted using the Random Forest algorithm, has led to promising results, including substantial improvements in key evaluation metrics. Performance indicators are as shown in Figure 2: Accuracy = 0.698725, ROC AUC = 0.678409, PR AUC = 0.893218, Precision = 0.885099, Recall = 0.543486, and F1 score = 0.588353. The experiment meticulously evaluated the Random Forest algorithm and machine learning techniques to gauge their effectiveness in generating investment recommendations. The dataset, sourced from Yahoo Finance API, was preprocessed with categorical features like MACD, SMA, BB, and EMA transformed into numerical

Algorithm 1: Enhanced voter-method trading strategies

Algorithm: Development of trading strategies

1. Load the data from summary.csv into a panda DataFrame object and define the feature columns.
   - data = read_csv(‘summary.csv’, parse_dates=[‘Date’], index_col=[‘Date’])
   - feature_cols = [‘Open, High, Low, Close, Adj Close, Volume, Trading indicators with criteria’]
2. Define the pre-action conditions for each trading indicator with criteria.
   - pre_action_conditions = Trading indicator 1: {‘sell’: sell_threshold, buy: buy_threshold, Trading indicator 2: ‘sell’: sell_threshold, buy: buy_threshold}
3. Define the weights for each trading indicator with criteria that determine their significance in the prediction calculation.
   - voter_weights = Trading indicator 1: weight1, Trading indicator 2: weight2, ...
4. Define a pre-action function to calculate the pre-action based on the technical indicators' majority vote for each stock data row.
   - def pre_action(row):
     - indicators = [‘Trading indicator 1’, ‘Trading indicator 2’, ...]
     - action_votes = {‘buy’: 0, ‘sell’: 1, ‘hold’: 2}
     - For indicators in indicators:
       - value = row [indicator]
       - if value == ‘buy’:
         - action_votes[‘buy’] += voter_weights[indicator]
       - elif value == ‘sell’:
         - action_votes[‘sell’] += voter_weights[indicator]
       - elif value == ‘hold’:
         - action_votes[‘hold’] += voter_weights[indicator]
     - max_votes = max(action_votes.values())
     - pre_action = [k for k, v in action_votes.items() if v == max_votes]
     - if len(pre_action) > 1:
       - pre_action = ‘hold’
     - else:
       - pre_action = pre_action[0]
     - If row[‘Adj Close’] > row[‘Close’]:
       - pre_action = ‘hold’
     - Return pre_action
5. Apply the pre_action function to each stock data row to get that row's pre-action value.
   - data[‘pre_action’] = data.apply(pre_action, axis=1)
6. Define the final_action function to calculate final action based on pre-action and price change for each stock data row.
   - def final_action(row):
     - action = row[‘pre_action’]
     - If row[‘Adj Close’] > row[‘Close’]:
       - action = hold
     - if action == buy and (row[‘Close’] > data[‘Close’].shift(1)).all():
       - action = ‘buy’
     - elif action == sell and (row[‘Close’] < data[‘Close’].shift(1)).all():
       - action = ‘sell’
     - else:
       - action = action
     - Return action

data[‘Action’] = data.apply(final_action, axis=1)

End of Algorithm

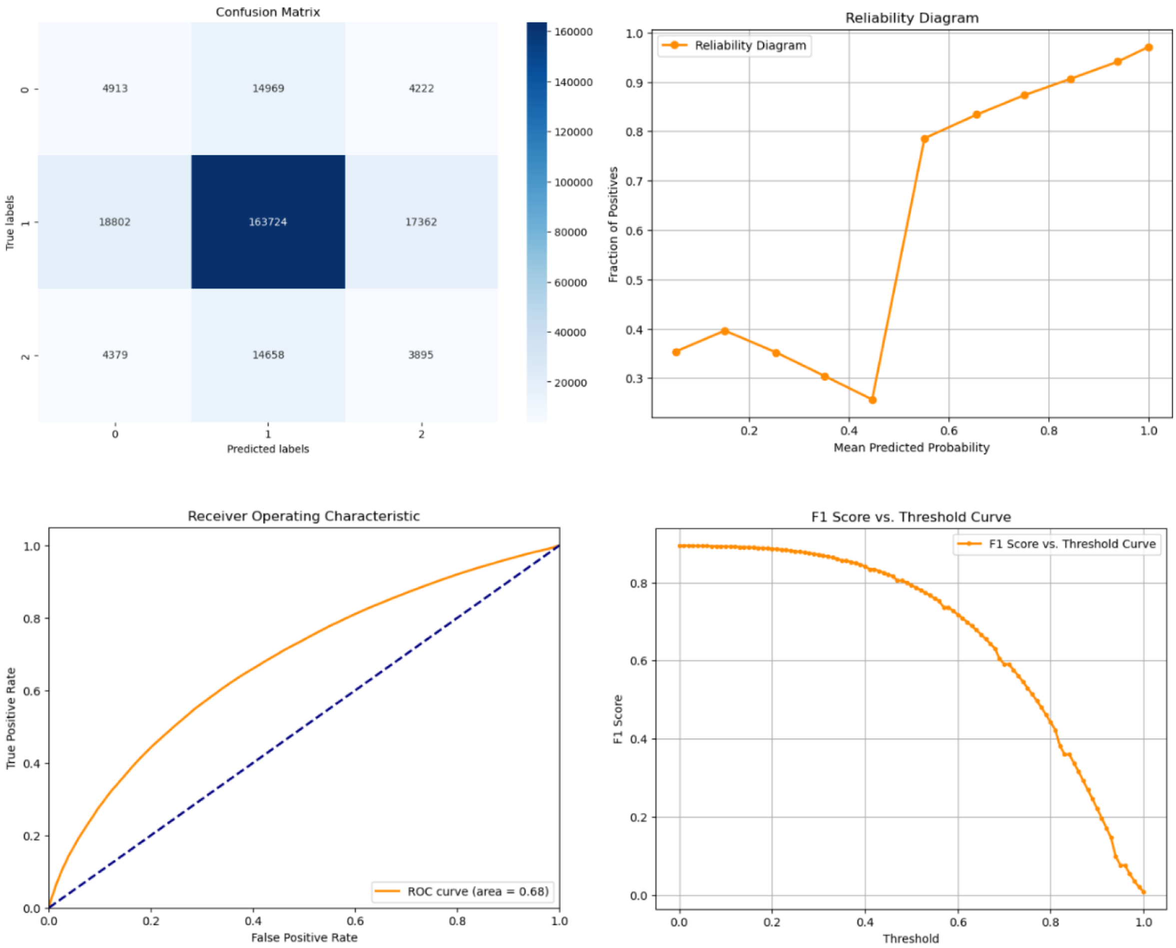

FIGURE 2. Results of the model evaluation

code. Following data preprocessing, the data set was divided into training and testing sets, with a targeted approach to address class imbalance using the synthetic minority oversampling technique (SMOTE). The Random Forest classifier underwent training on the SMOTE-augmented training data. The evaluation phase began with predicting the outcomes of the test set, computing the accuracy, and generating a detailed classification report.

Binary labels were then established, designating one class as positive facilitating subsequent performance metric calculations. Key performance indicators, including accuracy, ROC AUC, PR AUC, precision, recall, and F1 score, were consolidated and presented in a succinct data frame, providing a comprehensive overview of the model's efficacy. A set of visualizations was generated to enhance interpretability, including the confusion matrix, ROC curve, PR curve, Cumulative Gain Curve, K-S statistic plot, calibration curve, F1 score vs. Threshold Curve, Reliability Diagram, and learning curve. Each visualization contributed to a holistic analysis of the model's behavior across various evaluation perspectives. In summary, the rigorous experimental process, anchored using the Random Forest algorithm, yielded promising results, marked by substantial improvements in crucial evaluation metrics. The experiment process was integral to establishing a robust investment recommendation system. It encompassed the meticulous setup of a testing environment, recommendation system application, comprehensive evaluation of trading signals, in-depth result analysis, system optimization, and iterative refinements to enhance the recommendation system's performance continually.

Additionally, the code conducted an extensive time series analysis of historical stock data from the S&P 500 index, incorporating the computation of multiple technical indicators to generate, buy, sell, and hold signals. The Random Forest algorithm played a pivotal role in predicting actions for each data point, contributing to the overall versatility of the proposed framework for day trading. With its modular design that allows for customization and adaptation, this research paper emerges as a valuable resource for investors, traders, and individuals vested in the intricacies of the stock market.

4. Findings and Contributions.

4.1. Integration of an enhanced method and machine learning. This research successfully integrates the enhanced method with traditional technical indicators and advanced machine learning models, intending to enhance predictive accuracy and overall trading strategy performance. Algorithmic trading, powered by machine learning, democratizes market access, offering rapidness and precision. Research provides a framework to seamlessly combine time-honored indicators with machine learning, addressing the limitations of traditional strategies.

4.2. Framework and algorithm implementation. This research introduces a comprehensive framework for developing trading strategies, integrating S&P 500 index data, and employing the Random Forest algorithm for its ability to handle time-series data. Algorithm 1 outlines the systematic process, harmonizing technical analysis with machine learning for well-informed decisions.

The framework's experimental process, employing the Random Forest algorithm, yields promising results with substantial improvements in crucial evaluation metrics, including accuracy, ROC AUC, PR AUC, precision, recall, and F1 score. This underscores the effectiveness of the framework in generating investment recommendations.

4.3. Versatile framework for day trading. This research paper presents a versatile framework for day trading, leveraging machine learning techniques and the Random Forest algorithm. It performs extensive time series analysis, generating buy, sell, and hold signals based on technical indicators.

The framework's modularity allows for customization, accommodating additional technical indicators, alternative machine learning models, or exploration of diverse datasets. This adaptability positions the code as a valuable resource for traders, investors, and people interested in the stock market.

5. Conclusions. This research endeavor was conceived as a direct response to the intricate challenges traders and investors face as they navigate the tumultuous waters of today's volatile financial markets. Traditional trading strategies, firmly rooted in the basis of fundamental and technical analysis, often exhibit shortcomings in their ability to adapt to the ever-shifting dynamics of the market quickly. This limitation becomes evident when traditional strategies face the rapid adjustments required to thrive in the modern financial domain. Fundamental analysis, emphasizing long-term investment decisions, falters in the face of the rapid adaptations needed in the financial world. Similarly, technical analysis, renowned for its insights derived from historical price and volume data, often struggles to disentangle the intricate web of contemporary financial markets, where the influence of algorithmic and high-frequency trading looms large. Technical indicators, ranging from moving averages to oscillators like the relative strength index and volatility bands like Bollinger bands, represent invaluable tools for traders and investors. These instruments provide insights based on historical price data and act as key indicators to track market sentiment and momentum. Our research sets itself apart by advocating for the seamless integration of these time-honored technical indicators into a unified framework. When coupled with advanced data analysis and machine learning techniques, this integration aims to enhance their predictive capacity and, crucially, their adaptability to the dynamic nature of today's financial markets. This research serves as a testament to the evolving landscape of financial markets, where the integration of traditional analysis, machine learning, and sophisticated algorithms provides traders and investors with a powerful toolkit to navigate the complexities of modern financial markets successfully. With the foundation laid by this research, investors and traders can move forward with increased adaptability, precision, and resilience in the face of the dynamic financial landscape. The journey continues as we unlock new dimensions in the development of trading strategies driven by data, analysis, and the power of machine learning.

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