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Algorithmic Trading

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ABSTRACT :

Modernizing computers and advancements in Machine Learning have unlocked new avenues for enhancing trading strategies, such as identifying investment choices and accelerating trade execution through algorithms. Currently, algorithms account for 90% of trading activity and are utilized to establish a series of instructions that align with prevailing trends. The process of trading is streamlined by minimizing the impact of human emotions on decision-making. This concept has been around since the 20th century and is becoming increasingly competitive, with larger companies entering the market on a daily basis.

Keywords: Algorithmic Trading, high-frequency trading, Machine learning, Statistical Learning.

I. INTRODUCTION :

Black-box trading, often referred to as "algorithmic trading," is a system that executes traditional trades without human intervention; it represents a digital version of trading strategies that may rely on events, prices, patterns, news, volume, mathematical models, and more. Although the field is becoming increasingly competitive, access to data was once limited to actuaries and institutional traders, who leveraged this information to enhance their Sharpe ratios and annual returns. Research indicates that a new trend in algorithmic trading has emerged unexpectedly, with fintech-driven mobile applications significantly infiltrating the trading market due to the affordable data plans offered by major Indian telecom companies.

The retail trading sector has seen a boom following the launch of services like Jio and Airtel. Although SEBI approved trading apps that integrate fintech in 2010, their use is not as common as it once was. Some discount brokerage firms utilize artificial intelligence to offer investors tailor-made portfolios. By using educational resources, individuals can learn about various investment strategies and trading techniques. Zerodha's Kite Connect API serves as the platform for creating, testing, and executing trades. This service offers those capabilities. AI-powered, rule-based investment engines can evaluate billions of data points before suggesting investments to users, delivering insights that would take humans one data point per second and more than 31 years to replicate with the same accuracy. Pre-defined rules assist users in making trades and achieving gains.

The utilization of these also enables the creation of new wealth sources and facilitates systematic trading, without any human-emotional bias. All trades in the stock exchange will be covered by 100% soon. Done by Algo's. The use of machine learning enabled programmers, financial experts, and Developers to devise novel market-based methods for earning money. Algo trading is regarded as profitable, but it also has its drawbacks. Those who lack knowledge in code writing are discouraged from engaging in this practice as it could result in suboptimal returns. To address this, some platforms have developed no-code algo-trading services, such as Streak by Zerodha, which enable users to trade without coding and automate trades using Rule-based strategies. The author's research revealed that market volumes and algo-trading increased significantly between 2003 and 2012, as shown in Figure 1. It is anticipated that the global algo trading market will reach unprecedented levels in 2030.

Fig.1

A. Few advantages of algo trading:

a) Historical Assessment (Back testing)
b) Efficiency
c) Rule-Based implementation
d) Comparison
e) Higher Frequency

2.LITERATURE SURVEY

Over the past two decades, algorithmic trading has evolved from a niche tool used by institutional players to a widespread practice accessible to retail investors. This transformation has been fuelled by advancements in computing power, data availability, and the rise of financial technologies (fintech). Academic research and industry reports consistently highlight that algorithmic trading—also known as black-box trading—has redefined how financial markets operate by automating decision-making processes that once required human judgment.

1. Evolution and Core Mechanisms

Algorithmic trading operates through pre-programmed instructions that analyse market variables such as price movements, trading volume, and historical data. According to studies by *Hasbrouck and Saar (2013)*, these systems are capable of executing trades at speeds and frequencies that far exceed human capabilities, leading to increased market efficiency but also raising concerns about volatility and systemic risk.

2. Democratization of Trading through Fintech

Traditionally, access to real-time market data and trading infrastructure was limited to institutional investors and actuaries. However, the rise of fintech platforms has lowered the entry barrier for retail participants. In the Indian context, the launch of affordable mobile internet services by telecom giants like Jio and Airtel played a pivotal role. As highlighted in a report by *NASSCOM (2021)*, fintech adoption in India surged dramatically post-2016, with retail participation in stock markets reaching record highs, partly due to easy-to-use mobile trading apps.

3. SEBI Regulation and Growth of Discount Brokerages

The Securities and Exchange Board of India (SEBI) permitted the use of fintech-integrated trading platforms as early as 2010. This regulatory support paved the way for discount brokerage firms like Zerodha, Groww, and Upstox. These platforms not only reduced brokerage costs but also incorporated educational content and algorithmic capabilities to empower individual investors. For example, Zerodha's Kite Connect API allows developers to build and backtest trading strategies, enhancing the DIY (Do-It-Yourself) investment culture.

4. Artificial Intelligence and Rule-Based Investing

Recent literature points to a sharp rise in AI-driven investment strategies. AI and machine learning models are now capable of analyzing massive datasets and generating real-time insights that would take humans decades to process manually. A study by *Dixon et al. (2020)* emphasized how predictive models, natural language processing, and sentiment analysis have transformed how algorithms react to news, earnings, and macroeconomic indicators. Tools like Streak, a no-code trading platform, democratize algorithmic trading by enabling users to set rules and automate trades without programming knowledge.

5. Risks and Challenges

Despite its potential, algorithmic trading is not without risks. Market manipulation (such as spoofing), flash crashes, and the opacity of certain algorithms raise red flags for regulators. Moreover, individuals lacking programming or financial expertise may struggle to optimize their strategies, leading to poor returns. Scholars such as *Chaboud et al. (2014)* stress the need for risk management frameworks and better transparency in algo-based systems.

6. Future Outlook

Between 2003 and 2012, there was a marked increase in the share of algorithmic trades across global exchanges, including India. With continued investments in AI and cloud computing, industry forecasts project that the global algorithmic trading market will expand exponentially by 2030. Moreover, the integration of machine learning and real-time analytics is expected to make algo trading even more precise and scalable.

3.RELATED WORK

This section outlines the various algorithms that can be used for trading using machine learning. What are they? The software for trading algorithms employs Machine Learning.?Trading with Machine Learning techniques is now feasible exclusively through Random Forest, Probit regression (which uses neural networks to generate infinite loops), Genetic Algorithms like Deep NLP Neural Network and Support Vector Machine Regression, Random forests, and Gradient boosted decision trees.

A.Existing Software's –

a)Zerodha Streak: It is a useful tool for non-developers and non–programmers to use algebra without any prior knowledge of programming.

b)Algonomics: It is an algo trading platform, recognised as one of the best by NSEIT. High-volume transactions by investment banks, fund managers and retail algo traders benefit from its low latency execution.

c)Omnesys Nest :OmniS Nest is a highly advanced Fin-Tech trading platform that provides latency and performance advantages, making it ideally placed by high-net-worth individuals as well as institutional and retail traders. Its services include this feature.

B.Automated trading system:

ATS employs alpha trading strategies to automatically execute buy and sell orders on stock markets, yielding higher returns than traditional trading. Other computer software generates orders based on predetermined rules using events and news. To create an effective TS, we need to verify some parameters and perform certain tasks. These systems are also called event-based systems.

- Alpha (Trading Strategy)
- Backtesting

B.1.Alpha

Trading on the Exchange can lead to significant financial losses, making it essential to prioritize self-awareness over deciding which alpha to use. Discipline,emotional detachment, and patience are the key factors that contribute to a successful ATS. Our trades being made by algos will create challenges during the extended drawdown phase. Due to the inherent shelf life of Alpha, research into trading strategies that can sustain a profitable portfolio is essential. Additionally, it should be studied closely for any potential applications. Expertise in coding is essential for building robust trading systems, and programming languages like Python, R, and SQL, as well as for developing backtesting engines to manage orders and generate reports. This knowledge is crucial! By allowing consumers to develop innovative strategies and trading methods, the "Tech Stack" can be fully controlled. Ultimately, don't assume that you'll become wealthy overnight. It's not as simple as obtaining wealth, but rather it could be problematic for those who work hard to earn their money. Effective algorithmic trading necessitates a combination of study, care, patience, and knowledge.

B.2. Backtesting

To evaluate the effectiveness of a strategy, it is common to perform backtests. Backtesting is the fundamental requirement for creating trading strategies. It provides answers to intricate inquiries, such as the profitability of a trading strategy in past times. To optimize it, the optimization involves running simulations that produce dynamic results with a Sharpe ratio and returns before taking on any capital loss. The success of backtesting with high profits and low risk is likely to encourage the continuation of this strategy. When there is a negative outcome, we have the option to adjust parameters and improve the alpha before undertaking another round of backtesting. There are four major biases in backtesting.

Cognitive Bias:

This is applicable when an individual experiences a systemic mistake in thinking, which impairs their capacity to make decisions and assessments on objective information rather than subjective impressions.

Look-Ahead Bias:

A tendency to look ahead in time arises when data from a study is used that was not previously available during the analysis.

Survivorship Bias:

The research can yield erroneous outcomes and lead to capital loss. If data collection solely examines current observations while disregarding previously lost observations, it may be mistaken to believe in sample selection bias

C. Backtesting v/s Reality

A number of factors may be taken into account to backtest in order to achieve reasonable and realistic returns. Trading constraints, overfitting, unclean data, inappropriate management of transaction charges and other costs, market news changes, and backtest performance often cause deviations from real strategy deployment. Therefore, it is highly improbable that future backtesting outcomes will be in line with past results.

4.DATASETS AND FEATURE

Free stock data sources like Google (Gupta et al. 2019) and Yahoo. yfinance (Guptal 2018) is available. 2019. Real-time data can be obtained through paid APIs like Zerodh's Kite Connect, Market Stack, EOD Historical Data, Alpha Vantage, IEX Cloud App, Tiingo, and Intrinio. Additionally, applications such as Quandl and Polygon are available for use.

Figure (2) below illustrates the process that is taken to send data to the relevant systems, which are then deployed in the cloud. The gateway is used.

Features:

- The order book (Book Builder)
- Order Manager
- Strategy
- Command and control

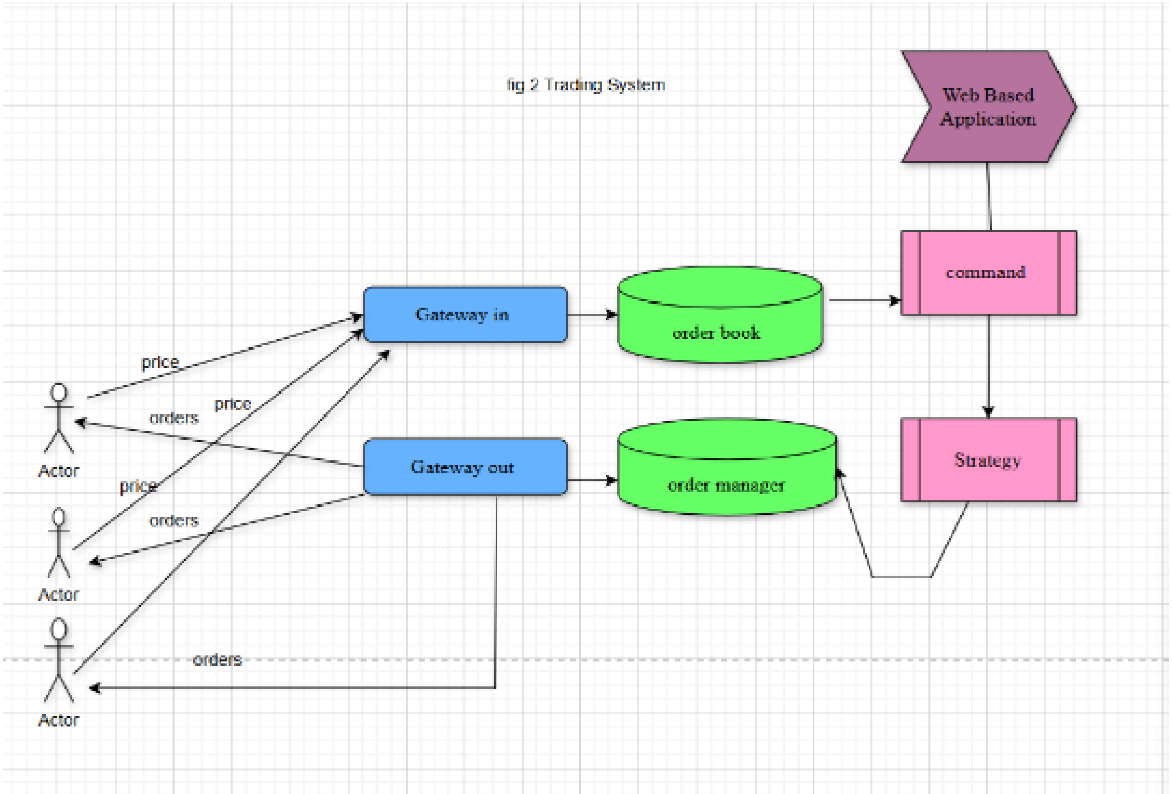

Figure 2. Trading System Design

5.CONCLUSION :

Although the earlier model didn't perform well enough for live trading—especially when looking at metrics like the Sharpe ratio and drawdown—focusing on the right model and fine-tuning key parameters led to much better results during backtesting. These improvements helped identify stronger entry and exit points, showing that with the right optimization, the strategy could be ready for live market conditions.

That said, live trading success isn't just about one-time setup. Regular monitoring and adjustments are crucial to keep up with changing market trends. Adding extra layers of risk management, like smart stop-loss settings and spreading out investments (diversification), can also make the model more stable over time. In the end, only real-time performance will show how well the strategy actually holds up in the market.

In summary, while the initial model may have fallen short in terms of risk-adjusted returns and overall stability, strategic model selection and optimization have shown that there's real potential for live deployment. The enhanced backtesting results, particularly in identifying high-probability trade entries and exits, are encouraging signs that the system can perform under real market conditions—provided it's supported by ongoing refinement.

However, transitioning from a simulated environment to live markets brings its own challenges. Market behavior is dynamic, and even the best models can underperform without consistent updates and oversight. Therefore, continuous monitoring, real-time validation, and adaptive changes are critical. Risk management techniques—like setting proper stop-loss levels, dynamic position sizing, and portfolio diversification—are not just add-ons, but essential pillars that support long-term success.

Ultimately, a model is only as good as its ability to adapt and deliver consistent performance in the face of evolving market conditions. With the right balance of automation, human oversight, and strategic flexibility, the optimized trading model stands a strong chance of not just surviving but thriving in the live trading arena.

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