JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AI-DRIVEN INVESTMENT AND PORTFOLIO MANAGEMENT

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Abstract

This paper explores the transformative role of AI-driven investment and portfolio management in Indian financial markets, focusing on efficiency, portfolio optimisation, risk mitigation, and investor behaviour. Artificial intelligence (AI), enhanced by machine learning (ML), natural language processing (NLP), and big data analytics, is reshaping how both institutional and retail investors manage assets. Regulatory liberalisation and the rapid adoption of digital investment platforms have accelerated this shift. The study examines how wealth management firms, robs-advisors, and trading platforms employ AI/ML for personalised investment suggestions, automated rebalancing, dynamic risk assessment, and strategy backtesting. These tools, once limited to institutional players, now enable retail investors to access sophisticatedportfoliostrategies. Adopting a mixed-methods approach, combining quantitative analysis of BSE/NSE-listed equities with qualitative insights from regulatory filings, industry reports, and academic literature, the research identifies benefits such as improved diversification, enhanced risk-adjusted returns, reduced behavioural biases, faster execution, and lower transaction costs. Challenges include over-reliance on algorithmic outputs, model overfitting, AI-driven short-term volatility, and systemic risks during market stress. While SEBI's regulations and AI-based surveillance address some concerns, issues of equitable accessandpotentialdatabiaspersist.The paper also highlights sentiment analysis, using NLP on financial news and social media, to predict market trends with strong correlation to asset price movements. Comparative analysis of AI-predicted portfolio performance versus actual results for select companies (2018–2025) demonstrates high predictive accuracy. A hybrid model combining AI-driven insights with human judgment isrecommendedtoenhancemarketefficiency,resilience,andinclusivity.

Keywords: AI, Portfolio Management, Risk Assessment, AT, Sentiment Analysis, NLP.

Introduction

Artificial Intelligence (AI) is reshaping investment and portfolio management in India, enabling faster, data-driven, and less biased decisions. Its integration with algorithmic trading (AT) and machine learning (ML) has created adaptive strategies that analyze vast datasets in real time, optimizing returns and managing risk. Once limited to large institutions, AI-powered predictive analytics, sentiment forecasting, and personalized portfolio recommendations are now accessible to retail investors.

Between 2018 and 2025, algorithmic trading in India surged from 30% to 58% of total trades, driven by high-speed infrastructure like colocation and Direct Market Access (DMA). Digital brokers such as *Zerodha* and *Groww* leverage AI for backtesting, volatility forecasting, and precise trade execution, while NLP tools process news and social media sentiment for timely portfolio adjustments.

Beyond execution, AI enhances portfolio management by assessing correlations, rebalancing dynamically, and simulating market scenarios. Sentiment analysis further enables proactive risk reduction and opportunity capture. Yet, challenges remain, over reliance on automation, volatility spikes, data quality issues, and unequal access pose systemic risks. Thus, a hybrid model, blending AI's efficiency with human oversight, is crucial.

This study examines two critical dimensions:
1. Prediction Accuracy - evaluating the alignment between Al-powered forecasts and actual market outcomes for select Indian companies from 2018 to 2025.
2. Market Impact - analyzing how Al-driven trading influences volatility, liquidity, and bid-ask spreads, and its implications for portfolio risk management.
By framing Al not only as a trading accelerator but also as a portfolio optimization tool, this research provides a comprehensive view of its transformative potential in India's capital markets, advocating for innovation balanced with governance, resilience, and inclusivity.

Need for the study

The rapid integration of Artificial Intelligence (AI) into investment and portfolio management is reshaping financial decision-making in India. It has brought major benefits, including faster execution and improved liquidity, but also challenges like volatility and systemic risks. With algorithmic trading participation rising sharply and AI platforms empowering retail investors, it is crucial to understand these evolving dynamics. This study aims to comprehensively analyse the implications of AI-driven algorithmic trading in India. It will assess prediction accuracy by comparing algorithmic forecasts with actual stock price movements for six leading Indian companies between 2018 and 2025, providing insight into AI's predictive power. Alongside accuracy, the research will examine broader market impact, studying volatility patterns, liquidity behaviour, and bid-ask spread dynamics. It will also evaluate how sentiment-driven signals, drawn from sources like social media and APIs, shape trading behaviour. By addressing these dimensions, the study offers a timely perspective on how AI is transforming India's markets. Its findings will contribute to fostering efficiency, resilience, and inclusivity in an increasingly automated financial landscape, bridging technological innovation with stable and transparent market operations.

Literature Review

Wilhelmina Addy, Adeola Ajayi-Nifise, Binaebi Bello and Olubusola Odeyemi (2024) discusses about **Algorithmic Trading and AI: A Review of Strategies and Market Impact**.This paper reviews AI's shift in algorithmic trading from simple codes to adaptive learning-based strategies. It highlights AI's role in efficiency, liquidity, and price discovery, while noting risks like bias and regulation, and ends with future market impacts.[1]

Dhananjaya U S, Dr. Giridhar K.V (2025) reviews about **Algorithmic Trading System in Indian Stock Market: A Study**.The study shows how algo trading in India enhances liquidity, pricing efficiency, and risk control while cutting costs and emotional bias. With tools like stop-loss orders and fast execution, it continues to strengthen stability as markets evolve.[2]

Vansh Momaya, Siddharth Hefa, Yash Bhate, Dr. Nilesh Marathe (2025) discuss about **Bridging AI and Financial Markets: A Sentiment Analysis Data Driven Approaches for Stock Market Prediction**.The paper explores AI models like BERT, LSTM, and ensembles for stock forecasting using sentiment from Twitter, Reddit, and news. Hybrid and reinforcement learning models improve accuracy and adaptability but face challenges of overfitting, interpretability, and rare-event data gaps.[3]

Smita Satish Patil, Pramod Kubsad, Savitha Kulkarni (2024) examine **Algorithmic Trading and Sentiment Analysis in Indian Stock Market**.By analyzing stock-related tweets (2018–2024), the study finds strong links between sentiment and stock trends, achieving under 5% prediction error for most companies, proving high model accuracy in real-time prediction.[4]

Pragya Saraswat, Puneet Garg, Zofiya Siddiqui (2025) review **AI & the Indian Stock Market: A Review of Applications in Investment Decision**.This review highlights AI's role in Indian markets through big data, NLP, and machine learning. Applications include trading, fraud detection, portfolio management, and sentiment analysis. Challenges like bias, privacy, and regulation remain, though AI promises efficiency and wider access.[5]

Geetika Arora and A. M. Sherry (2017) studied the **Evolution of Algo Trading and Its Future in India**.The paper traces algo trading's rise in India, showing AI-driven algorithms improve speed, reduce risk, and increase returns. In the cash segment, algo trades led to much higher volumes than non-algo trades, marking sharp growth on Dalal Street.[6]

Dr. K. Riyazahmed (2024) reviews **Algorithmic Trading Models, Aversion, and the Indian Scenario**.Reviewing 2019–2023 literature, this paper highlights models like LSTM, SVM, Gradient Boosting, and RNN for portfolio accuracy. It also discusses algorithm aversion but notes India's regulatory stance is shifting positively in support of algo adoption.[7]

Kamran Rizvi, Owais Ahmad Wani, Shakeel Akther, Dr. Nargis Akhter Wani and Dr Vidyasagar Singaram (2025) evaluates **Algorithmic Trading in India's Retail-Dominated Markets: Liquidity, Volatility, and Regulatory Challenges**.Analyzing NSE data (2020-2024), this study finds retail algo adoption tightened Nifty spreads but increased small-cap volatility. UPI integration spurred herding, and SEBI's 2022 cap curbed cancellations but widened spreads. It suggests tiered regulations for balance.[8]

Thibaut Theatea, Damien Ernsta (2020) evaluates **An Application of Deep Reinforcement Learning to Algorithmic Trading**.The paper introduces Trading Deep Q-Network (TDQN), a DRL model tailored for maximizing Sharpe ratio. Using artificial trajectories from limited data, TDQN shows promising trading performance and introduces a new evaluation approach.[9]

Medha Mathur, Satyam Mhadalekar, Sahil Mhatre, Vanita Mane (2021) discusses about **Algorithmic Trading Bot**.This project built a bot to trade at high speed based on predefined rules. It adapts to market conditions, executes both user and system strategies, reduces costs, improves liquidity, and targets optimal daily turnover for profits.[10]

Bhumika Gupta Monika Negi, Kanika Vishwakarma, Goldi Rawat and Priyanka Badhani (2017) cover the **Study of Twitter Sentiment Analysis using Machine Learning Algorithms on Python**.The paper reviews Twitter sentiment analysis, outlining challenges in handling tweet data and discussing machine learning and NLP methods, with a general Python-based framework for conducting sentiment analysis.[11]

Sharvil Shah, K Kumar and Ra. K. Saravanaguru (2016) show the **Sentimental Analysis of Twitter Data Using Classifier Algorithms**.Focusing on Twitter sentiment, the study applies hashtag classification, Naïve Bayes, and emoticon analysis in a hybrid model. It improves polarity classification and accuracy, supporting uses in reviews, product feedback, and consumer analysis.[12]

Objectives

1) To study the role of retail trading platforms such as *Zerodha* and *Groww*.
2) To assess the impact of algorithmic trading on market efficiency.
3) To evaluate the prediction accuracy of AI-based algorithmic trading models.

Research Methodology

This study follows a mixed-methods approach, combining both quantitative and qualitative analysis to evaluate the impact of AI-powered investment and portfoliomanagement in Indian financial- capital markets. Quantitative analysis focuses on metrics such as price prediction, volatility, bid-ask spreads, liquidity using data from the NSE, BSE, and SEBI. Qualitative insights are drawn from regulatory filings, academic literature, and platform documentation to understand broader market behaviour and sentiment trends.

Secondary data sources form the basis of this study. Historical stock prices, trading volumes, market depth, and order processing rates were collected for 6 major companies, including HDFC, Reliance, SBI, Cipla and more. Trading platform data from *Zerodha* and *Groww*, including API access, user metrics and strategy tools, were also analysed.

Sentiment signals from Twitter and news sources were examined for their correlation with stock prices. Descriptive statistics were used to study trends in liquidity and volatility from 2018 to 2025. The study focuses on Indian equity markets, particularly the equity derivatives segment. While evaluating tools like Zerodha's Streak and Groww's Stratzy, the research also notes limitations such as model overfitting, sentiment misclassification and regulatory gaps. Ethical considerations were maintained, using only publicly available and officially published data.

Scope of the study

The scope of this study is primarily focused on Indian financial markets, specifically analysing data from BSE and NSE. Temporally, the research covers the period from 2018 to 2025, for the comparative analysis of AI-derived price predictions against actual stock movements.

The study also comprehensively examines the transformative impact of investment and portfolio management and its integration with AI and ML. This includes a quantitative analysis of market dynamics, focusing on Market Volatility, Liquidity, Market Efficiency, Investor behaviour- Particularly examining how AI-enhanced platforms like *Zerodha* and *Groww* empower retail investor decision-making, Sentiment Analysis and Prediction Accuracy.

The analysis was concentrated on the Equity Derivatives Segment of these exchanges, where AT participation had significantly evolved. While acknowledging the broader global context, the study's empirical investigation was confined to the Indian market's unique regulatory and structural environment and what the trading algorithms did to the market (their effects on prices, etc.), not how they were secretly built or programmed internally.

Limitations

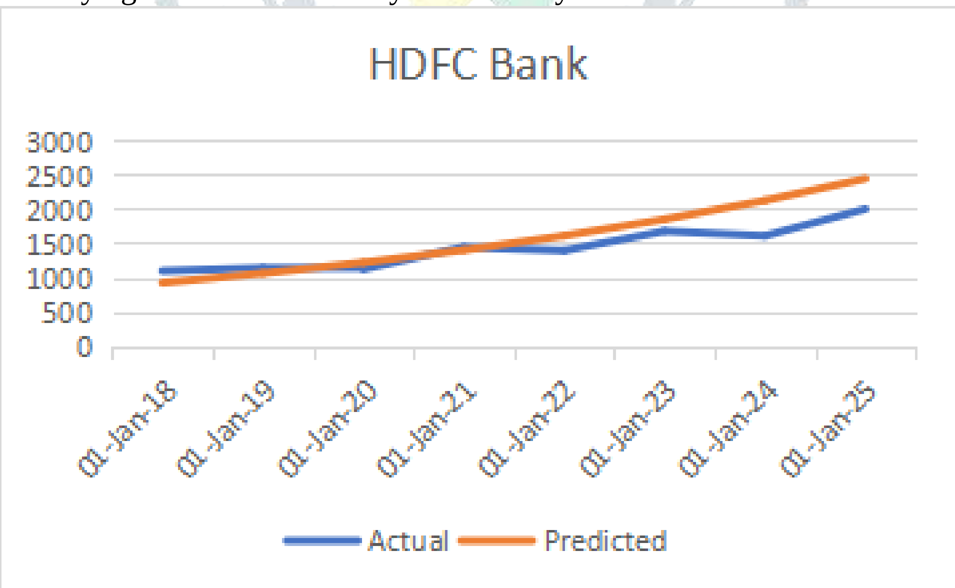
The integration of AI-driven investment and portfolio management in India faces several limitations that shaped this study.Data accessibility remains a major barrier. Due to paywalls and limited historical depth, especially for 2024-2025, this study relied on secondary sources and prior research instead of real-time platform data. Sentiment analysis also suffers from data quality issues; unstructured or biased inputssuch as social media or prior literaturecan distort sentiment readings and lead to flawed trading outcomes. Accessing real-time data from third-party APIs like *Groww's* is difficult since most are proprietary.While retail platforms democratize access, growing reliance on automation risks eroding human judgment, particularly during volatility. Many retail users also lack the financial literacy to handle complex algorithmic tools effectively. Sentiment analysis further struggles with subjectivity in languagesuch as sarcasm or ambiguityraising chances of misinterpretation and herding behavior.In conclusion, AI in investment and portfolio management presents strong opportunities but is constrained by data gaps, model weaknesses, regulatory needs, and investor preparedness. Addressing these requires continuous model refinement, tighter oversight, and stronger investor education.

Data Analysis

Our data analysis primarily utilizes **secondary data**, leveraging existing datasets from prominent financial institutions such as NSE, BSE and SEBI, supplemented by relevant academic literature. This approach provides access to extensive historical and current market information, crucial for evaluating the impact of algorithmic trading and AI on Indian financial markets. While acknowledging the limitations of using pre-collected data, careful validation and contextualisation of these sources enable an insightful examination of market dynamics and predictive model performance.

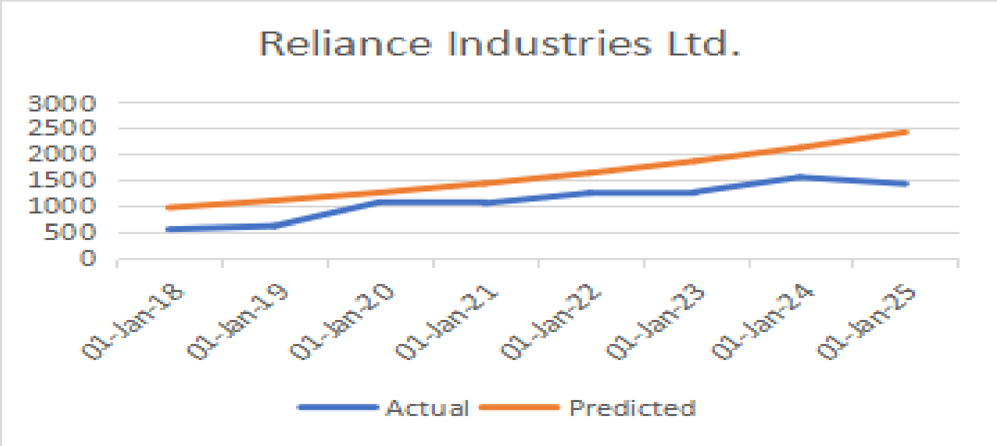
Analysis 1

This section presents a comparative analysis of actual versus predicted stock prices for selected 6 major Indian companies, along with their respective error rates for the year 2025, to evaluate the forecasting capabilities of the underlying models of from July 2018 to July 2025.



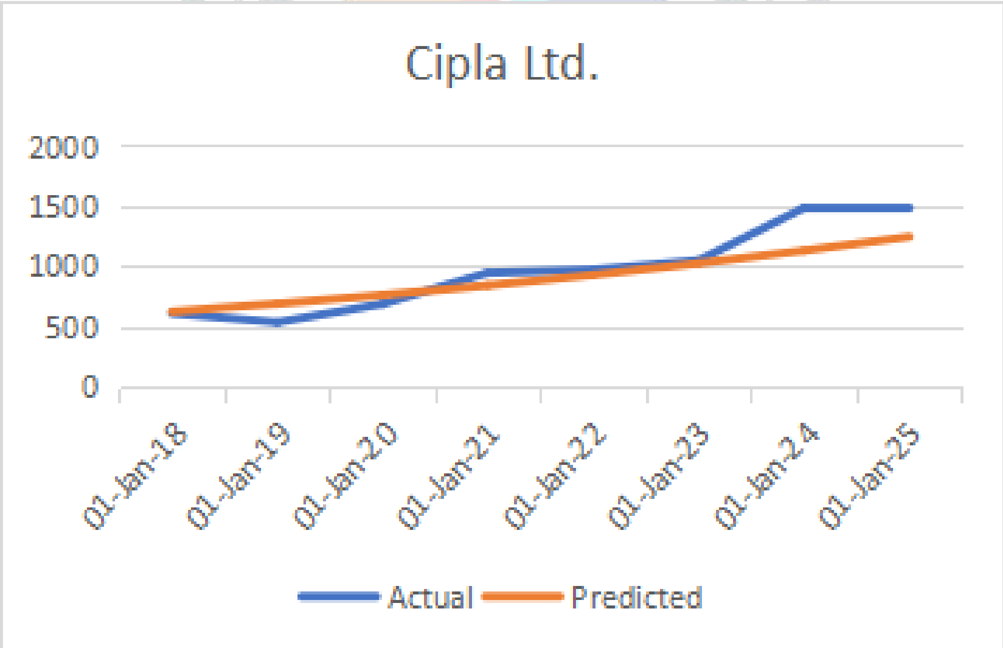
Source- NSE

The table and graph for HDFC Bank show a consistent upward trend in both actual and predicted stock prices from July 2018 to July 2025. The actual price rose from ₹1,094.53 in 2018 to ₹2,001.5 in 2025, while the predicted values increased from ₹920 to ₹2,446.07 over the same period. However, from 2022 onwards, the predicted prices began to significantly exceed the actual prices, suggesting a possible overestimation in the forecasting model. Notably, in July 2022, the actual price saw a slight dip to ₹1,392.5, whereas the predicted value continued rising to ₹1,609.09. The graph clearly shows this widening gap between actual and predicted prices after 2021, indicating a divergence from real market behavior.



Source: NSE

From 2018 to 2023, the actual stock price of Reliance steadily increased from ₹559.03 to ₹1555.15, showing strong growth, but slightly declined to ₹1428.6 in 2025. The predicted prices, however, showed a much steeper rise, going from ₹969 in 2018 to ₹2424.68 in 2024. The model consistently overestimated the prices, and the gap between actual and predicted values widened noticeably after 2020. The graph clearly highlights this divergence, especially in the last two years, suggesting the prediction model failed to capture the slowdown in actual growth.



Source: NSE

The table and graph for Cipla Ltd. show a comparison between actual and predicted stock prices from July 2018 to July 2025. While the predicted values closely follow the actual ones from 2018 to 2022, a growing gap appears from 2023 onward, with actual prices rising more sharply than predicted. The line graph reflects this trend, showing strong real-time growth in Cipla’s stock, especially between 2023 and 2024, indicating the model underestimates recent performance.

Asian Paints Ltd.

Year	Actual	Predicted
20-Jul-18	1434.85	1345.5
20-Jul-19	1369.1	1574.23
20-Jul-20	1712.05	1841.85
20-Jul-21	3083.75	2154.97
20-Jul-22	3067.4	2521.32
20-Jul-23	3517.7	2949.94
20-Jul-24	2946.05	3451.43
20-Jul-25	2375.4	4038.17

Source:NSE

The table and graph for Asian Paints Ltd. compare actual and predicted stock prices from 2018 to 2025. From 2018 to 2023, the actual stock price showed strong growth, peaking at ₹3517.7 in 2023. However, in 2024 and 2025, the actual price declined to ₹2375.4, while the predicted prices continued rising sharply, reaching ₹4038.17 by 2025. The graph shows this divergence clearly: initially, predicted values closely follow the actual trend, but from 2023 onward, there's a significant gap, indicating that the model overestimated future stock performance.

ONGC Ltd.

Year	Actual	Predicted
20-Jul-18	157.95	173.84
20-Jul-19	141.9	184.27
20-Jul-20	81	195.31
20-Jul-21	115.3	207.14
20-Jul-22	132.45	219.45
20-Jul-23	170.55	232.6
20-Jul-24	319.65	246.56
20-Jul-25	246.31	261.35

Source: NSE

The table and graph depict the actual versus predicted stock prices of ONGC Ltd. from July 2018 to July 2025. The actual prices (in blue line) show significant fluctuations, with a noticeable dip in 2020 (₹81) followed by a steady recovery and a sharp rise peaking in 2024 (₹319.65), before slightly declining in 2025 (₹246.31). In contrast, the predicted prices (orange line) show a consistent upward trend, gradually increasing from ₹173.84 in 2018 to ₹261.35 in 2025. The disparity between the actual and predicted values highlights the volatility in real market behavior versus the smoother projection made by the prediction model.

SBI

Year	Actual	Predicted
20-Jul-18	286.75	328.01
20-Jul-19	349.4	360.81
20-Jul-20	188.2	396.89
20-Jul-21	412.9	436.58
20-Jul-22	513.7	480.24
20-Jul-23	615.1	528.26
20-Jul-24	889.35	581.09
20-Jul-25	823.35	639.2

Source: NSE

The table and graph illustrate the actual versus predicted stock prices of SBI from July 2018 to July 2025. The actual prices (blue line) display noticeable fluctuations, with a sharp drop in 2020 (₹188.2), followed by a strong upward trend peaking in 2024 (₹889.35). In contrast, the predicted prices (orange line) follow a smoother and steady upward trajectory from ₹328.01 in 2018 to ₹639.2 in 2025. The divergence between the actual and predicted lines emphasizes how real market behaviour is more volatile and influenced by external factors, whereas the prediction model assumes a more linear growth pattern.

error % (2025)

Company	Actual Price	Predicted Price	Error Rate (%)
ONGC Ltd.	246.31	261.35	6.11%
SBI	823.35	639.20	22.37%
Cipla Ltd.	1473.90	1246.41	15.42%
Asian Paints Ltd.	2375.40	4038.17	69.93%
HDFC Bank	2001.50	2446.07	22.22%
Reliance Industries	1428.60	2424.68	69.74%

The table presents the error rates (%) for stock price predictions in 2025 for six companies, using the formula:

Error Rate = ((Predicted Price − Actual Price) / Actual Price) × 100.

ONGC Ltd. showed the most accurate prediction with only 6.11% error, while Cipla Ltd. also performed well at 15.42%. SBI and HDFC Bank had moderate errors of 22.37% and 22.22% respectively. However, predictions for Asian Paints Ltd. (69.93%) and Reliance Industries (69.74%) were significantly off, indicating overestimated values and poor prediction accuracy for these stocks.

In summary, while our predictive models identified general market trends, their accuracy varied across stocks and conditions. For some high-profile companies, the models often overestimated prices and smoothed out actual volatility. This shows the need to refine AI tools so they can better capture the complex, unpredictable movements of stock prices, rather than simply memorizing past data.

Analysis 2

This section shows a comparative analysis of India's two leading digital-first stockbroking platforms, *Zerodha* and *Groww*, focusing on their strategic approaches, market penetration, profitability, brokerage structures, and the functionalities of their algorithmic trading APIs. By examining these aspects, we aim to understand how these platforms contribute to the broader adoption of AI in investment and portfolio management.

the table below shows the comparison between *zerodha* and *groww* under different criteria-

Metric / Aspect	Zerodha	Groww
Active Clients (Feb 2025)	~7.96 million	~13.01 million
Market Share (Feb 2025)	~16%	~26%
Revenue March FY24 (approx.)	9372 Cr	3145 Cr
Net Profit March FY24 (approx.)	5496 Cr	535 Cr
Brokerage (Equity Delivery)	Free/₹0	₹20 or 0.1% of the trade value, with a minimum charge of ₹5.
Brokerage (Intraday)	₹20 per executed order or 0.3% (whichever is lower)	₹20 per executed order or 0.1% (whichever is lower)
Brokerage (F&O)	₹20 per executed order or 0.3% (whichever is lower)	₹20 per executed order
Algo Trading API Support	Yes (Official - Kite Connect)	Yes (Official - Groww Trading API)
API Cost (Market Data)	₹500/month	₹499 + taxes/month

API Order Rate Limit	10 per second	15 per second
API Live Data Rate Limit	N/A (implied by ₹500/month fee)	10 per second

Source: Zerodha[16] and Groww[15].

Zerodha and Groww are two major stockbroking platforms in India with contrasting strategies. As of February 2025, Groww leads with 13.01 million active clients (26% share), while Zerodha has 7.96 million (16%). Despite fewer users, Zerodha is far more profitable—posting ₹9372 crore revenue and ₹5496 crore profit in FY24, against Groww's ₹3145 crore revenue and ₹535 crore profit. In brokerage, Zerodha offers free equity delivery, while Groww charges ₹20 or 0.1% of trade value (minimum ₹5). For intraday and F&O, both charge ₹20 per order, but Zerodha caps it at 0.3%, making it cheaper for larger trades. Both support algo trading—Zerodha via Kite Connect and Groww via Groww API. Zerodha charges ₹500/month for market data (with live data bundled), while Groww charges ₹499 + tax. Groww allows 15 API orders/sec and 10 live data requests/sec, while Zerodha permits 10 orders/sec. In summary, Groww dominates in user base due to accessibility, but Zerodha remains more profitable and offers better value for active or high-frequency traders.

ZERODHA'S API		
Section	**Parameters**	**Details**
Kite Connect API Specifics	**Cost for Market Data (Monthly)**	₹500/-
	Order Rate Limit (per second)	10
Streak Specifics	**Live Strategies (Max)**	5
	Virtual Strategies (Max)	15
	Back test Limit (Dynamic Options Contracts)	50/day
	Instruments per Strategy (Max)	50
	Backtest Data Window (1-min candles)	30 days
	Backtest Data Window (1-day candles)	5 years

Source: Zerodha[16].

Zerodha offers its API services primarily through the Kite Connect API, which provides programmatic access to real-time market data and order placement, at a monthly cost of ₹500. It supports an order rate limit of 10 per second, making it suitable for moderate-frequency trading needs. While Kite, Zerodha's trading platform, serves as a high-performance interface for retail and active traders, featuring advanced tools like universal instrument search, market depth (20 levels), GTT and basket orders, and intuitive UI- it does not natively support strategy building or backtesting.
For this, users typically rely on Streak, Zerodha's no-code strategy development platform. Streak allows the deployment of up to 5 live strategies and 15 virtual strategies simultaneously. It supports backtesting with adaily cap of 50 dynamic options contracts, and accommodates up to 50 instruments per strategy. For historical data analysis, it provides access to 30 days of 1-minute candle data and 5 years of 1-day candle data, enabling comprehensive backtesting of strategies

GROWW'S API		
Section	**Parameters**	**Details**
Groww Trading API	**Tools**	External platforms like Stratzy.
	API Access	Groww API: Paid (₹499+tax); Stratzy/AlgoTest: Free access with Groww login.
Stratzy	**Broker Integration and Execution**	Native Groww support
	No. of expert strategies	108+ SEBI registered strategies
	Code	No code strategy builder
	Rate limit/API details	Not disclosed (third-party proprietary data)

	Execution speed	Not disclosed (third-party proprietary data)
Algo Test	**Broker Integration and Execution**	via Algo test's web AI
	Code	No code strategy builder
	Execution speed	1 second Approx.
	Strategy Limit	5 strategies/day
	Settlement timeline	T+30 working days (SEBI)

Source: Groww[15] and SEBI[14].

Groww provides trading API access through external platforms like Stratzy and AlgoTest, offering both free and paid access depending on the platform. Access through Stratzy or AlgoTest requires a paid Groww API subscription, priced at ₹499 plus tax. Alternatively, users can access Groww's features freely with Groww login for basic functionality.

With Stratzy, users gain access to over 108 SEBI-registered expert strategies with native Groww integration for direct execution. However, Stratzy does not support custom-coded strategies, as it follows a no-code model. Technical specifications such as rate limits and execution speed are not publicly disclosed, since they rely on third-party proprietary systems.

AlgoTest similarly uses a no-code interface and enables strategy deployment through its web-based AI. Users can execute up to 5 strategies per day, with an estimated execution speed of around 1 second. Like Stratzy, details on API rate limits are withheld. The standard SEBI settlement timeline of T+30 working days applies to both platforms.

In conclusion, while Groww's ease of access has attracted a larger user base, Zerodha's business model appears more profitable, catering effectively to active and high-frequency traders through its integrated and feature-rich ecosystem, offer different approaches influencing the diverse ways in which retail traders engage with automated systems in the Indian market.

Analysis 3

This section delves into the macro-level impact of algorithmic trading on the Indian financial market's liquidity and efficiency, as observed through key metrics between 2018 and 2023. By examining trends in bid-ask spreads, market depth, and daily trading volumes, this analysis provides empirical evidence of how increased algorithmic participation has shaped the overall trading environment.

Source- NSE and BSE Order Book Data, SEBI Co-location Service Reports (2020) and Algo-Trading Efficiency Review by IGIDR (2022) (Referred from literature paper)[17]

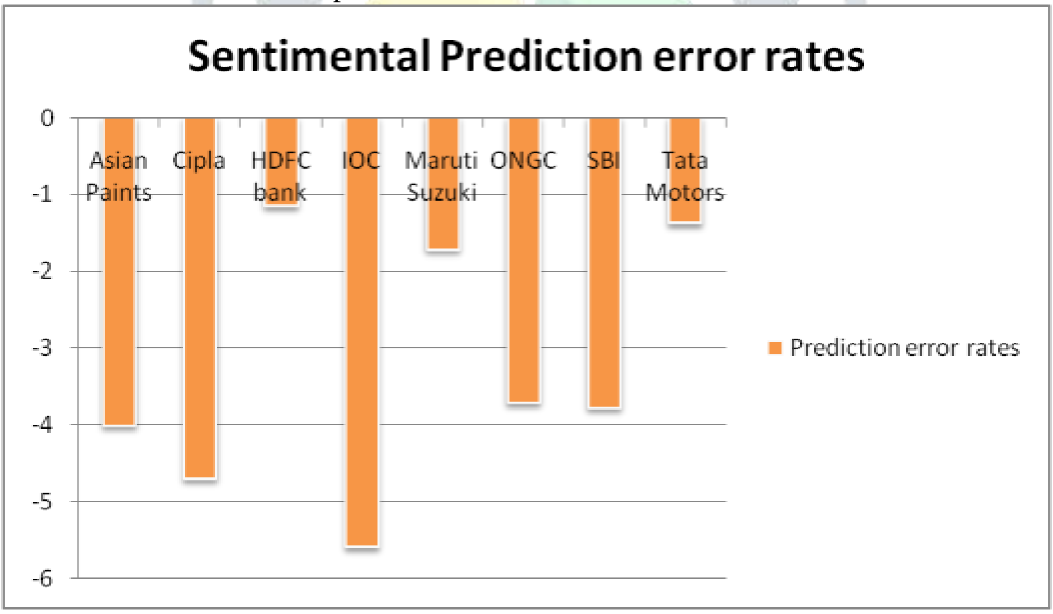
Year	Bid-Ask Spread (%)	Market Depth (Orders/Second)	Daily Trading Volume (Million)
2018	0.27	25	10
2019	0.25	30	12.2
2020	0.22	34	14.3
2021	0.2	40	17.8
2022	0.18	45	19.5
2023	0.16	50	21.2

note- 2024 and 2025 data are available on paid platforms that were beyond our capability to gather, thus not being included.

The table presents liquidity metrics for the years 2018 to 2023, focusing on three key indicators: Bid-Ask Spread (%), Market Depth (Orders/Second), and Daily Trading Volume (Million). Over time, the bid-ask spread has steadily decreased from 0.27% in 2018 to 0.16% in 2023, indicating improved market efficiency and tighter pricing. Simultaneously, market depth has grown significantly from 25 to 50 orders per second, reflecting stronger liquidity and more active participation. Likewise, daily trading volume has more than doubled, rising from 10 million to 21.2 million, suggesting increased investor interest and higher market activity. Overall, these trends point to a progressively more liquid and efficient trading environment.

Analysis 4

This section presents an evaluation of the sentiment analysis models performance by examining their prediction error rates across various companies.



Source- References[4]

The bar chart titled "Sentimental Prediction Error Rates" displays the prediction error rates for various companies based on sentiment analysis models. Each orange bar represents the percentage error between the predicted and actual stock prices for companies such as Asian Paints, Cipla, HDFC Bank, IOC, Maruti Suzuki, ONGC, SBI, and Tata Motors. All the bars show negative values, indicating that the predicted prices were consistently higher than the actual prices. Among them, IOC has the highest prediction error (around -5.5%), followed by Cipla and ONGC. This suggests that the sentiment-based model overestimated stock performance across all companies, with varying degrees of inaccuracy.

Conclusion

This study profoundly reveals the transformative impact of AI in investment and portfolio management and algorithmic trading (AT) on the Indian financial markets, analyzing their effects on market dynamics and predictive accuracy, and the pivotal role of retail trading platforms. Our analysis highlights AT's significant rise, driven by high-speed infrastructure, which has markedly enhanced market liquidity, tightened bid-ask spreads, and boosted daily trading volume, substantially contributing to market efficiency. However, prediction accuracy remains inconsistent. While AI-driven sentiment analysis using NLP showed high accuracy in correlating sentiment with market movements, specific stock analyses revealed varying degrees of overestimation, particularly for stocks like Asian Paints and Reliance, suggesting potential

overfitting, while others showed underestimation or lacked volatility capture. Retail trading platforms like *Zerodha* and *Groww* have been instrumental in democratizing AT, offering crucial tools for personalized suggestions, strategy backtesting, and sophisticated portfolio risk analysis to individual investors. While investors may possess strong market insight, the accuracy and reliability of AI-driven tools still require refinement to better support informed decision-making. Despite these evident benefits, challenges persist, including systemic risks during flash crashes, the rapid evolution of AI technology often outpacing regulatory frameworks, and the potential erosion of human judgment and financial literacy among retail investors. The inherent subjectivity of language can also lead to misinterpretations in sentiment analysis.
sIn conclusion, while AI and AT offer significant advancements in market efficiency and accessibility, their widespread adoption necessitates a balanced approach. This involves continuous model refinement, robust regulatory oversight, and comprehensive financial education for retail investors to foster critical thinking and mitigate risks, thereby building a resilient and inclusive financial landscape in India.

Suggestions

To make the most of algorithmic trading and AI ininvestment and portfolio management market, several practical steps should be taken. First, retail investors should not rely blindly on AI tools, instead, they should combine them with their own judgment and improve their understanding of risks through basic financial education. Trading platforms like *Zerodha* and *Groww* should make their AI models more transparent by showing users how confident the system is in its predictions and offering easy-to-understand visual tools that link public sentiment to stock movements. They should also regularly update their models to ensure they remain accurate and don't overfit old data. On the regulatory side, SEBI should make sure all traders, including small investors, have fair access to fast trading infrastructure. It should also require companies to audit their trading algorithms to prevent misuse or manipulation. Finally, researchers should work on building smarter, more flexible AI models that can handle real-time changes and understand different types of data, like news headlines, tweets, and charts. These steps can help create a safer, more transparent, and more inclusive trading environment.

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