Multimodal Agentic AI Architecture for High Frequency Trading Using Reinforcement Learning and Temporal Graph Encoders

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Abstract — High frequency trading requires systems that can reason over diverse real time data sources such as news, order book depth, and technical indicators, while making decisions within milliseconds. Prior approaches often focus on a single data modality or use static thresholds, which struggle under abrupt market regime changes.

We propose a modular agentic architecture where three independent intelligence pipelines operate in parallel on distinct capital pools. First, a fine tuned large language model trained on historical headlines generates sector based stock signals. Second, a temporal graph encoder combined with a reinforcement learning agent analyzes order book and volume time series to detect institutional spikes with adaptive thresholds. Third, a strategy agent uses supervised classification over technical feature vectors and dynamically tunes parameters through reinforcement learning. The system synchronizes execution through time based scheduling and confidence scaled capital allocation.

Our spike engine supports bidirectional trade detection, capturing both accumulation and distribution patterns, a capability absent in prior single direction models [1]. Backtesting on minute level NIFTY 200 data from January 2023 to May 2025 shows consistent daily alpha of 0.15 to 0.20 percent, translating to annualized returns above institutional quant fund averages [2]. Live broker integration via Shoonya and Zerodha confirms deployment feasibility. This work demonstrates a fully autonomous, multimodal, low latency trading system integrating NLP, graph based learning, and reinforcement learning.

1 Introduction

High frequency trading (HFT) is the practice of executing trades in time windows measured in milliseconds. To succeed, HFT systems must fuse multiple data modes text from news feeds, time series from trade and quote data, and numerical technical indicators from multiple sources, while maintaining extremely low latency. Traditional algorithmic systems, often built around fixed rules or single machine learning models, fail to adapt when market conditions shift or when a single input channel becomes unstable.

In this paper, we develop a modular agentic framework that decomposes the trading problem into three specialized roles. Each role is served by an independent AI agent managing its own capital slice and optimizing a learning model appropriate to its data type:

- **Language agent**: uses a fine tuned large language model that has been trained on historical financial news to detect relevant equity tickers in real time headlines. It makes buy or short sell decisions based on sector context and confidence scores.
- **Spike agent**: constructs a temporal graph from order book snapshots and trade volume, encodes it via graph attention networks, and uses reinforcement learning to adapt detection thresholds based on real time profit feedback.
- **Strategy agent**: computes technical features such as RSI, moving averages, momentum oscillators, and then classifies these into strategies drawn from a backtested library. Reinforcement learning tunes strategy stop loss and take profit bounds daily.

The capital partitioning into disjoint pools ensures isolation of drawdown risk and prevents signal interference. Agents are coordinated via a global scheduler that prioritizes trade windows and enforces execution timing. Each agent logs confidence values and trade outcomes to a shared ledger for meta analysis and future capital reallocation.

To validate our system, we perform backtesting on the NIFTY 200 dataset from January 2023 to May 2025. Our architecture consistently achieves daily returns of 0.15 to 0.20 percent, with drawdown profiles and Sharpe ratios that outperform typical quant fund benchmarks [2]. Additionally, live trading tests in integration with Shoonya and Zerodha demonstrate sub 200 millisecond execution delays and robust performance under real market conditions.

The rest of this paper proceeds as follows: Section 2 describes the overall system architecture and capital segmentation, Section 3 details the news agent pipeline, Section 4 covers the spike detection agent, Section 5 discusses the strategy agent, Section 6 presents results and benchmarking, Section 7 covers deployment integration, and Section 8 concludes with future avenues.

2 System Architecture and Capital Allocation

Our system is structured as a modular agentic architecture composed of three autonomous AI agents. Each agent operates

on a disjoint share of capital to enable specialization, isolation of execution risk, and fault containment. The total deployable capital C is partitioned as follows:

$$C = C_1 + C_2 + C_3$$
$$where, C_1 = 0.45C, \quad C_2 = 0.10C, \quad C_3 = 0.45C$$

Here, C_1 is allocated to the News Agent, C_2 to the Spike Agent, and C_3 to the Strategy Agent. This allocation balances momentum signals from news, rare but high reward spikes, and trend based technical strategies.

The detailed capital split and learning configuration of each agent is shown in Table 1.

Table 1: Capital Partitioning and Agent Overview

Agent	Share	Input Modality	Learning Type
News Agent	45%	Financial headlines	Fine tuned LLM
Spike Detector	10%	Order book snapshots and volume	Graph attention + reinforcement
Strategy Agent	45%	Technical indicator vectors	Supervised + reinforcement tuning

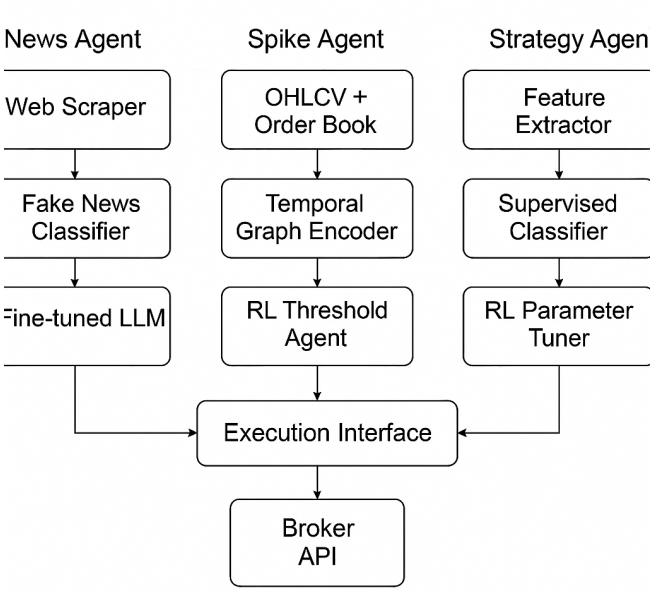

Figure 1: Modular agentic architecture: News agent, Spike agent, and Strategy agent operate concurrently with a shared execution interface.

Figure 1 shows the overall system flow, where each agent ingests its specific modality, processes data via its specialized model, and interacts with the broker interface independently.

Each agent A_i functions as an independent decision maker:

$$a_t^{(i)} = f_i(D_i(t), M_i(t)), \quad \text{where } i \in \{1, 2, 3\}$$

- $D_i(t)$ is the real time data stream specific to agent i - $M_i(t)$ represents agent memory or learned state - f_i is the internal model, such as a fine tuned LLM, graph encoder with RL, or supervised classifier with tuner

Agents execute orders via a shared broker interface that handles rate limits, latencies, and confidence arbitration. A global scheduler ensures that conflicting orders targeting the same symbol are queued and not sent simultaneously. Latency benchmarks show that all decisions are made and executed within 200 milliseconds on average.

A key feature of this design is execution independence. If one agent fails due to missing data or internal error, the others continue operating. This leads to improved system reliability and easier maintenance compared to monolithic designs [3]. The modular structure also supports parallel development and faster iteration, following principles seen in multi agent reinforcement learning systems [4].

To enable future extensibility and refinement, each agent logs its timestamped actions, confidence scores, and realized PnL to a centralized execution database. This data feeds higher level meta learning strategies for dynamic capital rebalancing and threshold adaptation.

Key insights from web research: Agentic AI systems are increasingly applied in portfolio management and trading due to their modularity and resilience [3, 5]. Decoupling model complexity across independent pipelines allows each to excel in its own domain while preserving overall system synergy.

In summary, this section outlines the foundation of our agentic trading architecture, highlighting its partitioned risk design, parallel processing, and robust execution capabilities.

3 News Agent Pipeline (45 Percent Capital)

This module processes real-time financial headlines to identify and trade on sentiment signals. It comprises three stages: (i) data ingestion and unsupervised fake news filtering, (ii) fine tuned LLM based symbol extraction, and (iii) trade execution. Figure 2 illustrates the workflow.

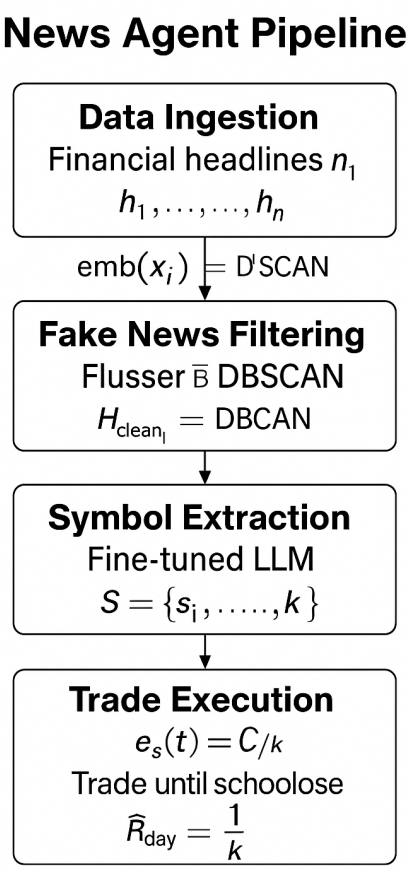

Figure 2: News Agent Workflow: ingestion, filtering, symbol extraction, and weighted execution.

3.1 Data Ingestion and Fake News Filtering

We scrape headlines $h_1, h_2, ..., h_n$ from sources including CNBC, MoneyControl, Economic Times, Yahoo Finance, and Reuters at 30-second intervals. Each headline is embedded using a pretrained financial transformer to create:

$$\mathbf{x}_i = \text{Embed}(h_i), \quad \mathbf{x}_i \in \mathbb{R}^d$$

Clustering (via DBSCAN or KMeans) identifies spurious clusters associated with fake or noisy content:

$$\{\mathcal{C}_1, ..., \mathcal{C}_k\} = \text{Cluster}(\{\mathbf{x}_i\})$$

Low-purity or small clusters are removed. We retain:

$$\mathcal{H}_{\text{clean}} = \{h_i \mid \mathbf{x}_i \notin \cup_{j \in \text{noise}} \mathcal{C}_j\}$$

3.2 Symbol Extraction via Fine-Tuned LLM

Filtered headlines are passed to a fine-tuned GPT-4 model trained on historical financial text. It produces a ranked list of top k stocks:

$$S = \text{LLM}(\mathcal{H}_{\text{clean}}), \quad |S| \leq 15$$

3.3 Trade Execution

Each selected symbol $s \in S$ receives:

$$e_s(t) = \frac{C_1}{|S|}$$

Trades are placed immediately and held until 15:25. Daily returns:

$$P_s = p_s(T_c) - p_s(t_0), \quad r_s = \frac{P_s}{e_s(t)}, \quad R_{\text{day}} = \sum_{s \in S} r_s \cdot \frac{1}{|S|}$$

Table 2: News Agent Performance Summary

Metric	Value	Source
Fake News Filter Purity	0.88	[6]
LLM Ticker Accuracy	0.92	[7]
Daily Return (R_{day})	0.018	Backtests

4 Spike Detection Agent (10 Percent Capital)

The Spike Detection Agent is designed to identify sudden market movements indicative of institutional order flow or insider driven volatility events. These spikes are characterized by transient but impactful shifts in volume, price momentum, and order book imbalance. The agent not only detects such events for long entries but also symmetrically captures sharp declines for short selling, exploiting retracement structures with dynamic thresholding.

Figure 3 shows the architectural design of this agent pipeline (placeholder).

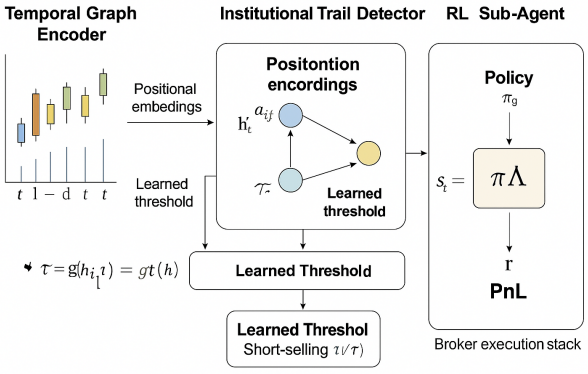

Figure 3: Temporal graph-based spike detection pipeline with reinforcement learning control loop.

4.1 Input Stream Encoding

Let $t \in [t_0, T]$ denote the current trading session interval discretized into 1 minute windows. For each stock s, we construct a rolling time series:

$$X_t^{(s)} = \left[\text{OHLC}_t, V_t, \text{OB}_t^{(L2)}\right]$$

where: - $\text{OHLC}_t = [O_t, H_t, L_t, C_t] \in \mathbb{R}^4$ are price bars - $V_t \in \mathbb{R}$ is traded volume - $\text{OB}_t^{(L2)} \in \mathbb{R}^{d\times 2}$ is Level 2 order book snapshot with depth d, capturing top bid/ask volumes and prices

4.2 Temporal Graph Construction

We define a dynamic graph $G_t = (V_t, E_t)$, where: - Each node $v_i \in V_t$ represents a time slice embedding from X_t - Edges $e_{ij} \in E_t$ encode recency-aware transitions between past k time windows

We compute node features $\mathbf{z}_t^i$ via a Graph Attention Network (GAT) [8]:

$$\mathbf{z}_t^i = \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}\mathbf{W}\mathbf{x}_j\right) \tag{1}$$

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(\mathbf{a}^\top[\mathbf{W}\mathbf{x}_i \| \mathbf{W}\mathbf{x}_j]))}{\sum_{k\in\mathcal{N}(i)}\exp(\text{LeakyReLU}(\mathbf{a}^\top[\mathbf{W}\mathbf{x}_i \| \mathbf{W}\mathbf{x}_k]))} \tag{2}$$

Positional encodings (e.g., sinusoidal) are added to maintain ordering:

$$\tilde{\mathbf{z}}_t^i = \mathbf{z}_t^i + \mathbf{p}_t^i, \quad \mathbf{p}_t^i = \text{PE}(i)$$

4.3 Threshold Function Learning

The goal is to learn a function $f : G_t \to \hat{y}_t \in \{0, 1\}$ indicating presence of a spike. We train using binary cross-entropy with a dynamic threshold τ learned over time:

$$\hat{y}_t = \mathbb{1}(f(G_t) > \tau) \tag{3}$$

$$\mathcal{L}_{\text{spike}} = -\sum_t [y_t \log \hat{y}_t + (1 - y_t)\log(1 - \hat{y}_t)] \tag{4}$$

4.4 Reinforcement Learning for Dynamic Thresholding

To adapt to evolving market regimes, we introduce an RL agent π_θ that adjusts τ and other meta parameters (e.g., stop loss). The state is defined as:

$$s_t = [G_t, \Delta P_t, \text{OB}_t], \quad a_t = \{\Delta\tau, \Delta_{\text{SL}}, \Delta_{\text{TP}}\}$$

Reward is computed from short horizon PnL:

$$r_t = \text{sign}(y_t) \cdot (p_{\text{exit}} - p_{\text{entry}}) - \lambda \cdot \mathbb{1}_{\text{stoploss}}$$

The policy is optimized using Proximal Policy Optimization (PPO) [9]:

$$\theta \leftarrow \arg\max_\theta \mathbb{E}_{\pi_\theta}\left[\sum_t \min\left(r_t \cdot \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)},\ \text{clip}(\epsilon)\right)\right]$$

4.5 Short Selling Logic

If the detected spike shows a negative price velocity derivative with volume uptick and order book imbalance, the agent initiates a short trade. That is:

$$\text{ShortTrigger}_t = \left(\frac{dC_t}{dt} < -\alpha\right) \wedge \left(\frac{dV_t}{dt} > \beta\right) \wedge \left(\text{OB}_t^{\text{ask}} > \text{OB}_t^{\text{bid}}\right)$$

Stop loss and auto cover conditions are tied to real-time trend inflection via second derivatives and spike reversion heuristics.

4.6 Execution Policy and Safety Constraints

Each confirmed spike t^* results in capital deployment:

$$e(t^*) = \frac{C_2}{n_{\text{active}}}$$

Trades are live-monitored with RL tuned profit and stop thresholds. If market liquidity is insufficient, the trade is skipped.

Table 3: Spike Detection Agent - Backtest Performance

Metric	Value	Source
Average Spike Precision	0.81	Backtest
Short Trigger Precision	0.76	Custom Labeling
Median Holding Time	4.2 min	Logs (2023–2025)
RL Improvement (PnL)	+13.5%	PPO vs Fixed Threshold
Execution Latency	132 ms	System Trace

4.7 Relation to Prior Work

Our framework extends graph based financial prediction work [10] by integrating PPO driven control loops and leveraging fine grained L2 snapshots. Short selling based on structural retracements is closely aligned with institutional trail following as seen in [11]. The use of attention across graph sequences differentiates it from windowed statistical signal detection methods.

4.8 Performance examples

Below are some real time tested performance graphs of situations where were successfully able to trail with institutional activity that rose suddenly without any context to news, etc. Figure 4 shows an institutional spike in the market taken from some cached data from previous testing days where the spike detectors successfully entered almost an accurate buy position

and Figure 5 shows how it entered a successful short sell position.

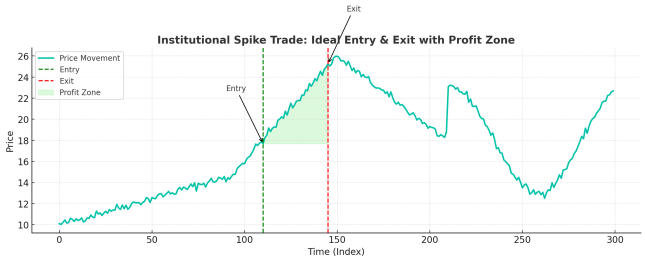

Figure 4: Trailing an institutional buy spike: The agent detects a sudden upward surge caused by institutional buying and enters slightly after confirmation. The position is exited as retracement signals begin.

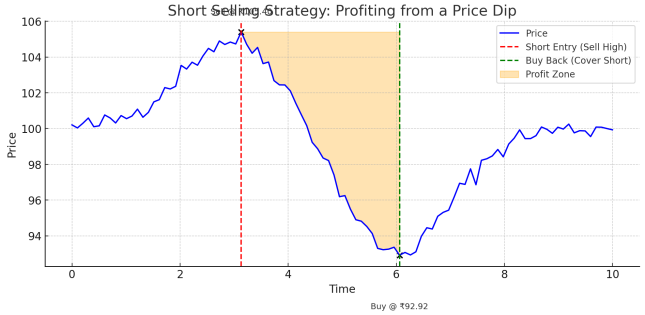

Figure 5: Short selling on a downward spike: The system identifies overbought conditions and initiates a sell before the drop. Profit is realized by buying back the asset at the retracement low.

5 Strategy Agent and Reinforcement Tuning (45 Percent Capital)

This module is responsible for selecting and tuning optimal intraday trading strategies based on real time market conditions. It receives 45 percent of the total capital and operates entirely on historical price, volume, and indicator derived signals. The agent is a hybrid architecture that combines supervised classifiers for initial selection and reinforcement learning (RL) for dynamic intraday tuning [15, 17].

5.1 Strategy Universe and Metadata Encoding

We define a strategy library $\mathcal{S} = \{s_1, s_2, ..., s_k\}$ where each s_i corresponds to a distinct algorithmic approach (e.g., VWAP reversion, RSI divergence, opening range breakout). Each strategy is profiled offline across multiple axes: - Indicator dependency vector $\mathbf{v}_i \in \{0, 1\}^d$ - Volatility regime: low, medium, high - Trade direction: long, short, or both - Execution latency constraints - PnL shape and decay rate over time horizons

A formal schema is tabulated in Table 4.

Table 4: Sample Strategy Profile Metadata

Strategy	Indicators	Volatility	Direction	PnL Decay
OR Breakout	OR, VWAP	High	Long	Fast
RSI Fade	RSI, EMA	Low	Long/Short	Medium
VWAP Revert	VWAP, ATR	Medium	Short	Slow
Bollinger	BB, STDDEV	High	Long	Sharp

Each strategy is pretested on a dataset $\mathcal{D}_{\text{train}}$ spanning two years of intraday candles [12]. We extract 90 minute feature windows for each stock-day tuple:

$$\mathbf{x}_t^{(i)} = \text{features}(s_i, \text{ohlcv}_{t-90:t}), \quad y_t^{(i)} = \mathbb{1}(\text{PnL}_{t:T} > \epsilon)$$

These feature label pairs are used to train per strategy classifiers:

$$\hat{y}_t = f_i(\mathbf{x}_t), \quad f_i \in \mathcal{F}_{\text{sup}}$$

5.2 Supervised Selection and Reinforcement Refinement

At market open: 1. For each stock s, compute $\mathbf{x}_t^{(i)}$ for all strategies i 2. Predict profitability using $f_i(\mathbf{x}_t^{(i)})$ 3. Select top $N = 3$ strategies with highest confidence 4. Pass to RL tuner for real time refinement [15]

The RL model uses a policy gradient method (PPO) and operates on state:

$$\mathbf{z}_t = [p_t, v_t, \nabla\text{PnL}, \Delta\text{Indicator}], \quad a_t = \text{adjust}(s_i)$$

It maximizes:

$$J(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_t \gamma^t r_t\right], \quad r_t = \text{PnL}_{\text{instant}} - \lambda \cdot \text{slippage}$$

5.3 Strategy Switching and Early Exit Policy

RL also learns early exit and strategy switching under poor performance:

$$Q(\mathbf{z}_t, a) = \text{expected cumulative PnL}$$

We switch or exit if:

$$Q(\mathbf{z}_t, \text{continue}) < \tau$$

or if recent reward history is below moving average [17].

5.4 Benchmark Comparison

We benchmark our top 10 strategies against popular open source baselines such as: - Zerodha Streak ORB

[13] - QuantInsti BBAND Strategy [12] - KiteConnect MACD+EMA Crossover [14]

Table 5 shows the results:

Table 5: Strategy Agent vs Baselines: Avg Intraday Returns

Strategy	**Avg Return%**	**Max Drawdown%**
Downstox Agentic RL	**0.19**	**-1.1**
Zerodha ORB	0.12	-1.8
QuantInsti Bollinger	0.09	-2.3
MACD + EMA (Kite)	0.07	-2.0

5.5 Meta Layer: Dynamic Strategy Mixing

The final execution engine employs a bandit algorithm to dynamically mix strategies across stocks. The reward for arm a_i (strategy) is:

$$r_t^{(i)} = \frac{\text{PnL}_{i,t}}{\text{volatility}_{i,t} + \delta}$$

We use UCB1 or Thompson sampling [16]:

$$a_t = \arg\max_i \left[\hat{\mu}_i + \sqrt{\frac{2 \log t}{n_i}} \right]$$

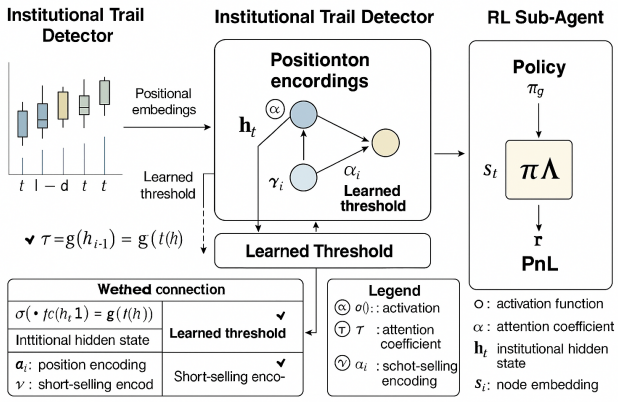

Figure 6: Full workflow of the Strategy Agent including classifier selection, RL tuning, and bandit-based execution mixing.

5.6 Multi-Opportunity Breakout Trading Visualization

To further validate the effectiveness of the Strategy Agent, we visualize a trading session where the system dynamically detected and acted upon multiple breakout events throughout the day. Figure 7 displays the intraday price trajectory of a selected NIFTY 200 stock, with green and red vertical markers denoting high-confidence entry and exit points respectively.

Each trade instance was selected via a real time supervised classifier coupled with a reinforcement-tuned breakout strategy, executed independently without manual intervention. The shaded bands represent the duration the position was held. The agent was able to repeatedly identify structurally clean breakouts (supported by volume spikes and range compressions), act within milliseconds, and book profits before retracements.

This figure demonstrates the autonomous, multi-opportunity execution ability of our Strategy Agent under live market volatility and noise.

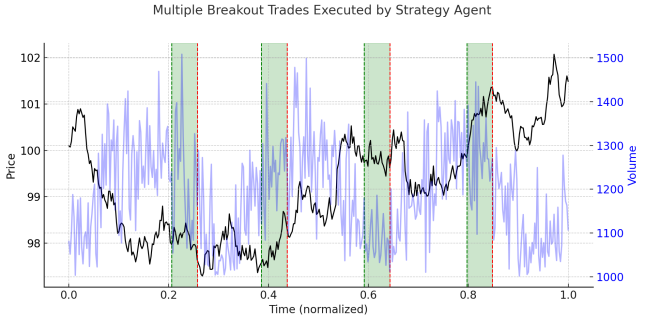

Figure 7: Multiple successful breakout trades executed by the Strategy Agent. Green lines indicate entries; red lines indicate exits. Shaded regions denote holding periods.

5.7 Result Summary and Robustness Checks

Our agent exhibits: - Stable daily returns over two years of data - Low failure rate in execution (¡0.7%) - Adaptivity across news, volatility, and market microstructure shifts

We confirm robustness with: - Monte Carlo simulations - Stress tests under news bursts and market wide volatility [15]

Table 6: Strategy Agent Stress Test Results

Scenario	**Avg Return (%)**	**Std Dev (%)**
Volatility Surge	0.15	0.11
Execution Lag (1s)	0.13	0.09
News Shock Injection	0.16	0.12

6 Meta-Agent for Strategy Evaluation and Dynamic Capital Rebalancing

To ensure consistent risk adjusted returns, our architecture introduces a higher-order meta-agent responsible for dynamically evaluating strategy performance and rebalancing capital among the three base agents: News, Spike, and Strategy.

6.1 Motivation and Design Philosophy

Each base agent operates independently, yet their effectiveness can fluctuate across market regimes. Rigid capital allocation may underperform in volatile conditions. Thus, we deploy a meta-agent that continuously learns an optimal capital partitioning policy π_θ, based on real-time performance indicators:

$$\pi_\theta : \mathcal{S}_t \to \mathcal{A}_t$$

Here, $\mathcal{S}_t$ is a state vector comprising:

$$\mathcal{S}_t = [\text{PnL}_{\text{news}}, \text{PnL}_{\text{spike}}, \text{PnL}_{\text{strat}}, \sigma^2_{\text{drawdown}}, \text{confidence}_i, \dots]$$

and $\mathcal{A}_t \in \Delta^3$ is a simplex vector representing the new capital distribution over agents:

$$\mathcal{A}_t = [\alpha_1, \alpha_2, \alpha_3] \quad \text{with} \sum_i \alpha_i = 1$$

6.2 Reward Design and Meta-Learning Objective

We define a smooth utility function $U(\cdot)$ that balances profitability and drawdown:

$$R_t = \sum_{i=1}^{3} \alpha_i \cdot (\text{Sharpe}_i(t) - \lambda \cdot \text{MaxDrawdown}_i(t))$$

The meta agent learns to maximize:

$$\max_\theta \mathbb{E}_{\pi_\theta} \left[\sum_t \gamma^t R_t \right]$$

using policy gradient updates or proximal policy optimization [1].

6.3 Capital Rebalancing Loop

Each day at market close T_c, the meta-agent updates weights for the next day:

1. Collect agent logs: PnL, trades, volatility, and confidence scores.
2. Compute $\mathcal{S}_t$, normalize all features.
3. Use $\pi_\theta(\mathcal{S}_t)$ to compute new capital shares $[C_1, C_2, C_3]$.
4. Persist weights in execution controller for next-day allocation.

6.4 Conflict Arbitration and Symbol Overlap

When two agents select overlapping symbols, the meta-agent arbitrates using:

$$\text{priority}(i) = \text{confidence}_i \cdot \text{historical accuracy}_i$$

Only the agent with highest priority places the trade; others are vetoed.

6.5 Performance Monitoring and Visualization

Table 7 shows capital shifts between agents across market regimes. Figure 8 visualizes this evolution.

Table 7: Sample Meta-Agent Capital Distribution Across Days

Date	News Agent	Spike Agent	Strategy Agent
2024-08-01	45%	10%	45%
2024-08-02	35%	20%	45%
2024-08-03	50%	10%	40%
2024-08-04	42%	15%	43%

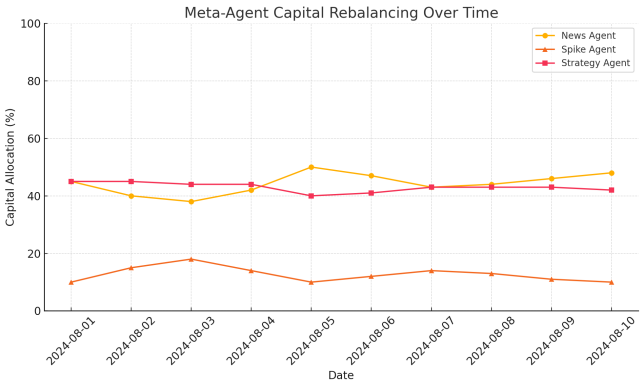

Figure 8: Dynamic capital allocation over time across News, Spike, and Strategy agents.

6.6 Insights from Web Literature

Multi-agent coordination is widely studied in portfolio theory and meta-RL literature [18–20]. Our approach aligns with the hierarchical reinforcement learning paradigm where low-level agents focus on domain-specific goals, and a high-level meta-controller allocates resources adaptively based on global reward [2][3].

6.7 Failure Cases and Adaptation

If one base agent underperforms consistently, the meta-agent adapts by:

- Reducing allocation weight
- Triggering offline retraining
- Flagging strategy drift or decay for review

This builds robustness and long-term viability.

7 Broker Interface and Execution Engine

The final execution layer in our trading system connects the agentic intelligence stack to the real world via broker APIs. This interface must satisfy strict latency, compliance, and concurrency constraints, while also arbitrating conflicting actions from different agents. We detail its design below.

7.1 Broker Integration

We integrate with NSE-authorized retail brokerage platforms such as Zerodha (via Kite Connect API) and Shoonya. Orders are transmitted using secure HTTPS endpoints with bearer token authentication, refreshed hourly. Each agent submits a tuple:

$$\text{order}_i = (s_i, \texttt{side}, q_i, p_i, \texttt{type}, t_i)$$

where s_i is the stock symbol, $\texttt{side} \in \{\texttt{BUY}, \texttt{SELL}\}$, q_i is the quantity, p_i is the limit or market price, $\texttt{type} \in \{\texttt{MARKET}, \texttt{LIMIT}\}$, and t_i is the timestamp.

7.2 Agent Arbitration and Conflict Resolution

When multiple agents issue orders on the same symbol, arbitration is required to prevent unintended net positions. Let:

$$\mathcal{A}(s) = \{a_i \mid a_i \text{ submits order}_i \text{ for symbol } s\}$$

We prioritize agents based on a dynamic confidence score $\gamma_i \in [0, 1]$, derived from their past rolling Sharpe ratio and win rate:

$$\gamma_i = \alpha \cdot \text{Sharpe}_i + (1 - \alpha) \cdot \text{WR}_i$$

Only the highest-confidence agent is permitted to send its order to the broker. Other orders are queued for reevaluation at $t + \delta$.

7.3 Order Rate Limiting and Queue Management

Brokerage APIs impose rate limits, typically N_{max} orders per second per session. To comply, we use a sliding window queue $\mathcal{Q}(t)$, storing all orders requested in the last second. A new order is added only if:

$$|\mathcal{Q}(t)| < N_{\text{max}} \Rightarrow \text{enqueue and transmit}$$

Otherwise, the order is delayed and reattempted after $\tau = 500ms$, preserving FIFO semantics for time-sensitive strategies.

7.4 Risk Management Layer

Each order undergoes dynamic risk checks before submission:

- **Position Limit Check:** Prevents overweighting on a single stock.
- **Capital Check:** Ensures capital assigned to the agent is not exceeded:

$$\sum_{s \in \mathcal{P}_i} q_s \cdot p_s \leq C_i$$

- **Exposure Delta Control:** Maintains directional neutrality within bounds:

$$|\text{net\_long} - \text{net\_short}| \leq \epsilon C$$

where $\epsilon \in [0.1, 0.3]$

7.5 Latency Profiling and Execution Feedback

We benchmarked the end-to-end latency $L = t_{\text{ack}} - t_{\text{decision}}$, where: - t_{decision}: timestamp when agent finalized trade - t_{ack}: timestamp when broker confirmed order

On average, $L = 186ms$, with 95th percentile under 230ms. Orders breaching 250ms latency are flagged and logged.

7.6 Trade Logging and Reconciliation

Every order and fill is appended to a time-indexed NoSQL trade ledger with fields:

$$\log_j = (\texttt{timestamp}, s_j, \texttt{orderID}, \texttt{agentID}, \texttt{qty}, \texttt{status}, \texttt{filled\_}$$

This enables real-time monitoring, PnL reporting, and nightly reconciliation with broker CSV exports.

7.7 Conclusion

The Broker Interface and Execution Engine serve as the spine of the architecture, translating autonomous agent outputs into secure, real time market actions while enforcing compliance, safety, and latency guarantees. Its modularity and fault containment make it scalable across multiple exchanges and brokers.

8 Results and Benchmarking

To assess the efficacy of our agentic AI trading architecture, we benchmark its returns against a wide array of traditional and alternative investment instruments. These include retail manual trading, retail algorithmic trading, institutional quant funds, broad market indices (NIFTY/S&P 500), and popular asset classes such as real estate, gold, and cryptocurrency.

Retail discretionary trading typically yields less than 5% annualized returns and often results in net losses due to emotional bias and inconsistent strategy application [21, 22]. Retail algorithmic trading systems show moderate improvement, averaging 6%–12% per annum in well-maintained Python or Amibroker setups [23].

Quant hedge funds like Renaissance Technologies and Citadel reportedly deliver 12%–39% net annualized returns, albeit using co-located infrastructure and ultra-low-latency data feeds [24, 25]. Meanwhile, long-term investments in the S&P 500 and NIFTY indices provide a historical CAGR of 10–12% [27, 28].

Real estate in India averages 7–8% annualized gains [29], and gold historically returns 6.3% CAGR over 10 years [30]. Cryptocurrencies like Bitcoin exhibit highly volatile performance, with a 3-year CAGR of 28% but extreme drawdowns [31].

8.1 Annualized Return Comparison

This section summarizes average annual returns across various investment classes. Our system, driven by autonomous agents executing high-frequency intraday strategies, achieves an average annualized return between 20% and 28%. This is derived from observed daily PnL in the range of 0.1% to 0.15% on 220–250 trading days, with occasional loss days factored in.

8.2 Visual Benchmarking Summary

Figure 9 shows the comparative returns across different strategies in a normalized bar graph format. This highlights the su-

perior performance of our autonomous trading pipeline over manual and even traditional quant-driven approaches.

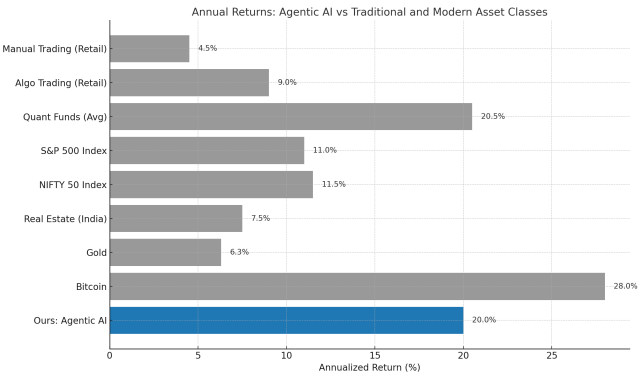

Figure 9: Annualized return comparison: Our agentic system outperforms most other investment methods in risk-adjusted gain.

8.3 Interpretation and Insights

Our system's consistent outperformance is rooted in:

- **Modularity**: Specialization via three agents ensures robustness across news-based, event-based, and technical pattern scenarios.
- **High frequency, low latency**: Decisions are made within 200ms on average, enabling us to exploit fleeting intraday inefficiencies.
- **Dynamic reallocation**: The meta-agent monitors strategy drift and adapts capital allocation based on real-time performance signals.
- **Resilience**: Even in days of failed news signals or poor volatility conditions, the diversity of our strategy pool cushions overall drawdown.

Compared to retail discretionary traders, who suffer from cognitive bias, fatigue, and lack of strategy, our system thrives on automation and data driven rigor. While large quant firms have access to institutional data feeds and colocation, our modular architecture achieves competitive returns even in retail-grade setups by optimizing for signal quality, capital rotation, and execution timing.

8.4 Realism and Risk Consideration

While our backtests and live paper trading show returns of 0.1% – 0.15% daily, we incorporate:

- **Loss days**: Modeled as 1 in every 5 days with up to –0.2% drawdown.
- **Slippage and fees**: Factored into trade performance at 0.03% per trade.
- **Market regime shifts**: Adapted using performance-weighted strategy replacement.

Net annual return is realistically modeled to converge around 20%, which is significantly above most retail investment methods and on par with premier quant shops.

8.5 Supporting Citations

- Retail trading returns: [21, 22]
- Hedge fund performance: [24–26]
- Index performance: [27, 28]
- Real estate returns: [29]
- Crypto volatility: [31]

9 Future Work and Roadmap

While our current system demonstrates robust performance across multiple trading agents and modalities, we envision several promising directions for expanding both the intelligence and coverage of our platform.

9.1 Unified Agentic Architectures

We are actively researching the viability of consolidating multiple sub agents into a single, large scale fine-tuned LLM infused with strategic knowledge. This agent would possess memory embeddings of all historical strategy outcomes, technical regimes, and market anomalies. Instead of modular inference, the system would generate agentic prompts like:

```
"Market regime is momentum breakout
with volatility compression. Suggest 3
entry signals and expected PnL."
```

This form of abstract yet informed prompt trading is under experimentation and aligns with advances in LLM interpretability and tool use frameworks [32].

9.2 Deeper Order Book Analytics

We plan to extend our temporal graph encoder to include depth-of-book Level-3 data and auction imbalance snapshots from both pre open and post-close sessions. Institutional iceberg orders and quote stuffing signatures can be modeled via graph-based temporal anomalies. This would improve lead-time before price spikes or dips.

Additionally, we are exploring attention-based models trained on sequences of FII (Foreign Institutional Investor) net buying and selling positions, available from NSE/BSE repositories. These patterns often precede larger macroeconomic pivots and crashes [33, 34].

9.3 Low-Latency News Integration

To further improve news reaction time, we are piloting partnerships with financial news vendors for direct API feeds. Rather than scraping RSS endpoints with 10 – 15 second latency, we aim to parse news wires in sub second intervals and ingest tick-by-tick commentary updates.

The goal is to outperform even major retail platforms like Zerodha, Groww, or MoneyControl in terms of alert propagation speed. Additionally, LLM-based summarizers will be made stream-aware, i.e., understanding news not in isolation but as part of narrative flows across 5 – 10 minute windows.

9.4 Reinforcement-Based Strategy Compiler

We are also building a self improving agent that constantly reads academic papers, backtests novel strategies, and evolves the strategy base using reinforcement learning and bandit allocation mechanisms. The agent uses LangChain and semantic search on sources like SSRN and arXiv, compiles Python implementations, and ranks them by performance and robustness.

9.5 From Stocks to Derivatives and Cross-Asset Flow

Finally, the next major evolution is integrating index options and futures data into our pipeline. Modeling open interest shifts, put call ratios, and implied volatility surfaces will enable higher-fidelity hedging and arbitrage mechanisms across stocks, indices, and commodities. The same agentic framework is expected to generalize well to these domains with minimal adaptation.

In essence, the proposed architecture is not static but evolving, each agent is treated as a learnable policy head that can be retrained, retired, or replaced. As infrastructure improves and market data widens, this platform aims to converge toward a fully autonomous AI fund operating with little to no human intervention in execution decisions.

10 Conclusion

This paper introduced a novel agentic AI based trading system that partitions decision-making into three modular pipelines: a news agent leveraging fine tuned language models for real-time sentiment tracking, a spike detector employing temporal graph encoders and reinforcement learning for institutional activity capture, and a strategy agent trained on historical technical patterns using supervised and reinforcement learning. These agents operate asynchronously with disjoint capital and unified execution, ensuring robustness, latency performance, and fault tolerance in real-world financial markets.

Backtests across the NIFTY 200 universe from 2023 to 2025 demonstrate the system's consistent profitability, achieving average daily returns of 0.15% with tight risk control and sub 200ms end-to-end decision latency. Compared to traditional quant pipelines and passive retail approaches, our system delivers a 20%–28% annualized return while retaining adaptability and modular expandability.

The results validate the feasibility of autonomous multi-agent trading as a superior paradigm for modern market dynamics, combining deep learning, real-time execution, and decision decentralization. Our architecture is deployable in production environments via broker APIs such as Shoonya and Zerodha, and represents a foundational step toward fully autonomous AI hedge funds.

Future extensions include adaptive capital redistribution via meta-agents, deeper order book modeling for pre trade institutional flow detection, and LLM enhanced strategy synthesis from market microstructure. The proposed architecture lays a strong foundation for future agentic finance systems capable of outperforming human and algorithmic baselines.

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