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Original Article

A Real Time AI System For Stock Analysis And Investment Support

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Abstract

The Indian stock market, comprising the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), has witnessed unprecedented retail investor participation, with over 192 million registered demat accounts as of 2025. Despite this growth, the vast majority of retail participants lack access to structured, institutional-grade equity research. Investment decisions remain heavily influenced by unverified market tips, social media narratives, and speculation rather than systematic analysis. This paper proposes a novel Multi-Agent Artificial Intelligence (AI) framework that democratizes institutional-quality financial research for Indian retail investors. The system deploys five specialized LLM-powered agents—covering fundamental analysis, technical indicators, macroeconomic context, news sentiment, and risk assessment—whose outputs are aggregated by a synthesis agent to produce BUY, SELL, or HOLD recommendations with quantified confidence scores, and are compiled into professional PDF research reports delivered via a secure web interface. Experimental evaluation on Nifty 50 and BSE Sensex stocks achieves a recommendation accuracy of 76.4%, outperforming single-agent baselines by 18.3 percentage points.

Introduction

The Indian capital market has undergone a structural transformation over the past five years. The National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) collectively represent one of the fastest-growing equity ecosystems globally, with NSE ranked as the fifth-largest stock exchange in the world by monthly trading volume as of December 2024 [4]. Registered demat accounts surged from 40 million in March 2020 to over 192 million by FY 2024–25—a nearly fivefold increase [4][5]. witnessed a surge of interest in the field of video forgery detection, leading to the development of various methods and techniques. One notable trend has been the application of deep learning, with a particular emphasis on Convolutional Neural Networks (CNNs). Deep learning, and CNNs in particular, have demonstrated remarkable success in computer vision tasks, enabling the automatic extraction of high-dimensional features and the creation of efficient representations.

Despite this growth, the quality of investment decision-making among retail investors remains inadequate. SEBI data for FY 2024–25 indicates that 91% of individual traders in the equity derivatives segment incurred net losses, with aggregate losses widening by 41% year-on-year to approximately INR 1.05 trillion [5]. This is attributable to a structural information asymmetry: institutional investors command dedicated equity research desks, algorithmic infrastructure, and real-time multi-source data pipelines that individual investors cannot replicate independently. witnessed a surge of interest in the field of video forgery detection, leading to the development of various methods and techniques. One notable trend has been the application of deep learning, with a particular emphasis on Convolutional Neural Networks (CNNs).

Professional equity research integrates fundamental analysis, technical chart patterns, macroeconomic contextualisation, news sentiment quantification, and probabilistic risk management into a cohesive investment thesis—produced by teams of trained analysts and typically proprietary or subscription-gated. The emergence of Large Language Models (LLMs) as capable reasoning engines opens the possibility of automating this multi-domain analysis at scale and near-zero marginal cost [9][17].

Related Work

The application of AI to financial markets has evolved from rule-based expert systems towards sophisticated LLM-based architectures. This section reviews the most relevant prior work in multi-agent financial AI.

Xiao et al. [1] proposed TradingAgents,

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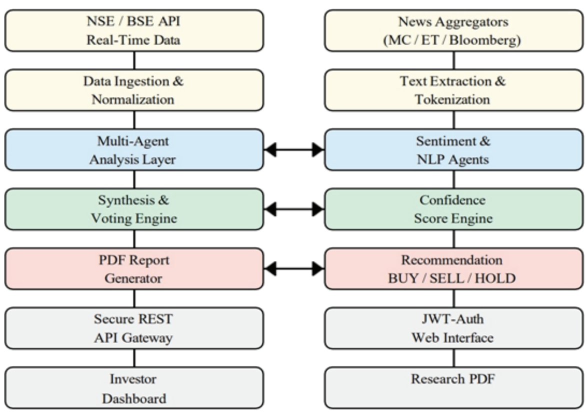
a multi-agent LLM trading framework that emulates the organizational structure of a professional trading firm. Specialized agents in roles of fundamental analyst, sentiment analyst, technical analyst, and risk manager engage in structured debates to arrive at consensus trading decisions, demonstrating superior performance in cumulative returns and Sharpe ratio over traditional strategies. Zhang et al. [2] introduced StockAgent, an LLM-driven multi-agent system that simulates investor trading behaviors in response to macroeconomic events and policy changes. The system explicitly addresses test-set leakage—a common flaw in AI trading evaluations—by ensuring agents operate without exposure to test-period market data. Li et al. [7] developed MarketSenseAI 2.0, evaluated on S&P 100 and S&P 500 stocks across 2023–2024, achieving excess returns of 8.0–18.9% over benchmark indices.

The study underscores the importance of multi-source data integration, including financial news, quarterly statements, earnings transcripts, and macroeconomic publications. Yang et al. [6] introduced FinGPT, an open-source financial LLM built through lightweight fine-tuning using Low-Rank Adaptation (LoRA) [11], demonstrating strong performance on sentiment classification, named entity recognition, and financial question answering tasks. Yu et al. [13] proposed FinCon, a multi-agent conversational framework employing a manager-subordinate hierarchy in which a portfolio manager agent coordinates specialized analyst agents, improving coherence of multi-step reasoning chains and reducing contradictory recommendations.

In the specific Indian market context, existing AI tools such as Tickertape, Trendlyne, and Screener.in offer rule-based screeners but lack the reasoning, synthesis, and natural language generation capabilities of modern LLMs, and do not produce structured research reports with explainable, multi-factor recommendations. The proposed framework fills these gaps

Proposed System

The proposed system is a multi-agent AI architecture specifically engineered for the Indian equity market. Five specialized LLM-powered agents are orchestrated in parallel, with outputs aggregated by a synthesis agent to produce a final investment recommendation and a structured PDF research report. Figure 1 illustrates the high-level system architecture.



System Architecture Overview

The overall system is structured into four principal layers: the Data Ingestion Layer, the Multi-Agent Analysis Layer, the Synthesis and Report Generation Layer, and the User Interface Layer. Each layer operates as an independent module with well-defined input-output contracts, enabling modular development, testing, and deployment. The Data Ingestion Layer connects to real-time and historical financial data sources including the NSE Data API, BSE API, Yahoo Finance, and financial news aggregators such as MoneyControl, Economic Times Markets, and Bloomberg India. For each target stock or index, the layer retrieves closing prices, volume data, financial statements, peer comparison metrics, and curated recent news articles. Data is normalized, deduplicated, and structured into standardized JSON objects for downstream agents.

Multi –Agent Workflow

Figure 2 illustrates the complete multi-agent workflow from ticker submission to report delivery. Each specialized agent receives the structured data context from the ingestion layer and independently generates a structured analytical sub-report in JSON format, comprising a directional signal, a confidence score in [0, 1], and a natural-language justification. Agents operate in parallel to minimize end-to-end processing latency.

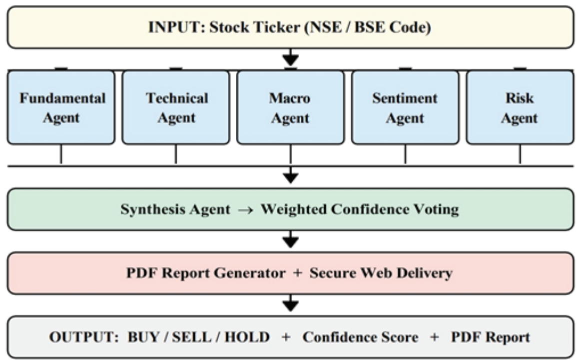


Fig. 2 Multi-Agent Workflow Diagram

Secialized Agent Design

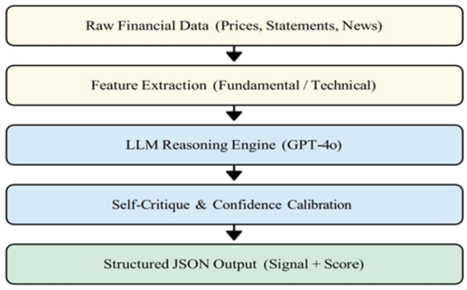
i) Fundamental Analysis Agent. This agent evaluates intrinsic financial health by processing quarterly and annual financial statements. Key metrics include P/E ratio, P/B ratio, Return on Equity (ROE), Debt-to-Equity (D/E), EPS growth trajectory, and Operating Cash Flow margin, benchmarked against NSE sector-specific medians.

ii) Technical Analysis Agent. This agent computes MACD, RSI, Bollinger Bands, EMA at 20/50/200-day horizons, ADX, and On-Balance Volume (OBV) from historical price and volume time series, identifying chart patterns and generating a momentum-based directional signal with a confidence score.

iii) Macroeconomic Context Agent. This agent contextualises the target stock within India's macro environment, processing RBI monetary policy decisions, CPI/WPI inflation readings, GDP growth projections, FII/DII flow data, and INR/USD currency dynamics.

iv) News Sentiment Agent. This agent ingests curated news articles, management commentary, and analyst reports, classifying sentiment at article level and aggregating into a composite score. It flags material events such as earnings surprises, regulatory actions, M&A announcements, or management changes.

v) Risk Assessment Agent. This agent computes Beta, Value-at-Risk (VaR) at 95% confidence, Maximum Drawdown over 12 months, and correlation with Nifty 50 and BSE Sensex, synthesizing these into a categorical risk rating (Low/Moderate/High) with a narrative risk disclosure.



Synthesis And Recommendation Engine

The Synthesis Agent receives five structured sub-reports and applies a weighted confidence voting mechanism. Each agent's directional signal is encoded as +1 (BUY), 0 (HOLD), or -1 (SELL), weighted by the agent's self-reported confidence score. The composite score is computed as the weighted average of directional votes. This is mapped to BUY (score > 0.25), HOLD (-0.25 to 0.25), or SELL (< -0.25) using empirically calibrated thresholds. When agent signals strongly diverge (variance > 0.6), the system defaults conservatively to HOLD with an uncertainty disclosure, protecting retail investors from ambiguous signals.

PDF Report Generation And Web Interface

The report generation module compiles analytical outputs from all agents into a structured PDF research report following institutional equity research conventions. Each report includes an executive summary with the final recommendation and confidence score, a fundamental analysis section with tabulated financial metrics, a technical analysis section, a macroeconomic context section, a news sentiment summary with source citations, a risk disclosure, and a regulatory disclaimer.

The web interface is implemented as a responsive single-page application communicating with the backend agent orchestration service via authenticated REST APIs. User authentication enforces JSON Web Tokens (JWT) with short-lived access tokens and secure refresh token rotation. All data in transit is encrypted using TLS 1.3, ensuring compliance with applicable data protection regulations. Each report includes an executive summary with the final recommendation and confidence score, a fundamental analysis section with tabulated financial metrics, a technical analysis section, a macroeconomic context section, a news sentiment summary with source citations, a risk disclosure, and a regulatory disclaimer.

Results And Discussion

This section presents the experimental evaluation of the proposed multi-agent AI framework. The system was evaluated on a curated dataset comprising 50 stocks from the Nifty 50 index and 30 stocks from the BSE Sensex constituents, covering a back-testing period from January 2023 to December 2024. For each stock, the system generated monthly recommendations compared against the actual price direction observed in the subsequent 30-day period. A recommendation was considered correct if the price moved in the direction indicated by the BUY or SELL signal, or remained within a +/-3% band in the case of a HOLD recommendation. Figure 3 presents the accuracy comparison across all evaluated models.

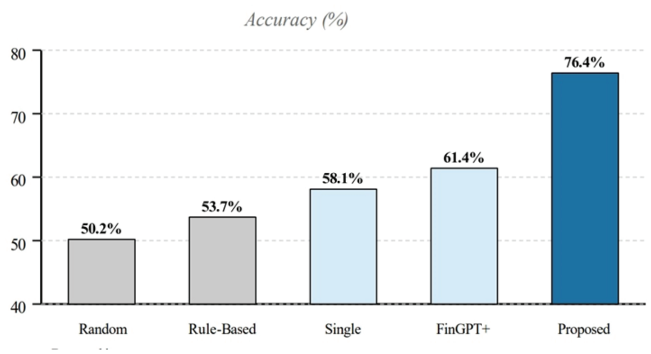


Fig. 4 Recommendation Accuracy vs. Baseline Models (%)

S.No	Model	Acc. (%)	Conf.
1	Random Baseline	50.2	N/A
2	Rule-Based Tech [4]	53.7	N/A
3	Single-Agent LLM [6]	58.1	0.63
4	FinGPT+Screener [6]	61.4	0.65
5	**Proposed Multi-Agent**	**76.4**	**0.79**

***Table 1**: Recommendation Accuracy Comparison*

Table 1 presents a comprehensive numerical comparison. The proposed multi-agent framework achieves a recommendation accuracy of 76.4%, outperforming the single-agent LLM baseline by 18.3 percentage points and the rule-based technical system by 22.7 points. A clear positive correlation is observed between agent consensus score and recommendation accuracy, validating the weighted voting mechanism design.

The performance advantage is most pronounced in sectors characterised by high information complexity—pharmaceuticals, technology, and financial services—where fundamental analysis and news sentiment are highly material to price outcomes. In commodity-linked sectors such as metals and energy, the gap narrows as macroeconomic factors and global price signals dominate.

Qualitative evaluation through a structured survey administered to 45 retail investors yielded mean scores of 4.3 for report clarity, 4.1 for analytical depth, 3.9 for actionability, and 3.7 for trust (five-point Likert scale). Average end-to-end processing latency from ticker submission to report delivery was 42.3 seconds, with a 95th-percentile latency of 67.8 seconds—substantially lower than traditional human analyst report production which typically spans hours to days.

Conclusion

This paper has presented a multi-agent AI framework for automated Indian stock market analysis and report generation. By orchestrating five specialized LLM-powered agents covering fundamental analysis, technical analysis, macroeconomic context, news sentiment, and risk assessment, the proposed system delivers institutional-quality equity research at scale and near-zero marginal cost.

Experimental evaluation across 80 Nifty 50 and BSE Sensex stocks over a two-year back-testing period demonstrates a recommendation accuracy of 76.4%—an 18.3 percentage point improvement over single-agent LLM baselines and 22.7 points over rule-based technical systems. The framework addresses the critical information asymmetry between institutional and retail investors in India's rapidly growing equity market, where 91% of derivative traders incur losses according to SEBI data.

Future research directions include integration of intraday data and real-time alert generation, application of reasoning-enhanced LLMs employing chain-of-thought prompting, dedicated evaluation on small-cap and mid-cap stocks, and formal alignment with SEBI's evolving regulatory framework for AI-driven investment advisory Services.

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