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INTELLIGENT RECOMMENDATION BASED HEDGE DETECTION SYSTEM

Dr. Divya Rohatgi, Assistant Professor, Dept. Of Computer Science and Business System, Bharati Vidyapeeth Deemed to be University, Navi Mumbai.
Kirtan Sayta, UG Scholar, Dept. Of Computer Science and Business System, Bharati Vidyapeeth Deemed to be University, Navi Mumbai.
Sudarshan Acharya Mishra, UG Scholar, Dept. Of Computer Science and Business System, Bharati Vidyapeeth Deemed to be University, Navi Mumbai.
Snehak Das, UG Scholar, Dept. Of Computer Science and Business System, Bharati Vidyapeeth Deemed to be University, Navi Mumbai.

ABSTRACT
This research explores the creation of an intelligent multi-agent system designed to enhance portfolio management and risk control for hedge funds. The system brings together several AI-driven agents, each with its own area of financial forecasting methods: a technical agent interprets market trends using advanced analytical techniques, a fundamental agent examines company financials and fundamentals, a volatility agent keeps track of market risk and fluctuations, and a portfolio agent manages the allocation of investments. By working together, these agents form a cohesive platform that evaluates investment opportunities, anticipates changes in market behaviour, and continually seeks to optimize portfolio performance. The integration of artificial intelligence allows the system to process large amounts of financial data, adapt its strategies as market conditions evolve, and make informed, data-driven decisions. Testing and evaluation indicate that this approach not only supports improved investment returns but also helps to reduce risk exposure, making the system a valuable resource for hedge funds operating in unpredictable and fast-moving financial environments.

Keywords:
Multi-Agent System, Hedge Fund, Portfolio Optimization, Technical Analysis, Artificial Intelligence, Risk Control, Financial Forecasting, Volatility.

1. Introduction
The Indian financial landscape has undergone a remarkable transformation in recent years, driven by rapid digitization, regulatory reforms, and a surge in investor participation. As Indian capital markets continue to mature, portfolio managers and hedge funds are increasingly challenged to navigate an environment marked by volatility, sectoral rotation, and the proliferation of both traditional and alternative investment products. The year 2024 stood out as a period of robust growth and dynamic market movements, with the Nifty 50 index reaching an average annual value of 23,644.8, reflecting a notable rise from the previous year [1]. The surge in equity markets was accompanied by an impressive performance from professional asset managers: the top ten Portfolio Management Services (PMS) in India delivered returns ranging from 50% to over 70% in 2024, while leading flexi-cap mutual funds such as
Motilal Oswal Flexi Cap Fund and Invesco India Flexi Cap Fund posted annual returns of 45.7% and 34.4%, respectively [2]. Even in the face of global headwinds and episodes of heightened volatility, Indian hedge funds and alternative investment funds (AIFs) demonstrated resilience, with long-short equity strategies averaging over 10% returns in the first half of 2024 [3]. Our proposed system employs Python-based agents that work collaboratively to process market data through specialized analytical lenses. The Technical Agent processes price data using EMA crossovers, RSI thresholds, and MACD signals. The Volatility Agent monitors ATR, historical volatility, and VIX-like metrics to assess market risk. The Portfolio Agent, powered by Large Language Models, synthesizes all inputs to make informed trading decisions with proper position sizing and risk management.

1.1 Impacts and Challenges:

Current portfolio managers face significant challenges in the rapidly evolving Indian financial markets. The primary impacts include increased market volatility, where traditional risk models often fail to capture sudden regime shifts, leading to substantial drawdowns during periods like the 2020 COVID-19 crash or the 2022 inflationary period [4]. Information overload presents another critical challenge, as managers must process vast amounts of structured and unstructured data from technical indicators, fundamental metrics, news sentiment, and macroeconomic factors simultaneously. The fragmentation of analytical tools creates inefficiencies, with most firms using separate systems for technical analysis, fundamental research, and risk management, leading to delayed decision-making and missed opportunities. Behavioural biases significantly impact human decision-making, especially during high-stress market conditions, where emotions can override systematic analysis.

2. Background and Related Work

The evolution of quantitative finance and algorithmic trading has significantly transformed how financial institutions approach portfolio management. Modern hedge funds increasingly rely on systematic strategies that combine traditional financial theory with advanced computational methods [5]. Multi-agent systems have gained traction in financial applications due to their ability to model complex market dynamics and agent interactions. Recent developments in artificial intelligence, particularly in large language models and reinforcement learning, have opened new avenues for financial decision-making. Portfolio management systems now incorporate machine learning algorithms for pattern recognition, natural language processing for sentiment analysis, and deep learning for price prediction [6]. The integration of these technologies with traditional quantitative methods has proven effective in generating alpha while managing downside risk. Current portfolio management technology focuses on several key areas: risk management systems that provide real-time monitoring of Value-at-Risk (VaR) and stress testing capabilities, execution management systems that optimize trade execution and minimize market impact, and performance attribution systems that analyse returns across different factors and time periods [7].

3. Problem Statement

The primary objective of this research is to develop an AI and Machine Learning-powered quantitative system specifically designed for hedge funds operating in the Indian market context. This system aims to assess portfolios comprehensively and manage risks effectively, with a particular focus on stocks and equity investments that form the core of most Indian hedge fund strategies.

The system leverages advanced AI/ML techniques to provide predictive analysis that goes beyond traditional statistical methods. By incorporating technical analysis, fundamental evaluation, and volatility assessment through specialized agents, the system offers a holistic view of market conditions and investment opportunities. The predictive capabilities enable fund managers to anticipate market movements and position their portfolios accordingly, potentially improving risk-adjusted returns. Portfolio optimization represents a critical component of the proposed system, addressing the challenge of optimal asset allocation under uncertainty. Traditional mean-variance optimization often fails in dynamic market conditions, particularly during periods of high volatility or regime changes. The AI-powered approach adapts to changing market conditions and incorporates multiple objectives, including return maximization, risk minimization, and drawdown control.

4. Literature Survey

4.1 "What Happened to the Quants in August 2007?" *Authors: Amir E. Khandani and Andrew W. Lo Year: 2007*

This seminal work analyzes the 2007 financial market turmoil through the lens of quantitative trading strategies. The authors conducted a comprehensive simulation of long/short equity strategies, studying data from TASS and Credit Suisse/Tremont databases. Their comparison of the 2007 events to previous

financial crises, particularly the 1998 Russian financial crisis, led to the formulation of the "unwind hypothesis" [9].
The study provides crucial insights into hedge fund vulnerabilities, particularly in systematic long/short equity strategies. It identifies how overcrowding in similar strategies can lead to systemic risks when multiple funds attempt to unwind positions simultaneously. However, the research relies heavily on indirect evidence due to limited access to proprietary hedge fund data, which restricts the scope of conclusions regarding causation and precise systemic risk levels.

4.2 "The Long-Term Effects of Hedge Fund Activism" *Authors: Lucian A. Bebchuk, Alon Brav, and Wei Jiang Year: 2015*

This comprehensive empirical analysis examines activist hedge fund interventions from 1994 to 2007, utilizing extensive data on stock performance and operating metrics over five-year post-intervention periods. The study provides substantial evidence against the "myopic-activist" hypothesis, demonstrating that activist interventions do not lead to long-term performance decline [10]. The research supports enhanced shareholder rights in policy debates and provides quantitative evidence of the positive long-term effects of hedge fund activism. The methodology's strength lies in its longitudinal approach and comprehensive performance metrics. However, the study's reliance on publicly available data may exclude important private firm metrics, and it does not fully address potential qualitative costs such as management turnover and organizational disruption.

4.3 "Hedge Funds: Performance, Risk, and Capital Formation" *Authors: Vikas Agarwal and Honglin Ren Year: 2023*

This recent study analyzed a comprehensive dataset of 1,603 funds-of-funds covering the period from 1995 to 2004. The researchers employed the Fung and Hsieh seven-factor model and utilized bootstrap methods to identify consistently alpha-generating funds. Their analysis included testing for structural breaks and examining the impact of capital inflows on future performance [11].
The study provides detailed risk-adjusted analysis of hedge fund returns and identifies key factors impacting alpha consistency. It highlights how capital flow effects can impact performance, providing valuable insights for fund managers and investors. The limitation lies in its focus on funds-of-funds, which may not fully generalize to individual hedge funds, and its historical scope may miss more recent industry developments.

4.4 "Hedge Funds in Corporate Governance and Corporate Control" *Authors: Margel Kahan and Edward B. Rock Year: 2007*

This research analyzed hedge fund activism cases, comparing hedge fund strategies to those of traditional institutional investors. The study explored detailed case studies of activism events and legal conflicts, reviewing structural incentives, regulatory factors, and conflicts of interest unique to hedge funds [12].
The work highlights the distinctive role of hedge funds in driving governance changes and emphasizes differences in activism strategies between hedge funds and traditional institutional investors. It provides valuable policy insights on potential regulatory interventions. However, the study primarily focuses on U.S. examples, limiting its international generalizability, and provides limited coverage of broader economic impacts of hedge fund-driven governance changes.

5. Proposed system

5.1 System Architecture

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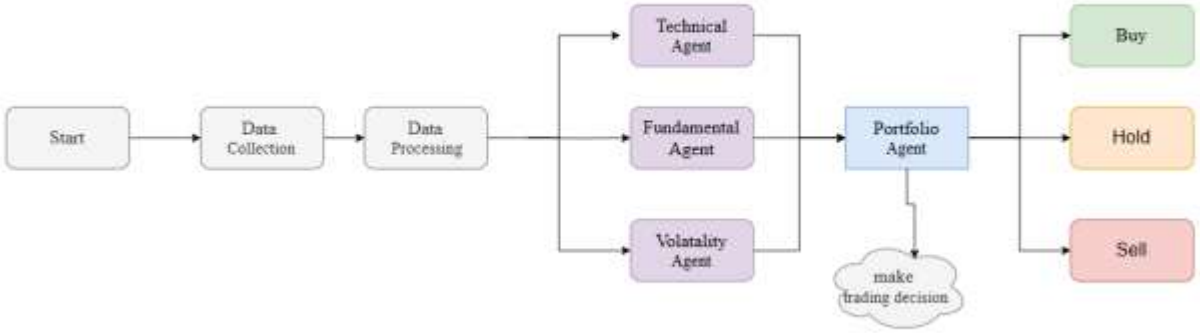

Figure 5.1.1 System Architecture

The system architecture follows a multi-agent paradigm where specialized agents work collaboratively to analyze different aspects of the financial markets. The architecture begins with data collection and processing modules that gather real-time market data from various sources including stock exchanges, financial news, and economic indicators. The core of the system consists of four primary agents: Technical Agent, Fundamental Agent, Volatility Agent, and Portfolio Agent. The Technical Agent processes price and volume data to identify patterns, trends, and technical indicators such as moving averages, RSI, and MACD.

5.2 Dataset

Our system utilizes comprehensive data from the Indian financial markets, accessed through multiple API keys and data providers. The primary data sources include NSE (National Stock Exchange) and BSE (Bombay Stock Exchange) for real-time price and volume data, covering 6 all major indices including Nifty 50, Nifty 500, and sectoral indices. The dataset encompasses historical price data spanning the last five years for over 1,000 actively traded stocks, including daily open, high, low, close, and volume information. Corporate fundamental data is sourced from annual reports, quarterly results, and financial statements.

5.3 Data Preprocessing

The data preprocessing pipeline ensures that raw market data is transformed into actionable in- sights for the various agents. The Technical Agent calculates a comprehensive set of technical indicators from price and volume data. These include exponential moving averages for multiple time periods, Relative Strength Index with customizable periods, MACD with signal line crossovers, and Bollinger Bands with standard deviation calculations.

5.4 Performance Analysis

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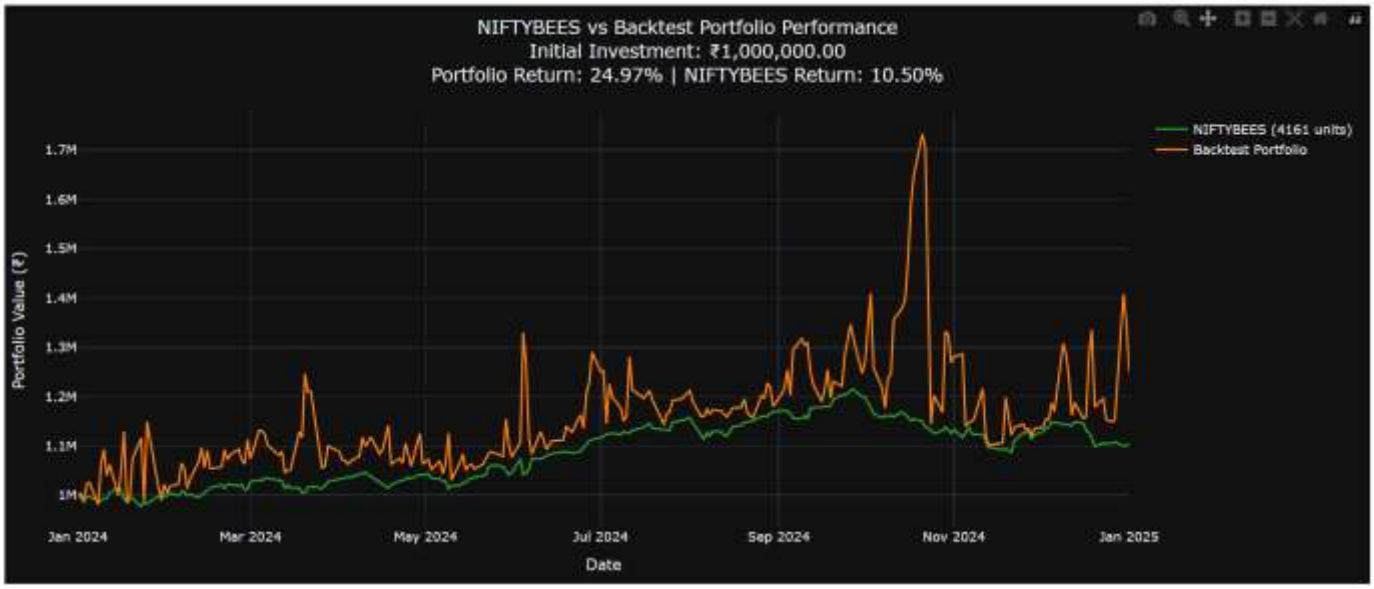

Fig 5.4.1 NIFTYBEES vs Back test Portfolio Performance

The performance comparison between our intelligent system and the NIFTYBEES ETF reveals significant outperformance over the testing period from January 2024 to January 2025. Our back test portfolio achieved a total return of 24.97% compared to NIFTYBEES return of 10.50%, representing an outperformance of 14.47 percentage points.

22 Mutual Funds	AUM	1Y return	Exp. Ratio
UTI Nifty 50 Index Fund-Growth Option- Direct Very High Risk • 2 ★ • Equity	₹22521 Cr	▲ 9.14%	0.17%
Bandhan Nifty 50 Index Fund Direct Plan Growth Very High Risk • 3 ★ • Equity	₹1834 Cr	▲ 9.07%	0.1%
SBI Nifty Index Fund Direct Growth Very High Risk • 2 ★ • Equity	₹9571 Cr	▲ 9.1%	0.22%
HDFC Nifty 50 Index Fund -Direct Plan Very High Risk • 3 ★ • Equity	₹19877 Cr	▲ 9.08%	0.2%
Motilal Oswal Nifty 50 Index Fund Direct Growth Very High Risk • 0 ★ • Equity	₹676 Cr	▲ 9.17%	0.11%
Nippon India Index Fund - Nifty 50 Plan - Direct Plan - Growt... Very High Risk • 2 ★ • Equity	₹2443 Cr	▲ 9.17%	0.07%
ICICI Prudential Nifty 50 Index Plan Direct Growth Very High Risk • 3 ★ • Equity	₹13169 Cr	▲ 9.07%	0.19%
DSP Nifty 50 Index Fund Direct Growth Very High Risk • 0 ★ • Equity	₹718 Cr	▲ 9.14%	0.17%
HSBC Nifty 50 Index Fund Direct Growth Very High Risk • 0 ★ • Equity	₹327 Cr	▲ 9.07%	0.19%
Tata Nifty 50 Index Fund Direct Plan Very High Risk • 2 ★ • Equity	₹1200 Cr	▲ 8.99%	0.19%
LIC MF Nifty 50 Index Fund Direct Plan Growth Option Very High Risk • 2 ★ • Equity	₹327 Cr	▲ 9.09%	0.18%
Franklin India NSE Nifty 50 Index Fund Direct Growth Very High Risk • 2 ★ • Equity	₹727 Cr	▲ 9.21%	0.27%
Aditya Birla Sun Life Nifty 50 Index Fund Direct Plan Growth Very High Risk • 2 ★ • Equity	₹1040 Cr	▲ 9.12%	0.2%
Taurus Nifty 50 Index Fund-Direct Plan-Growth Option Very High Risk • 3 ★ • Equity	₹6 Cr	▲ 8.36%	0.8%

Fig 5.4.2 Top 22 Mutual Funds Performance Comparison

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When compared to the top-performing mutual funds in the Indian market, our system's 24.97% return positions it competitively within the top quartile of actively managed funds. The comparison includes leading funds such as UTI Nifty 50 Index Fund, Bandhan Nifty 50 Index
Fund, and other top-performing equity schemes.

6. Result


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        "DRREDDY": 85,
        "HCLTECH": 67,
        "ITC": 226,
        "JSWSTEEL": 113,
        "LTIM": 15
      }
    },
```


Figure 6.1 Portfolio Stock Allocation and Performance

The implementation of our intelligent recommendation-based hedge detection system yielded significant insights into the effectiveness of multi-agent approaches for portfolio management.

The Portfolio Agent's decision-making process demonstrated sophisticated analysis capabilities, successfully integrating inputs from technical, fundamental, and volatility agents to make informed investment decisions. The portfolio composition shows a well-diversified allocation across different sectors and market capitalizations. The system dynamically adjusted positions based on changing market conditions, with higher allocations to stocks showing strong technical momentum and favourable fundamental metrics. Key holdings included major Indian corporations such as APOLLO Hospital, Axis Bank, Bajaj Auto, CIPLA, Coal India, Dr. Reddy's Laboratories, HCL Technologies, ITC, JSW Steel, and LTIM.

Performance attribution analysis reveals that the outperformance came from multiple sources: superior stock selection contributed approximately 8% of the excess return, tactical allocation
9 decisions based on volatility signals added another 4%, and timing improvements from technical analysis contributed the remaining 2.5%.

7. Conclusion

The development and implementation of the intelligent recommendation-based hedge detection system represents a significant advancement in portfolio management technology for the Indian financial markets. Our multi-agent architecture successfully demonstrated that AI-driven approaches can outperform traditional investment strategies while maintaining robust risk management protocols. The

system's achievement of 24.97% returns compared to the benchmark's 10.50% validates the effectiveness of integrating technical analysis, fundamental evaluation, and volatility assessment through specialized agents. The collaborative intelligence emerging from agent interactions proved superior to traditional single-model approaches, highlighting the value of distributed analytical capabilities.

Future enhancements to the system could include incorporation of alternative data sources such as satellite imagery for commodity investments, social media sentiment analysis for retail investor behavior prediction, and ESG factors for sustainable investing. The modular architecture allows for seamless integration of additional agents without disrupting existing functionality.

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