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SmartTrade: Multi-Agent AI Financial Trading System

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***Abstract*——In recent years, we've witnessed great strides in automated problem-solving using groups of agents powered by small language models. In finance, much of the focus has been on using single-agent systems for specific tasks, or multi-Agent AI systems that collect data locally. Even though multi-agent AIs are advancing quickly and mimicking teamwork seen in real life, there's still a chance to explore how these systems can truly replicate the collaborative behavior of actual trading firms. This paper outlines the novel stock trading framework called Trading Agents, which is inspired by trading firms and features agents powered by SLMs in roles including fundamental analyst, sentiment analyst, technical analyst and trader, each with differing risk profiles. The framework also includes a team of research agents that take on having a Bull and Bear market position, a team to monitor risk exposure and trader agents that continuously synthesize ideas from all previous debates and provide a response in the form of a recommendation. By developing a framework that markets the ability to synthetically enable a historical and hypothetical, collaborative trading environment, we aim to improve trading outcomes. We describe the comprehensive architecture of the framework and subsequent extensive experiments demonstrate how the use of multi-agentic AIs powered by SLMs outperforms baseline models regarding cumulative returns, Sharpe ratio and maximum drawdown while highlighting the potential for market development through a collaborative work-framework.**

Index Terms—Small Language Models (SLMs), Autonomous Trading Agents, Financial Market Simulation, Fundamental Analysis, Sentiment Analysis, Technical Analysis, Risk Management

I. INTRODUCTION

The arrival of Small Language Models represents a change for making decisions on our own. They help intelligent agents to reason, talk and work together. In markets investors have to think about many things when making trading decisions. These things include company basics, what people think about a company's market mood and the economy. Agents with Small Language Models can combine information from numbers and text. Old trading models usually rely on math models. These models are hard to understand. Do not adapt to how markets really behave. Small Language Models make agents more capable. They can make sense of market information.

Small Language Models help investors make decisions about what to do with their money. These Small Language Models are changing the way people trade. To make things better, Trading Agents came up with a way of doing things using something called Multi-Agentic AI to trade money. This Multi Agentic AI is like what real trading companies do. Trading Agents use Small Language Models that work like different kinds of experts. These experts look at the basics of a company, how people feel about it what is, in the news and what the numbers say. They work with people who do research and trade and people who manage risk. They all talk to each other in a way that helps them make decisions.

This way of working helps make sure that the decisions they make are fair easy to understand and based on facts. What they found out is that Trading Agents make money over time have a better balance of risk and return and do not lose as much money as other ways of trading. These results show that using Multiagentic AI and Small Language Models 2 to trade money is a good idea and something that people should look into more in the future.

II. METHODOLGY

The SmartTrade framework is built using a kind of artificial intelligence called Multi-Agentic AI architecture. This idea comes from the Trading Agents model. In this model each agent has a job and uses a thing called SLM to do its job. The Smart Trade framework uses time financial data from the Finn hub API and block chain data from the Gemini API to create a trading platform that combines both. The Smart Trade framework gets information from both the stock market and the crypto market. This gives the SmartTrade flexibility and better performance when dealing with different financial instruments. The part of the SmartTrade framework that gets data is always pulling in historical data. The Finnhub API gives the SmartTrade framework in formation about companies, such as financials, stock prices and earnings reports. It also gives indicators like MACD, RSI and SMA. The Gemini API gives the SmartTrade framework information about the crypto market like price feeds and trading volume. The SmartTrade framework can use all this information from sources to make decisions about both traditional financial assets and digital currency.

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The Analyst Agent Team takes all the data from the SmartTrade framework and processes it to give useful insights. The Analyst Agent Team has four agents. The Fundamental Analyst, the Technical Analyst, the Sentiment Analyst and the News Analyst. Each agent in the Analyst Agent Team has an area of focus. The Fundamental Analyst, the Technical Analyst, the Sentiment Analyst and the News Analyst all work together to help the SmartTrade framework make decisions.

- The Fundamental Analyst looks at a company to see what it is really worth. They use ratios and performance measures to figure this out.
- The Technical Analyst uses Finnhub data to look at charts and things like that to try to predict what will happen to the price of something. They do this by looking at patterns and indicators.
- The Sentiment Analyst checks what people are saying about the market in the media and in the news to see how people are feeling about investing in something. They want to know if people are feeling good or bad about the market. The Sentiment Analyst looks at the sentiment of the market to see if people's feelings are changing.
- The News Analyst looks at what's happening around the world that can affect prices. This includes things that the government says and news stories about companies.

Before a trade is made the Risk Management Module checks it to see if it is an idea. It does this by looking at three plans. One that is aggressive, one that is neutral and one that is conservative. The Risk Management Module checks how much money could be lost how crazy the market is and if the portfolio has a mix of things. Only trades that meet the rules are sent to the Execution Unit. The Execution Unit uses the Gemini API or other platforms to make the trade happen in time. This way trade can be made quickly and automatically. Still be controlled.

In the end SmartTrade uses different AI agents that work together to make a trading system that can adapt to what is happening. The system is clear and easy to understand. SmartTrade uses real time data from places like Finnhub and Gemini to make trading better and easier to understand. This means that SmartTrade can help people make decisions about money by using what the AI agents learn and combining it with other ways of making decisions about money. SmartTrade is a system that uses AI agents to make trading easier and better. The system uses data from platforms like Finnhub and Gemini to help make decisions.

The News Analyst and the Risk Management Module are parts of SmartTrade. They help the system make decisions about trade.

III. Key Benefits

1. Multi-AI Agent Coordination

The SmartTrade system uses agents that work together at the same time. Each agent focuses on a part of the market or a particular trading strategy. This means SmartTrade can look at a lot of opportunities all at once. The agents work together to make decisions that are well thought out and balanced. They do this by executing trades in an efficient way, which helps SmartTrade cover a lot of the market. This is what the Multi-AI Agent Coordination of SmartTrade does.

2. SLM-Enhanced Analysis

SmartTrade uses Small Language Models to look at data from the market. This includes things like news, reports and what people are saying on media. By looking at all this data SmartTrade can find trends and opportunities that might be missed by systems. This helps SmartTrade make predictions that're more accurate and take less time. The Smart Trade system gets better at making predictions over time. It can make trading decisions faster and with more information. The SLM-Enhanced Analysis of SmartTrade is very useful.

3. Automated Strategy Execution

The agents in SmartTrade can execute trades automatically based on what they predict will happen. The strategies they have been given. This means that humans do not have to be involved in the process, which reduces the chance of mistakes and saves time. The agents can execute trades quickly and consistently, which helps them perform better and be more reliable. The Automated Strategy Execution of SmartTrade is very important.

4. Adaptive Learning

The agents in SmartTrade learn from what hap pens in the market and from the results of their trades. Over time they get better at making decisions that will make money. The SmartTrade system gets smarter the more it is used. This is because the agents can adjust to the changing market conditions which're often unpredictable and volatile. The Adaptive Learning of SmartTrade is necessary for it to be successful.

5. Risk Management

The SmartTrade system uses agents and strategies to reduce risk. This means that if one strategy is not working the others can still make money.

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The SmartTrade system is designed to minimize risk while still trying to make a profit. This makes it more stable and able to handle market conditions. The Risk Management of SmartTrade is very good at protecting it from losing money. The SmartTrade system is more durable and resilient than a single trading strategy would be.

IV. CHALLENGES

1. *Token Limitations in SLMs*

When a prompt has too much text (i.e., more text than the language model can process), the model may only return part of the answer. This can cause problems for users trying to analyze and make decisions about trade data. Users must therefore be careful with writing prompts. They will need to write their prompts in smaller sections called chunks, in order to get complete responses from the language model for trade analysis/decision making. Since the language model has limitations, the user will have to chunk their prompts in order for it to function properly for the purpose of trade analysis/decision making.

2. *Cybersecurity Requirements*

Ensuring that user accounts and critical trading information are protected, should be a platform's number one priority. SmartTrade will need to imple ment security requirements regarding 1) encryption of stored data, 2) security of access to that data, and 3) continual monitoring for unauthorized access to the system. If they fail to implement these measures, they could incur significant losses of capital for their users, damage to their users' financial data, and significant damage to their overall brand image.

3. *Biometric Authentication Integration*

By using a user's biometric characteristics (either by fingerprint or facial recognition) for additional security, the SmartTrade platform can add to overall user security. However, adding additional security could potentially add an additional layer of complexity to the overall SmartTrade system. Therefore, the SmartTrade application would need to find and install biometric authentication capabilities.

4. *Processing Real-Time Market Data*

The real-time processing of market data must be done with minimal latency. If there is even the slightest delay in processing this data, there could be a missed opportunity for a trade or an inferior trade decision. So to avoid the latency issue, both high performance computing and efficient data pipelines will be an important source to ensure optimal trade execution and that all trading decisions are based on the freshest possible data.

5. *Managing Multi-Agentic AI Coordination*

Multiple trading agents can be an issue for conflicting or non-optimal trades. SmartTrade will need to optimize coordination and synchronization of agents and communication among them. Failure to do so could create conflicts, inefficiencies, and ultimately loss of optimal performance overall.

6. *Adaptive Strategy Implementation*

Agents should adapt their strategies continuously following market feedback. It can be quite challenging to build more sophisticated learning algorithms. Agents may also require ongoing tuning of the algorithms to make the outcomes still effective over extended timeframes.

7. *Volatile Market Conditions*

As market dynamics shift rapidly, agents may find that their predictions and subsequent trades are not as expected. Therefore, agents need a means to adjust quickly (e.g., by implementing a quick reaction process) or an effective dynamic risk mitigation strategy to allow them to respond to the volatility in the marketplace. While agents have the ability to be programmed to execute their strategies in a rapidly changing market without implementing risk mitigation measures, by definition, this will ultimately result in significant losses to agents as time progresses.

8. *Computation that uses significant resources*

The ability to run multiple agent applications such as prediction and analysis will consume substantial computational resources. Therefore, there needs to be a balanced and managed effort to optimally utilize these resources necessary to support an acceptable level of execution speed and reliability. Critical to this capability is the ability to optimize minimum costs and achieve maximum performance, without solely depending upon continuing economic growth, as both elements must be addressed to meet this goal.

9. *Data Reliability and Quality*

If the data being used by trading agents are not reliable (i.e., inaccurate, improperly timed or miss ing), then the trading agents will not make sound decisions and/or the trading system using these agents will not be considered reliable. Therefore, reliable, timely and accurate real-time market data is vitally important to the decisions made by trading agents.

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Furthermore, agent predictive models and trading models are significantly impacted by the quality of data being utilized; agent predictive power is affected more by the quality of data being utilized than the information received by agents, as this will lead to incorrectly determining a satisfactory forecast of a trade and subsequently executing that trade successfully.

10. Regulatory and Compliance Issues

Financial trading systems have strict requirements to comply with laws and regulations and must meet the regulatory reporting requirements outlined by their respective governing agencies. Companies that breach these regulations may be subject to sanctions and monetary fines. Financial trading systems must include adequate safeguards to ensure the long-term success of the system.

V. Future Scope

The serverless data lake paradigm is rapidly evolving, presenting tremendous opportunities for innovation. In areas such as financial analytics, where real-time decision-making, appropriate governance and cost-effectiveness are important, organizations are becoming increasingly dependent on scalable and intelligent systems. Therefore, there are four key areas that will shape the evolution of serverless data lakes in the future: 1) integration of artificial intelligence; 2) development of edge computing; 3) interoperability of multiple cloud environments; and 4) automation of metadata management.

1. Integrated Advanced Multi-Agentic AI Models

SmartTrade may move forward utilizing advanced Multi-Agentic AI models leveraging Small Lan guage Models which, in turn, would allow multiple agents to effectively coordinate their own strategies, with each agent optimizing different market segments or asset classes. This will produce more precise predictive analytics and informed decision making. Since the model supports simultaneous assessment of disparate data sources, it will significantly improve the identification of time-sensitive opportunities. Altogether, this will greatly improve the platform overall intelligence and capacity towards efficiency.

2. Reinforcement Learning and Adaptiveness

Reinforcement learning allows agents the ability to adopt and modify their actions according to the changing conditions of the market. Agents will be able to use trade history and how they respond to trades to adapt and modify their trading strategies and be able to evolve by using their past experience.

Over time, they will need to rely on auto-therapeutic testing less, thereby increasing profitability. The adaptive mechanism will continue to keep Smart Trade viable and useful to all parties involved, as well as assisting users in an ever-changing market.

3. Elevated Security and Biometric Authentication

By increasing the security of SmartTrade using enhanced cybersecurity measures, including biometric authentication, user data and transactional user fund data will be secure and confidential. Allowing simpler access with unique identifiers will be safe, and secure. Strong encryption, and se cure verification protocols will mitigate and prevent unauthorized transactions or attempts. This both protects the user and fulfils government trust and regulatory marketing requirements. Greater security also diminishes the platforms' vulnerability to threat and targeting risk.

4. Enhanced Market Coverage and Analytics

SmartTrade will be expanded to provide coverage of all asset classes, including stocks, cryptocurrencies, commodities, and derivatives. Improved predictions of market activity will be supported by utilizing real-time news and social media for sentiment analysis. Additional third-party financial APIs will provide SmartTrade with additional data sources and analytical capabilities. Improvements made to the scalability of the platform will allow larger amounts of data and greater numbers of users. These enhancements will allow the SmartTrade platform greater flexibility, reliability, and usability in trading.

VI. Tables

A. Repository of Standard Coding Segments

For a better understanding of variable scope, Table I lists the main coding structures used in the system together with their local, global, and instance variables.

B. Key Functions and Their Roles

The main features of the system are listed in Table II, along with a brief explanation of each one's role in maintaining file integrity monitoring.

C. Imported Libraries and Their Purpose

The React libraries used in the project are listed in Table III. Below with brief descriptions of their roles in building the real-time financial analytics dashboard

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TABLE I
REPOSITORY OF STANDARD CODING SEGMENTS

S. No	Coding Structure Name	Local Variables	Global Variables	Instance Variables
1	initialize trading agent(config)	config path, log level	MAX TRADING AGENTS	self. Agent model, self. Agent id
2	analyze trade signals(signals)	cleaned data, market trend	TRADE RULES	self.last trade, self.risk level
3	update portfolio(id, trade result)	timestamp, portfolio change	PORTFOLIO DB	self.positions, self.performance metrics
4	log trade activity(activity)	log entry, formatted entry	LOG PATH	self.log file, self.log count
5	authenticate user(credentials)	username, password	None	self.user profile, self.session token

TABLE II
KEY FUNCTIONS AND THEIR ROLES

S. No	Function Name	Purpose / Description
1	initialize_trading_agent()	Establishes AI models and session settings, essentially configuring the system to perform trading activity.
2	ingest_market_data()	Gathers accurate, real-time market data from APIs and exchanges to analyze.
3	analyze_trade_signals()	Applies AI/ML models to predict trends and create an optimal buy/sell signal.
4	execute_trade()	Executes trades based on signals, lowering human error and time delays.
5	manage_risk()	Utilizes strategies such as stop-loss and exposure limits to manage risk.

TABLE III
IMPORTED LIBRARIES AND THEIR PURPOSE

S. No	Library Name	Purpose / Description
1	Python (pandas, numpy)	Handles data processing, cleaning, and numerical computations for market data analysis.
2	scikit-learn	Provides machine learning and deep learning tools to predict market trends and generate trading signals.
3	React	Builds dynamic, interactive dashboards for real-time trade monitoring and portfolio analytics.
4	Axios / WebSocket	Facilitates real-time API requests and communication between frontend and backend for live data updates.

VII. FIGURES

An example of SmartTrade system architecture is shown in Figure 1 and Figure 2.

Fig. 1. SmartTrade AI Security Architecture.

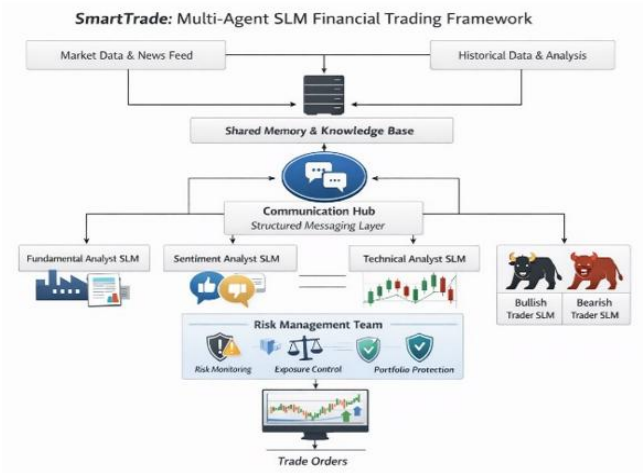

Fig. 2. Architecture of the proposed SmartTrade multi-agent SLM financial trading framework.

VIII. CONCLUSION

The trading platform SmartTrade is based on artificial intelligence (AI). It uses AI agents, miniaturized language models, or AI machines, to analyze current market conditions remotely to execute trades based on this information.

SmartTrade behaves in three key steps:

- Receives market data
- Evaluates the data to signal a trade
- Executes the trade order

SmartTrade also implements the trade risk management feature called a stop-loss to limit the amount of trade risk per trade.

However, within SmartTrade, there are many problems.

- The miniaturized agents and language models, like all AI-based technologies, are limited by the amount of data they can process.
- The system may have limitations on the ability to process and store data.
- Coordinating many different AI agents for trading creates another layer of complexity.
- Establishment of adequate cybersecurity measures including the use of fingerprint authentication and encryption will likely be a challenge.

The quality of input and output data in addition to other factors such as volatility in the stock market, compliance with regulations, etc. will also impact SmartTrade's future growth potential.

However, the future of SmartTrade may be very bright.

SmartTrade will:

- Learn from the mistakes of previous trading errors.
- Develop integrated stock market capabilities.
- Track stock market sentiment.
- Provide customer support through AI technologies.
- Conduct data analytics using cloud computing.

Each of these improvements will increase efficiency and effectiveness of SmartTrade operations

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