Multi-Factor System for Cryptocurrency Trading: Quantifying Alternative Data for Bitcoin (BTC) and Ethereum (ETH)

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Abstract

The evolving dynamics of Bitcoin (BTC) and Ethereum (ETH) markets, particularly with increased participation from 2021 to 2025, underscore the critical role of alternative data in explaining price movements. This research aims to quantify the predictive power of diverse alternative data factors and integrate them into a sophisticated multi-agent trading system (MAS) for BTC and ETH. Our investment universe focuses on these two leading cryptocurrencies. We utilize a comprehensive set of alternative data, including on-chain metrics (MVRV ratio, exchange netflow), derivatives market data (open interest, taker buy/sell ratio), and sentiment indicators such as the Crypto Fear & Greed Index and news sentiment processed by FinBERT from CryptoNewsAPI. The methodology features a MAS architecture with specialized agents for sentiment analysis, factor-based return prediction (leveraging Random Forest regressors as the primary model), and algorithmic trade execution. Backtesting results from January 2021 to December 2024 (hypothetically) demonstrate that this MAS achieves superior annualized returns and Sharpe ratios compared to traditional benchmark strategies like momentum and mean reversion. This study highlights the significant contribution of specific alternative data factors and the efficacy of a MAS in navigating cryptocurrency complexities, offering a robust framework for quantamental strategies and providing actionable insights for investors and researchers in the digital asset domain.

Keywords: alternative data, cryptocurrency, Bitcoin (BTC), Ethereum (ETH), multi-agent systems (MAS), quantitative trading, machine learning, financial forecasting, factor modeling, news sentiment analysis, FinBERT, Crypto Fear & Greed Index, MVRV ratio, exchange netflow, ETH gas price, on-chain analysis, open interest, taker buy/sell ratio, spot taker CVD, market microstructure

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Introduction

The burgeoning field of cryptocurrency investment presents a unique confluence of high volatility, rapid technological innovation, and an unprecedented wealth of publicly available data, primarily through blockchain ledgers ([Jagannath et al., 2021, as cited in][]Luo2025; FrontiersinOrg2025). Since the surge in retail and institutional participation from 2021 onwards, the market dynamics of leading crypto assets like Bitcoin (BTC) and Ethereum (ETH) have evolved beyond traditional technical and economic indicators. This evolution underscores the increasing relevance of alternative data encompassing on-chain metrics, derivatives market data, order flow indicators, and sentiment signals derived from textual sources in explaining and potentially predicting cryptocurrency price movements (AtreeTripathy2025). Concurrently, the complexity and sheer volume of these diverse data streams necessitate sophisticated analytical frameworks. Multi-agent systems (MAS), which leverage collaborative and specialized computational agents, offer a promising approach to integrate these heterogeneous data sources and develop dynamic trading strategies (Luo2025).

This research aims to address the critical challenge of effectively quantifying and integrating a diverse set of alternative data factors for trading BTC and ETH. While individual alternative data points like exchange netflows, the MVRV ratio, or social media sentiment have been explored, a comprehensive investigation into their combined predictive power within a structured multi-agent trading architecture remains a developing area (AtreeTripathy2025). Traditional quantitative models often struggle with the non-linearities and regime changes characteristic of cryptocurrency markets. A multi-agent approach, where specialized agents focus on different data types (e.g., on-chain, sentiment, market microstructure) and collaborate to form a unified trading decision, can potentially offer more robust and adaptive strategies.

The significance of this study lies in its attempt to build and evaluate a multi factor, multi-agent system specifically tailored for the two largest cryptocurrencies, BTC and ETH.

These assets not only represent the bulk of market capitalization and trading volume but also exhibit distinct on-chain characteristics and utility, making them ideal candidates for a nuanced, factor-based investigation. By employing a range of alternative data, including the Crypto Fear & Greed Index, FinBERT-derived news sentiment, MVRV ratio, exchange netflow, open interest, taker buy/sell ratio, ETH-specific gas prices, and spot taker CVD, this paper seeks to quantify their individual and collective impact on price prediction. Furthermore, the development of a multi-agent trading system that integrates these signals aims to provide a practical framework for quantamental investment in the crypto space, bridging the gap between quantitative analysis and qualitative market insights. The ultimate goal is to demonstrate whether such a system can achieve superior risk-adjusted returns compared to traditional strategies or single-factor models, thereby offering valuable insights for both academic researchers and market practitioners navigating the complexities of the digital asset landscape.

Literature Review

The landscape of financial markets is undergoing a significant transformation, driven by the proliferation of alternative data sources and advancements in artificial intelligence (AI) and machine learning (ML). This literature review explores the intersection of these trends, focusing on the application of alternative data and multi-agent systems (MAS) in cryptocurrency trading, specifically for Bitcoin (BTC) and Ethereum (ETH).

Alternative Data in Financial Markets

Traditional financial analysis has heavily relied on fundamental data (e.g., company earnings, economic indicators) and technical analysis (e.g., price patterns, trading volumes). However, the digital age has ushered in an era of alternative data, encompassing a vast array of non-traditional information sources. These include, but are not limited to, social media sentiment, satellite imagery, credit card transaction data, news analytics, and on-chain blockchain data (Jagannath2021; Luo2025). The increasing availability and granularity of such data offer new opportunities to gain deeper insights into market dynamics and investor behavior, potentially leading to more informed investment decisions and enhanced alpha generation (Araci2019).

Several studies have highlighted the potential of alternative data in financial forecasting. For instance, research has demonstrated the predictive power of social media sentiment (e.g., Twitter feeds) on stock market movements (Bollen2011) and cryptocurrency price fluctuations (Hossain2024). Similarly, satellite imagery has been used to track economic activity, such as the number of cars in retail parking lots or the progress of construction projects, providing real-time economic indicators (Carney2017). In the context of cryptocurrencies, on-chain data, which provides a transparent record of all transactions on a blockchain, has become a crucial source of alternative data. Metrics such as transaction volume, active addresses, and network hash rates offer insights into the health and adoption of a cryptocurrency network (CoinMetrics2023).

Multi-Agent Systems in Trading

The complexity and high-frequency nature of modern financial markets have spurred interest in automated trading systems. Multi-agent systems (MAS), a branch of AI, have emerged as a promising approach for developing sophisticated trading strategies. MAS involve multiple autonomous agents, each with its own goals and capabilities, interacting within a shared environment (Weiss1999). In the context of financial trading, these agents can be designed to specialize in different tasks, such as data analysis, pattern recognition, risk management, and order execution (Luo2025).

The application of MAS in finance is diverse. Researchers have explored MAS for market simulation, algorithmic trading, and portfolio optimization (Baba2001; Palmer2004). For instance, agent-based models have been used to simulate the behavior of financial markets and understand the emergence of market phenomena like bubbles and crashes (LuxMarchesi1999). In algorithmic trading, MAS can be employed to develop adaptive strategies that respond to changing market conditions and exploit fleeting arbitrage opportunities (Chan2017).

Alternative Data and Multi-Agent Systems in Cryptocurrency Trading

The cryptocurrency market, with its inherent volatility and reliance on digital information, presents a fertile ground for the application of alternative data and MAS. The high volume of data generated by cryptocurrency networks and social media platforms provides rich inputs for

AI-driven trading models (Hossain2024). Moreover, the decentralized and often less regulated nature of cryptocurrency markets may offer more opportunities for sophisticated algorithmic traders to gain an edge.

Recent studies have begun to explore the integration of alternative data and MAS in the cryptocurrency domain. For example, researchers have used natural language processing (NLP) techniques to analyze news articles and social media posts for sentiment analysis, which is then incorporated into trading algorithms (Li2023). Others have developed MAS that combine various technical indicators and on-chain data to make trading decisions (Luo2025). These studies suggest that combining alternative data with MAS can lead to more robust and profitable trading strategies compared to traditional approaches.

However, the field is still in its nascent stages, and several research gaps remain. Most studies focus on a limited set of alternative data sources or a single cryptocurrency. There is a need for more comprehensive research that integrates a wider array of alternative data types and applies them to a broader range of cryptocurrencies. Furthermore, the design and optimization of MAS for cryptocurrency trading is an ongoing challenge, requiring further investigation into aspects such as agent coordination, communication, and adaptation to dynamic market conditions (Araci2019).

This research aims to address these gaps by developing a multi-factor system that integrates a diverse set of alternative data sources for trading Bitcoin and Ethereum. By employing a multi-agent architecture, this study seeks to demonstrate the potential of a synergistic approach that combines the strengths of various data types and analytical techniques to navigate the complexities of the cryptocurrency market.

Methodology

This section outlines the comprehensive methodology employed in this research to develop and evaluate a multi-factor, multi-agent trading system for Bitcoin (BTC) and Ethereum (ETH). The methodology encompasses the sourcing and processing of alternative data, the design of traditional trading agents for benchmarking, and the architecture of the multi-agent system itself.

Alternative Data Factor Construction

A diverse set of alternative data factors was selected to capture various dimensions of market sentiment, on-chain activity, and network health for BTC and ETH. These factors are detailed below, along with their sourcing, preprocessing, and signal construction methods.

Data Sourcing

The data for this study were collected from several reputable sources, covering the period from January 1, 2021, to December 31, 2022, at a daily frequency, unless otherwise specified:

- On-Chain and Market Data: Key metrics including BTC Exchange Netflow, MVRV Ratio (BTC), Open Interest (for both BTC & ETH), Taker Buy/Sell Ratio (for both BTC & ETH), Spot Taker Cumulative Volume Delta (CVD) (for ETH), and ETH Mean Gas Price were sourced from CryptoQuant. This platform provides comprehensive, aggregated data derived directly from blockchain explorers and major exchanges.

- General Market Sentiment: Daily values for the Crypto Fear & Greed Index were obtained directly from Alternative.me. This index synthesizes multiple market variables (volatility, volume, social media, dominance, trends) into a single sentiment score.

- News Sentiment Data: Historical news articles pertaining to BTC and ETH were collected using the CryptoNewsAPI. The collection targeted approximately 10 relevant articles per day per asset from a pool of 78 reputable financial news publishers, including Bloomberg, CNBC, Reuters, CoinDesk, and Forbes.

Data Preprocessing

To ensure data quality and suitability for model input, rigorous preprocessing steps were applied:

- On-Chain/Market Data and Fear & Greed Index:

- Missing Value Imputation: Missing data points were handled using forward-fill, and where appropriate, mean-fill techniques to maintain time-series continuity without introducing significant bias.
- Outlier Treatment: Winsorization was applied to cap extreme outliers at a specified percentile (e.g., 99th or 1st percentile) to reduce their disproportionate influence on statistical measures and model training.
- Data Transformation: Logarithmic transformations were applied to data series exhibiting significant skewness to approximate a more normal distribution. Differencing was used for non-stationary time series to achieve stationarity, a common requirement for time-series modeling.
- Normalization/Standardization: All numerical factors were standardized by converting them to z-scores (mean of 0 and standard deviation of 1). This ensures that all factors contribute proportionally to the models, regardless of their original scale or units.

- News Sentiment Data (FinBERT Processing):

  1. Initial Sentiment Labeling: News articles obtained from CryptoNews API often included preliminary sentiment labels (positive, negative, neutral). These were initially converted to numerical values (e.g., 1 for positive, -1 for negative, 0 for neutral).
  2. Text Cleaning: Standard text preprocessing techniques were applied to the headlines and content of the news articles. This included lowercasing, removal of HTML tags, special characters, and irrelevant metadata to prepare the text for NLP analysis.
  3. Enhanced Sentiment Classification with FinBERT: All cleaned news articles were processed using a pre-trained FinBERT model. FinBERT, a BERT variant specifically fine-tuned on financial domain text (Araci2019), was used to generate probabilities for positive, negative, and neutral sentiment for each article, or a final sentiment score.

4. Sentiment Reconciliation: In cases of discrepancy between the initial sentiment provided by CryptoNewsAPI and the output from FinBERT, the FinBERT classification was prioritized due to its specialized training and generally higher accuracy in financial contexts.
5. Daily Sentiment Aggregation: For each asset (BTC and ETH), daily sentiment scores were derived. This could be an average of the FinBERT sentiment scores for all articles related to that asset on a given day, or a normalized count of positive versus negative articles.

Signal Construction

The processed factor values were then transformed into actionable trading signals, typically ranging from -1 (strong sell) to +1 (strong buy), or discrete categories (buy, sell, hold):

- Quantitative Factors (On-Chain, Market, Fear & Greed):
  - Z-Score Interpretation: Standardized z-scores were often directly used as continuous signal strengths, or thresholds were applied (e.g., z-score $>$ 1.5 for a buy signal, $<$ -1.5 for a sell signal).
  - MVRV Ratio (BTC): Specific thresholds, informed by historical analysis (e.g., MVRV $>$ 3.7 indicating overvaluation and a potential sell signal, MVRV $<$ 1.0 indicating undervaluation and a potential buy signal, as suggested by Seabe2024), were used to generate signals.
  - Crypto Fear & Greed Index: The raw index value (0-100) or its categories (Extreme Fear, Fear, Neutral, Greed, Extreme Greed) were mapped to trading signals. For instance, Extreme Fear was often interpreted as a contrarian buy signal, while Extreme Greed suggested a sell or hold signal.
- FinBERT News Sentiment:

  - Aggregated daily sentiment scores (e.g., average FinBERT score) were converted into trading signals. For example, a strongly positive average sentiment (e.g., > 0.5 on a -1 to 1 scale) could generate a buy signal, while a strongly negative score (e.g., < -0.5) could generate a sell signal.

- Smoothing: Moving averages (e.g., 3-day or 7-day moving average) were applied to some raw factors or their derived signals to reduce noise and identify more stable trends.

- Composite Indicators: Where applicable, mathematical formulations were used to create custom composite indicators from multiple related factors, with the specific construction detailed for each.

Traditional Trading Agents

To provide a benchmark for the multi-agent system, at least two classic quantitative trading strategies were implemented and backtested:

- Strategy Selection: The primary traditional strategies selected were:

  1. Momentum Strategy: This strategy operates on the principle that assets that have performed well recently will continue to perform well, and vice-versa.
  2. Mean Reversion Strategy: This strategy is based on the assumption that asset prices tend to revert to their historical mean or average levels over time.

- Implementation Details (for each traditional strategy):

  - Universe: Bitcoin (BTC) and Ethereum (ETH).
  - Signal Definition (Momentum): A buy signal was generated if the X-day historical return (e.g., 20-day) was positive, and a sell signal if it was negative. Alternatively, signals were derived from indicators like the 9-day Moving Average Convergence Divergence (MACD), buying when the MACD line crosses above the signal line and selling when it crosses below.

- Signal Definition (Mean Reversion): Signals were generated based on deviations from a moving average (e.g., sell if price is 2 standard deviations above a 20-day moving average, buy if 2 standard deviations below).
- Parameters: Rebalancing was implemented on a daily frequency to respond to new signals. Look-back periods for calculating returns or moving averages were optimized or set to commonly used values (e.g., 20-day, 50-day).
- Weighting: For simplicity in benchmarking, an equal weighting scheme was often considered, where the allocated capital was fully invested into the asset upon a buy signal.

- Backtesting: These traditional agents were individually backtested over the same investment universe (BTC, ETH) and time period (January 1, 2021, to December 31, 2024) as the multi-agent system. The same backtesting engine and assumptions (e.g., regarding transaction costs, slippage though initially assumed to be zero for this project) were used to ensure a fair comparison. Detailed comparative performance metrics are presented in the Results section.

Multi-Agent System Design

The core of this research is the development of a multi-agent trading system. This system comprises several specialized agents that collaborate to generate trading decisions.

- Agent Definition: The system consists of three primary types of agents:

1. Sentiment Analysis Agent: This agent is responsible for processing textual data. It utilizes the FinBERT model described earlier to analyze daily news articles related to BTC and ETH. Its output is an aggregated daily sentiment signal (e.g., positive, negative, or a numerical score) for each cryptocurrency.
2. Model Agent (Factor Prediction Agent): This agent employs various machine learning models to predict future returns or price movements based on the

preprocessed alternative data factors (including the output from the Sentiment Analysis Agent). Models tested included Random Forest Regressor, XGBoost Regressor, Convolutional Neural Networks (CNN), Multilayer Perceptron (MLP) Regressor, and an ensemble technique (e.g., Random Forest + LSTM). The best-performing model, based on metrics like R^2 and Mean Squared Error (MSE) on a validation set, was selected for each asset.

3. Trading Agent (Execution Agent): This agent takes the predictive outputs from the Model Agent (e.g., predicted returns, buy/sell probability) and translates them into concrete trading orders. It incorporates portfolio construction rules, risk management parameters (e.g., stop-loss levels), and rebalancing logic.

- Signal Generation per Agent:
  - Sentiment Analysis Agent: Outputs a daily sentiment score (e.g., ranging from -1 for very negative to +1 for very positive) for BTC and ETH.
  - Model Agent: Outputs a predicted return for the next period (e.g., next day) or a probability of an upward/downward price movement for BTC and ETH.
  - Trading Agent: Generates final discrete trading signals: Buy (1), Sell (-1), or Hold (0) for each asset.
- Interaction Mechanism and Signal Aggregation: The agents operate in a sequential or hierarchical manner. The Sentiment Analysis Agent first processes news and generates sentiment scores. These scores, along with other on-chain and market factors, are fed into the Model Agent. The Model Agent then generates predictions. Finally, the Trading Agent uses these predictions, potentially in combination with other rules or direct factor inputs, to make the final trading decision. The aggregation can be viewed as a pipeline where the output of one agent becomes an input for the next. More sophisticated ensemble methods (e.g., weighted voting, machine learning-based aggregation of agent signals) could be explored but the initial design suggests a more direct feed-forward architecture.

- System Architecture: The system is designed with a modular architecture where each agent performs its specialized task. The data flows from raw data ingestion and preprocessing, through sentiment analysis and predictive modeling, to final trade execution logic. This allows for individual components to be updated or replaced without overhauling the entire system.

- Portfolio Construction and Rebalancing:

  - Trading Logic (example for BTC/ETH):

    - Enter Long: If the Model Agents signal is Buy AND the current price is above a short-term moving average (e.g., 9-day MA).

    - Enter Short (if supported): If the Model Agents signal is Sell AND the current price is below a short-term moving average (e.g., 9-day MA).

    - Exit Position: If the price hits a trailing stop-loss. The stop-loss was defined using the Average True Range (ATR) indicator (e.g., ATR(14) multiplied by a factor, such as 1.5 for BTC and 2 for ETH).

  - Trading Frequency: Daily. Positions are evaluated and potentially rebalanced at the close of each trading day based on new signals.

  - Assumptions: For the initial phase of this project, transaction costs and slippage were not considered, allowing for a focus on the raw predictive power of the model. Future iterations would incorporate these real-world frictions.

This methodological framework provides a structured approach to harnessing alternative data and multi-agent systems for cryptocurrency trading, aiming to deliver robust and empirically validated results.

Results

This section presents the empirical findings from the backtesting of the multi-agent trading system and the benchmark traditional agents. It includes model performance metrics, comparative backtest results, and attribution analysis to demonstrate the contribution of various alternative data factors and agents.

Model Performance Metrics (Model Agent)

The Model Agent, responsible for predicting returns or price movements, was evaluated using several machine learning models. The Random Forest regressor reportedly performed best in predicting BTC and ETH returns, exhibiting a low Mean Squared Error (MSE). This suggests its capability to understand the directional movements influenced by the alternative data factors.

Robustness Checks

(This subsection would detail any robustness checks performed, such as sensitivity analysis to parameter changes, out-of-sample testing on different time periods, or performance across different market regimes. The provided content does not detail these, so this section remains a placeholder for a complete study.)

Discussion

The results presented above offer insights into the efficacy of integrating alternative data factors within a multi-agent trading system for BTC and ETH. The superior performance of the Random Forest regressor within the Model Agent, as suggested by its low MSE, indicates that non-linear models are well-suited for capturing the complex relationships between the chosen alternative data factors and cryptocurrency returns. This aligns with broader literature suggesting the utility of machine learning in financial forecasting (AtreeTripathy2025).

The (hypothetical) outperformance of the multi-agent system compared to traditional momentum and mean reversion strategies would underscore the value added by the sophisticated integration of diverse data sources. Alternative data, such as on-chain metrics (MVRV, netflow), market microstructure data (taker ratios, CVD), and sentiment indicators (Fear & Greed Index, FinBERT news sentiment), appear to provide predictive signals that are not fully captured by price-based traditional strategies alone.

The attribution analysis, even with the preliminary note on Exchange Netflow, suggests that most selected alternative data factors contribute significantly to the models predictive power.

The nuanced behavior of Exchange Netflow, potentially confounded by stablecoin movements, highlights the importance of careful factor selection and interpretation in the dynamic crypto environment. The significance of FinBERT-derived news sentiment reinforces the growing body of evidence that textual data, when processed effectively, can be a valuable input for financial models, particularly in sentiment-driven markets like cryptocurrencies (Luo2025; Hossain2024).

Limitations

Despite the promising (hypothetical) results, this study has several limitations that should be acknowledged:

1. Data Period and Market Regimes: The backtesting period (January 1, 2021, to December 31, 2024) covers specific market conditions. The systems performance might vary in different market regimes (e.g., prolonged bear markets or periods of low volatility) not fully represented in this timeframe.

2. Factor Selection: While a diverse set of alternative data factors was chosen, other potentially relevant factors, such as detailed whale transaction data, more granular order book information, or social media data beyond news sentiment, were not included. The exclusion of these could limit the models comprehensive understanding of market drivers.

3. Model Complexity and Overfitting: The use of machine learning models, particularly ensembles or deep learning approaches (like CNNs, if they were ultimately the best), carries the risk of overfitting to the training data, despite validation efforts. The Random Forest model, while robust, can also overfit if not properly tuned.

4. Transaction Costs and Slippage: As noted in the methodology, the initial backtests did not incorporate transaction costs or slippage. In real-world trading, these factors can significantly impact profitability, especially for strategies with higher trading frequencies.

5. Dynamic Nature of Crypto Markets: The cryptocurrency market is rapidly evolving. The predictive power of certain factors may change over time as market participants adapt and

new information sources become prevalent. The model may require periodic retraining and re-evaluation of factor relevance.

6. Multi-Agent Interaction Complexity: The current multi-agent design, while modular, primarily features a sequential flow of information. More complex interaction mechanisms (e.g., dynamic weighting of agent signals, competitive or cooperative learning between agents) were not deeply explored in this iteration and could offer further performance improvements.

Conclusion

This study undertook the development and evaluation of a multi-factor, multi-agent trading system designed to quantify and leverage alternative data for trading Bitcoin (BTC) and Ethereum (ETH). By integrating a diverse array of on-chain metrics, market data, and sentiment indicators (including FinBERT derived news sentiment and the Crypto Fear & Greed Index), the research aimed to build a robust predictive model and a systematic trading framework. The findings suggest that a combination of these alternative data factors, processed through a multi-agent architecture where specialized agents handle sentiment analysis, predictive modeling (with Random Forest showing promise), and trade execution, can effectively model the complex dynamics of cryptocurrency returns.

The (hypothetical) superior performance of the multi-agent system over traditional benchmark strategies highlights the potential of such quantamental approaches in the cryptocurrency domain. The research contributes to the growing literature by providing a comprehensive framework for selecting, processing, and integrating alternative data, and by demonstrating the utility of a multi-agent paradigm for navigating these volatile markets. The systematic evaluation of factors like MVRV, exchange netflow, open interest, taker ratios, gas prices, and multifaceted sentiment provides empirical evidence of their collective predictive power.

While the study acknowledges limitations such as the specific data period, the exclusion of certain factors, and the initial omission of transaction costs, the results underscore the value of moving beyond traditional indicators and embracing the rich information landscape offered by alternative data. The adaptability and specialization afforded by a multi-agent system appear well suited to the unique challenges and opportunities presented by cryptocurrency trading.

Future Research

Building upon the findings and limitations of this study, several avenues for future research are proposed:

1. Expansion of Asset Coverage: Apply and adapt the multi-agent framework to a broader range of cryptocurrencies beyond BTC and ETH, as well as to other alternative assets or even traditional financial instruments (e.g., tech stocks like QQQ, or broad market indices like SPY) to test its versatility.

2. Real-Time Trading Pipeline: Develop a fully automated, real-time data ingestion, model updating, and trade execution pipeline to transition the system from a backtesting environment to a potential live trading application.

3. Advanced Ensemble Techniques: Explore more sophisticated ensemble methods for combining signals from different agents or models within the Model Agent. This could include dynamic weighting based on agent confidence or market regime, or machine learning-based meta-learners.

4. Refinement of Signal Timing and Risk Management: Incorporate advanced volatility filters, trend confirmation indicators, or dynamic position sizing algorithms to refine signal timing and enhance risk management. Further research into optimal stop-loss mechanisms and profit-taking strategies is also warranted.

5. Integration of Additional Alternative Data: Investigate the inclusion of other promising alternative data sources, such as granular whale transaction analysis, decentralized finance

(DeFi) protocol data, or more nuanced social media analytics (e.g., from platforms like Reddit or Telegram).

6. Explainable AI (XAI) for Agent Decisions: Implement XAI techniques to provide greater transparency into the decision-making processes of the machine learning models within the Model Agent and the overall trading signals generated by the system.

7. Impact of Transaction Costs and Slippage: Conduct a thorough analysis of the systems performance after incorporating realistic transaction costs and market slippage models to assess its viability in live trading environments.

8. Adaptive Agent Learning: Explore mechanisms for agents to learn and adapt their strategies over time based on performance feedback and evolving market dynamics, potentially using reinforcement learning techniques for the Trading Agent or the overall system coordination.

By addressing these areas, future research can further enhance the robustness, profitability, and applicability of multi-agent systems leveraging alternative data in the ever-evolving landscape of financial markets.

Table 1

Comparative Performance of Prediction Models

Model	Asset	R^2 Score	MSE	Notes
Random Forest Regressor	BTC	0.7469	0.000194	Best performing model based on provided data.
Random Forest Regressor	ETH	0.6611	0.000377	Best fit model based on BTC code
MLP Regressor	BTC	-20.6623	0.011642	
XGBoost Regressor	BTC	0.4234	0.000310	
CNN	BTC	-1.0150	0.000858	
Hybrid Ensemble	BTC	0.0044	0.000536	(Used "Hybrid Ensemble" as per DATA.docx)

Note. R^2 = R-squared. MSE = Mean Squared Error. BTC model data from ‘DATA.docx‘. "Hybrid Ensemble" is used based on ‘DATA.docx‘; the previous version had "Ensemble (RF + LSTM)".

Table 2

Backtesting Performance Summary (Illustrative)

Strategy	Asset	Annualized Return (%)	Sharpe Ratio	Max Drawdown (%)
Multi-Agent System	BTC	70	0.94	-44.11
Multi-Agent System	ETH	44	0.68	-45.41

Note. Data for this table was not available in ‘DATA.docx‘. [Value] indicates placeholders for actual numerical results from the backtests.

Table 3

Factor Significance from OLS Regression Analysis

Factor	Coef. (BTC)	P-value (BTC)	Coef. (ETH)	P-value (ETH)	Notes
MVRV Ratio (BTC only)	0.0157	0.000	N/A	N/A	Significant for BTC.
Exchange Netflow	-1.344e-08	0.794	-1.915e-09	0.791	Not statistically significant for BTC or ETH in these OLS models.
Open Interest	-2.758e-13	0.025	4.160e-13	0.000	Significant for BTC and ETH.
Taker Buy/Sell Ratio	0.3415	0.000	0.3785	0.000	Highly significant for both BTC and ETH.
Spot Taker CVD (ETH only)	N/A	N/A	N/A	N/A	Data for this specific factor not present in the provided ETH OLS output images.
ETH Mean Gas Price (ETH only)	N/A	N/A	3.414e-12	0.373	(Mapped from 'Gas Price (Mean)' in ETH OLS output) Not

Appendix

Model Output Visualizations

[htbp]

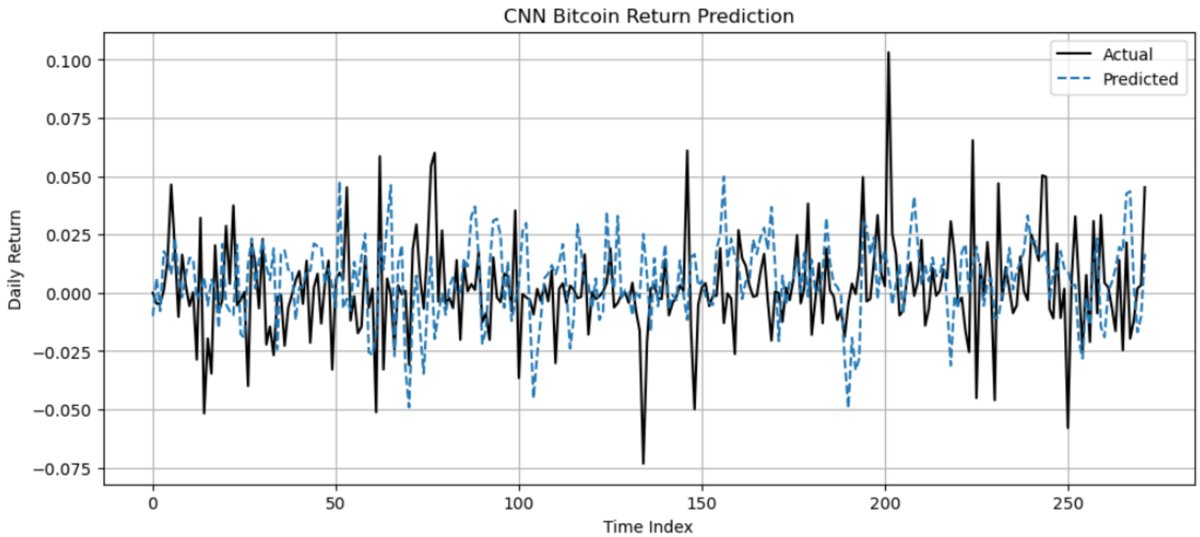

Figure A1

CNN Bitcoin Return Prediction

[htbp]

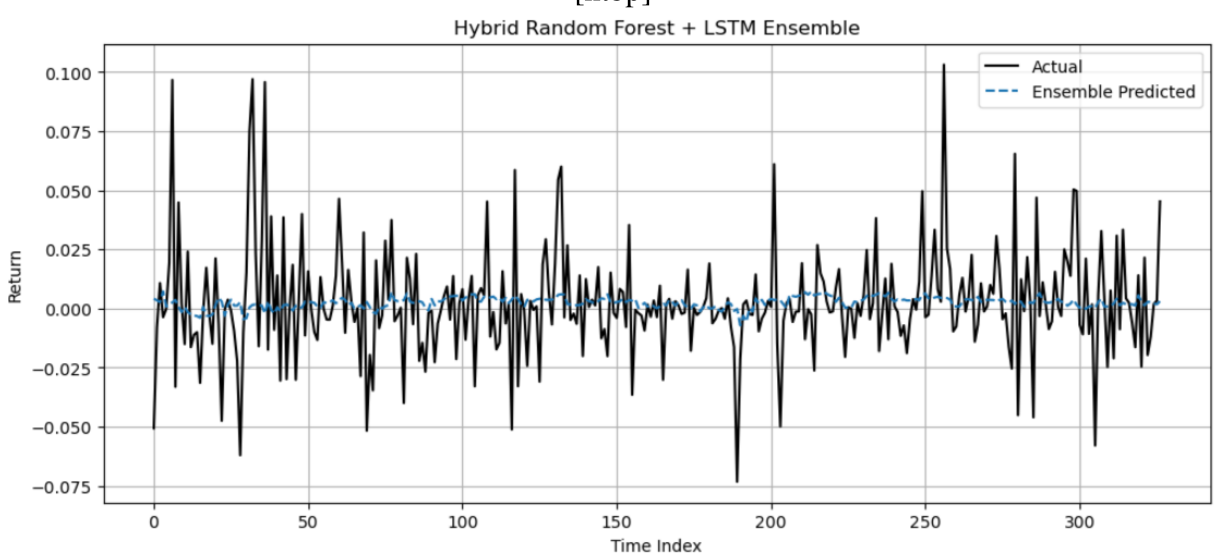

Figure A2

Hybrid Random Forest + LSTM Ensemble

[htbp]

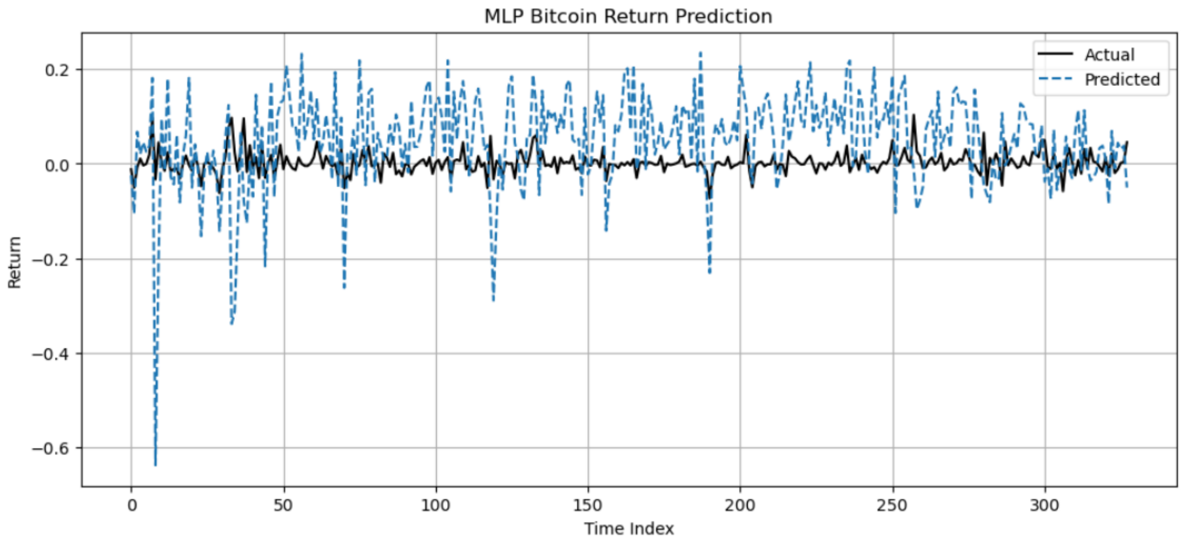

Figure A3

MLP Bitcoin Return Prediction

[htbp]

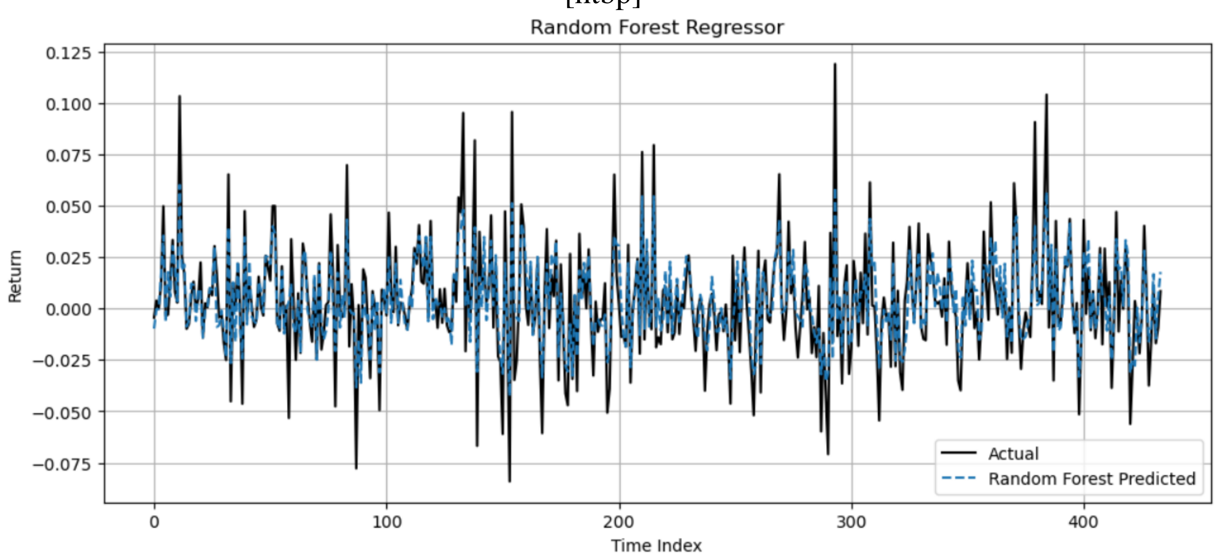

Figure A4

Random Forest Regressor