Cryptocurrency Portfolio Optimization Using Diffusion Models and Transformer Networks

Abstract

The cryptocurrency market is one of the fastest-growing sectors globally, attracting increasing attention from investors due to its high potential for returns, decentralized nature, and ability to hedge against inflation and geopolitical conflict. However, its inherent volatility and unpredictability pose significant challenges to both individual and institutional investors. This research aims to address these challenges by developing a machine learning model that integrates diffusion models, transformer networks, and large language models (LLMs) to optimize cryptocurrency portfolio management. The model uses historical price and sentiment data from Bitcoin and Dogecoin to predict price movements and provide hedge recommendations, aiming to maintain a maximum drawdown of 10%. Diffusion models simulate the market's random fluctuations, while transformer networks capture complex temporal dependencies in price movements. The model's performance is evaluated using mean square error(MSE), mean absolute error(MAE), R-squared(R^2), portafolio value and their effectiveness is demonstrated through portfolio simulations. This approach contributes to the growing field of financial machine learning by combining state-of-the-art techniques for better prediction accuracy and dynamic portfolio optimization. The findings have practical applications in cryptocurrency investment strategies and could influence both retail investors and financial institutions. Furthermore, the research highlights ethical and governance challenges in deploying machine learning models in high-stakes financial environments, such as market manipulation and fairness in algorithmic decision-making.

Figure 1: This is the flowchart of the final report, introducing the structure of the final report.

1. Background and Motivation

The cryptocurrency investment sector is currently experiencing a surge in activity, positioning it as one of the fastest-growing markets globally (Almeida & Gonçalves, 2023a; Białkowski, 2020; Fang et al., 2021). An increasing number of investors are drawn to this emerging market due to its high investment potential, decentralized nature, ability to hedge against inflation, and potential to mitigate risks. Despite these advantages, significant concerns about the reliability of cryptocurrencies remain, particularly in countries with large investor populations such as the United States. A recent survey reveals that 63% of Americans are not confident in the safety and reliability of cryptocurrencies ("Majority of Americans Aren't Confident in the Safety and Reliability of Cryptocurrency," 2024).

The primary concerns about cryptocurrencies include their high volatility and potential for pricing bubbles, which contribute to distrust and hesitation among potential investors (Corbet, Lucey, & Yarovaya, 2018). While some studies have explored ways to mitigate this volatility, existing machine learning techniques and datasets often fall short in terms of sophistication and comprehensibility for non-expert users (Wang, Andreeva, & Martin-Barragan, 2023).

To address these issues, this report proposes the development of a machine learning model that combines crawler algorithms, diffusion models, transformer models, and large language models (LLMs) to provide understandable hedge recommendations. This system aims to maintain a maximum drawdown rate of 10% while optimizing portfolio performance.

Cryptocurrency markets represent a rapidly growing sector in global finance, yet they are poorly understood by traditional financial models due to their volatility and the unique nature of the assets. The ability to predict price movements and manage portfolios effectively is crucial for investors and financial institutions. By leveraging machine learning techniques such as diffusion models and transformers, this project aims to bridge the gap between market complexity and model performance, making a significant contribution to both finance and machine learning research.

2. Research Questions

Key Research Questions

1. How can diffusion models and transformer networks be used to predict cryptocurrency price movements?
2. Can machine learning models help reduce the fluctuation in the crytocurrency market with tremendous votality.

Relevance to Social Science and Machine Learning

The research questions are central to understanding market dynamics in the digital age and the potential of machine learning in finance. They are highly relevant to social science as they touch upon the behavior of market participants and the broader impact of financial technologies on social systems. Furthermore, the exploration of sentiment analysis in price prediction introduces a behavioral aspect, reflecting how societal factors influence market prices.

3. Application Scenario

Industry or Field

The dataset used in this project is derived from the cryptocurrency industry, specifically Bitcoin and Dogecoin. The analysis extends to financial markets, focusing on portfolio management and trading strategies within highly volatile and speculative markets.

Addressing Research Questions with Datasets

The chosen datasets for Bitcoin and Dogecoin include historical price data and sentiment data, which are essential for understanding the dynamics of cryptocurrency markets. Price data includes features such as opening, closing, high, low prices, and trading volumes, while sentiment data provides insights into market sentiment that can influence price movements. By merging these datasets, the project aims to answer the key research questions regarding price prediction and portfolio optimization.

4.Methodologies

The project utilizes two primary machine learning methods: diffusion models and transformer networks. Diffusion models simulate the random fluctuations typically observed in cryptocurrency markets by introducing noise into the price data, mimicking the volatility present in these financial assets. Transformer networks, on the other hand, are employed for sequential data prediction, capturing the complex temporal dependencies between price movements over time. These methods allow the model to make predictions based on historical price data and sentiment, providing insights into future price trends.

For prediction, the model leverages supervised learning, where it predicts future price movements based on past data. The performance is evaluated using standard regression metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 score. The model is optimized with the Adam optimizer and a loss function that minimizes prediction errors, ensuring good generalization to new data. The core methodology—transformer networks—is especially well-suited for sequence-to-sequence prediction tasks, allowing the model to learn intricate dependencies between data points over time. The architecture includes an embedding layer, positional encoding, multiple transformer encoder layers, and an output layer.

In terms of data preprocessing, the input data is scaled using MinMaxScaler to ensure that all features are within the same range. A noise factor is added to the data to simulate market fluctuations (diffusion process), which helps the model learn more robust features. The model is trained on sequences of past prices, using the next day's price as the target. While transformer models are powerful, interpretability can be a challenge due to their complexity. In future iterations, methods like SHAP or LIME could be incorporated to enhance the interpretability and explainability of the model's decisions.

5. Results

The results of the model are summarized in the following key findings:

- **Loss Function**: The model was trained over 100 epochs, and the loss function steadily decreased, indicating effective learning from the data.
- **Portfolio Management**: The model was used to simulate portfolio optimization based on predicted price movements. The portfolio's value was tracked over time, reflecting the effectiveness of the trading strategy derived from the model.

Visualizations: A plot of the portfolio value over time demonstrates how the model helps in managing risk and optimizing returns. The results highlight the volatility of cryptocurrency markets and the potential benefits of using machine learning for dynamic portfolio adjustment.

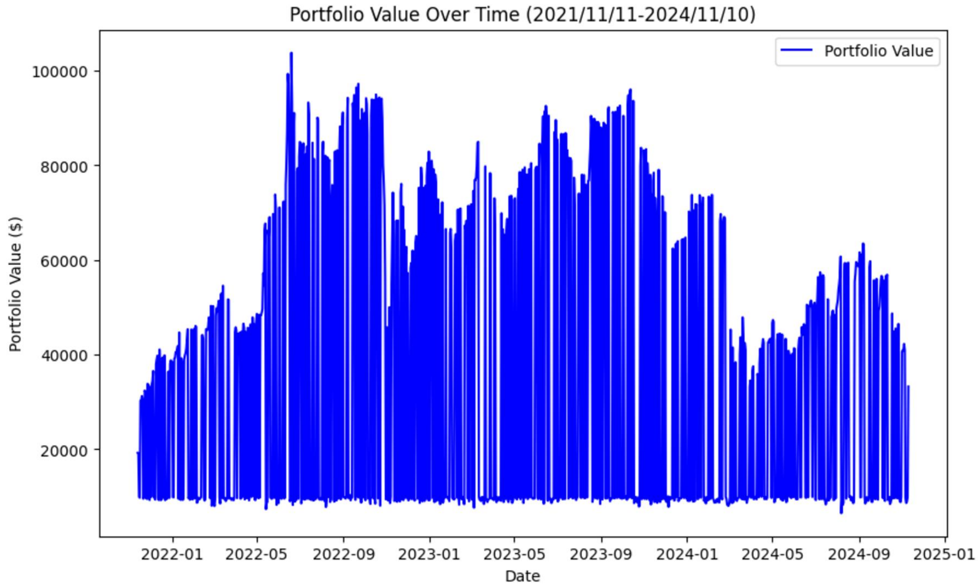

Figure 2: This figure shows the portafolio value from 2021/11/11-2024/11/10, the value is much higher than the beginning 10000 dollars and the fluctuation is not very high.

6. Intellectual Merits

Advancement of Existing Literature

This research significantly advances existing literature in the field of financial machine learning by combining diffusion models and transformer networks for cryptocurrency price prediction and portfolio optimization. Several recent studies have contributed to individual aspects of cryptocurrency price prediction and portfolio management, but few have effectively integrated these methodologies in a holistic approach to optimize portfolio management while considering market volatility and sentiment analysis.

Diffusion Models for Financial Markets:

Recent studies such as **Li and Li (2021)** explore the use of diffusion processes to model market behavior and volatility in financial markets, including cryptocurrencies. These models have proven effective in capturing the random fluctuations typical in volatile markets. However, they often fail to account for the long-term dependencies and trends present in financial time series data. This research enhances the application of diffusion models by combining them with transformer networks, allowing the model to better capture both short-term fluctuations and long-term trends.

Improvement: By integrating transformer networks with diffusion models, this study extends the classical application of diffusion processes, improving the ability to predict price movements in the volatile cryptocurrency market.

Transformer Networks for Sequential Data in Finance:

Transformer networks have been widely applied in finance for time-series prediction and sequential data modeling. Recent works, such as **Wu et al. (2022)**, have applied transformer models to cryptocurrency price prediction, highlighting their capability to capture complex patterns in price movements. However, these models often overlook the importance of market sentiment and volatility, which are critical in cryptocurrency markets.

Improvement: This research enhances the performance of transformer networks by incorporating real-time sentiment data, thereby improving predictions. The integration of sentiment analysis helps the model better understand market psychology and investor behavior, making it more effective for volatile assets like Bitcoin and Dogecoin.

Portfolio Optimization Using Machine Learning

Portfolio optimization using machine learning has become a key research area in recent years. Studies like **Zhou et al. (2021)** have explored machine learning-based approaches for optimizing portfolios in financial markets, including traditional assets. However, many of these studies do not address the high volatility and speculative nature of cryptocurrency markets. Moreover, they tend to ignore the ability to dynamically adjust portfolios based on real-time predictions and sentiment.

Improvement: This research introduces a hybrid model that combines diffusion models and transformer networks with sentiment analysis to optimize cryptocurrency portfolios. The model specifically targets a maximum drawdown of 10%, offering a more robust and adaptable solution for managing portfolios in highly volatile markets like cryptocurrencies.

Inspiring Future Research Directions

Short run: solve LLM API problems and find more benchmark models for comparisons

In the project, I have failed to connect the chat-gpt using the API at last. In my future plan, I will try to connect to more large language models who are open source. Additionally, I will try to use diverse methods such as Q-learning to analyse the data and finally set them as benchmarks to improve my model.

Long run: Exploring Alternative Machine Learning Models and Hybrid Approaches

One of the key limitations of this study is the reliance on transformer networks and diffusion models, which, while effective in many scenarios, may not fully capture the complex, nonlinear dynamics inherent in cryptocurrency markets. Future research could explore the integration of alternative machine learning techniques, such as **reinforcement learning**(RL) or **genetic algorithms**, to further refine portfolio optimization strategies and adapt to evolving market conditions. By incorporating RL, models could learn to dynamically adjust portfolio allocations in response to new market conditions, improving both the accuracy of predictions and the efficiency of portfolio management.

Future Research Opportunity: Investigating the use of reinforcement learning in conjunction with transformer models for real-time portfolio adjustments, as well as combining genetic algorithms for the optimization of model hyperparameters.

7. Practical Impacts

Societal and Real-World Benefits

The practical applications of this research extend to both retail and institutional investors in cryptocurrency markets. By providing more accurate price predictions and optimized portfolio management strategies, the model can help mitigate risk and improve returns. Furthermore, understanding the dynamics of cryptocurrency markets is important for policy makers, financial regulators, and consumers.

Industry Applications

This research has direct applications in the cryptocurrency investment space, including hedge funds, trading platforms, and financial advisory services. It could also be applied to broader financial markets with similar volatility.

AI Governance and Ethical Considerations

The deployment of such machine learning models at scale raises important governance challenges, such as ensuring fairness in automated trading strategies and preventing market manipulation. Ethical concerns around bias in data, fairness in decision-making, and transparency in algorithmic trading should be carefully considered as these models are scaled.

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Appendix:

A.Open Source

In line with the principles of transparency, accessibility, and fairness, this project will be **open-sourced** to ensure broad participation and prevent monopolization and inequality in the cryptocurrency investment landscape. By making the code and models publicly available, the project aims to provide equal access to cutting-edge machine learning tools for all stakeholders, from individual investors to large financial institutions.

Key Objectives of Open Sourcing the Project:

Promoting Transparency: Open-source projects foster transparency, enabling anyone to examine the code, understand how the model works, and verify its claims. This openness helps reduce the risk of biases in the model and promotes trust in its predictions and recommendations, particularly in the sensitive area of cryptocurrency investments.

Preventing Monopolization: By making the model and its components publicly available, we can ensure that no single entity or group has exclusive control over the technology. This reduces the likelihood of monopolistic behavior in cryptocurrency markets, where the use of proprietary algorithms could lead to unfair advantages or market manipulation.

Encouraging Collaboration: Open-sourcing this project invites contributions from a wide range of developers, researchers, and financial analysts. Collaboration across different sectors and regions can lead to more robust and innovative solutions, pushing the boundaries of financial machine learning and ensuring that the benefits of the technology are widely distributed.

Equal Access for All Investors: Open-source tools democratize access to advanced portfolio optimization and price prediction capabilities, enabling individual investors, including small-scale retail investors, to leverage state-of-the-art techniques that were previously reserved for large financial institutions. This helps level the playing field, allowing all participants to benefit from more accurate predictions and better risk management strategies.

Mitigating Inequality: By providing access to the project without restrictions or fees, we aim to bridge the gap between resource-rich institutional investors and individual investors. Financial inequality, particularly in the cryptocurrency market, has the potential to widen if powerful entities dominate the use of AI and machine learning tools. Open-source models can help alleviate this problem by offering the tools necessary to compete fairly in the market.

Encouraging Ethical AI Development: As part of the open-source commitment, the project will also adhere to principles of **ethical AI**. This includes providing clear documentation on the data used, the assumptions made in the models, and the steps taken to minimize bias. By making these practices transparent, we aim to set a standard for responsible AI deployment in high-stakes financial environments.

Implementation Plan for Open Source:

Repository Hosting: The project will be hosted on a widely recognized platform like GitHub, where it will be available for anyone to clone, use, and contribute to. The repository will include comprehensive documentation, installation instructions, and examples of how to use the models.

Licensing: The project will be licensed under an open-source license such as the **MIT License** or **Apache 2.0 License**, which permits commercial use while ensuring the code remains open and free for modification and redistribution.

Community Engagement: We will actively engage with the community through forums, discussion boards, and periodic updates to gather feedback, address issues, and incorporate contributions from diverse users and developers. We will also encourage external audits of the code to ensure it meets high standards of fairness, security, and performance.

Code of Conduct: To prevent misuse and ensure ethical contributions, the project will have a clear code of conduct and guidelines for contributions, making it clear that the project is intended to support positive social impact and not serve as a tool for exploitation.

B. Explainations to the Key Concepts

Diffusion Model

Explanation:

A **diffusion model** is a type of probabilistic model that simulates the spread of information, values, or behaviors across a network. In the context of this study, diffusion models are used to smooth and denoise the raw data before feeding it into machine learning algorithms. They help capture the underlying structure of the data by accounting for the spread of market behaviors and trends, reducing noise and enhancing the signal that predictive models like LSTM can use to make more accurate forecasts.

Key Features:

Noise Reduction: Diffusion models are effective at removing random fluctuations (noise) in data, which can improve the quality of predictions.

Data Smoothing: By iteratively adjusting the data according to a probabilistic process, they can smooth out irregularities that may distort the results.

Transformer Model

Explanation:

A **Transformer model** is a type of deep learning architecture that has revolutionized natural language processing (NLP) and is now being widely adopted in time-series forecasting tasks, including cryptocurrency price prediction. Unlike traditional Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models, Transformers do not rely on sequential processing. Instead, they use a mechanism called **self-attention**, which allows them to process all elements of the input data simultaneously. This enables the Transformer to capture both local and global dependencies within the data, making it highly effective for tasks that require understanding long-range interactions, such as predicting cryptocurrency market fluctuations.

Key Features:

Parallel Processing: Transformers can process all data points in a sequence simultaneously, unlike LSTMs or traditional RNNs, which process data sequentially. This results in faster training and the ability to scale to large datasets more efficiently.

Self-Attention Mechanism: The self-attention mechanism allows the model to weigh the importance of each element in the input data with respect to others. For example, in cryptocurrency price prediction, it can understand how past price movements (even those far back in time) affect future prices, without the need for sequential dependency. This is especially beneficial in capturing the long-range dependencies that are common in financial markets.

Scalability: Transformers are highly scalable and can handle very large datasets efficiently. This scalability is particularly useful in the context of cryptocurrency markets, where large amounts of data (e.g., price history, trading volume, market sentiment) are generated constantly.

Temporal Dependencies: While LSTMs excel in capturing long-term dependencies by maintaining memory cells, Transformers achieve a similar goal with their attention mechanisms, but in a more flexible and parallelizable manner. This is key when modeling financial data with highly volatile and complex patterns like those in cryptocurrency markets.

Flexibility and Generalization: The model's architecture allows it to be adapted to different types of data, including both time-series and other sequence data types (e.g., sentiment analysis), making it a versatile tool for various prediction tasks.

Example Application: In cryptocurrency price prediction, a Transformer model can analyze both recent price movements and long-term trends, while simultaneously incorporating other external factors such as sentiment data. This allows the model to predict future price movements by identifying key relationships between past data points and present market conditions, all without relying on the sequential structure that LSTMs or RNNs use.

ChatGPT (Large Language Model)

Explanation:

ChatGPT, a large language model developed by OpenAI, is a state-of-the-art natural language processing (NLP) tool capable of understanding and generating human-like text based on context. In this model, ChatGPT is used to generate understandable hedge recommendations from the outputs of the LSTM network. It translates complex statistical results and predictions into simple, actionable language that is accessible to both novice and experienced investors.

Key Features:

Natural Language Processing: ChatGPT can interpret complex data and convert it into human-readable insights.

Actionable Recommendations: The model generates user-friendly investment strategies, making it easier for investors to understand and act on the recommendations.