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Optimizing Cryptocurrency Portfolio Rebalancing: A Machine Learning Approach

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Abstract

Ever since the introduction of Bitcoin, cryptocurrencies have attracted interest from many due to their potential for appreciation. They have also been stigmatized for their volatility, low correlation with traditional assets, and uncertain regulatory conditions. Nevertheless, many cryptocurrencies still attract the attention of major players in finance. As in the management of a portfolio of other assets, there is a need to regularly rebalance the portfolio to optimize returns across different time horizons. This study evaluates four machine learning models, Logistic Regression, Decision Tree, K-Nearest Neighbors, and Gradient Boosting, for identifying optimal cryptocurrency rebalancing decisions. Using a momentum-based approach with a 30-day forward window, the models are trained to classify assets as hold or rebalance based on future price movement. Our approach is based on feature engineering and hyperparameter tuning. Results show that tree-based models, such as Decision Tree and Gradient Boosting, demonstrate superior classification performance in identifying optimal rebalancing moments. However, the study also highlights the limitations of using historical data exclusively without referring to other external factors such as market sentiment and regulatory changes. Overall, the study makes a contribution to the field of cryptocurrency portfolio management by providing one of the first comparative evaluations of multiple ML architectures for cryptocurrency rebalancing decisions, demonstrating the potential of machine learning to improve portfolio management in highly volatile markets.

Keywords

Cryptocurrencies, portfolio management, machine learning

Introduction

The development of the cryptocurrency market has introduced new ways of managing assets. This market is developing rapidly and unpredictably (Just & Echaust, 2024). Due to excessive price volatility, lack of correlation to traditional assets, and changing regulations, traditional portfolio management methods are no longer sufficient (Brière et al., 2015; Just & Echaust, 2024).

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Nowadays, Bitcoin (BTC) is no longer the only cryptocurrency available for investment. More than 6,000 virtual currencies currently in existence, including Ethereum (ETH), Cardano (ADA), and Solana (SOL), require new and technical approaches to manage them (Kondrat & Drala, 2019). Cryptocurrencies are virtual currencies used independently of banks and governments. They are not regulated by traditional institutions.

In this context, rebalancing the portfolio becomes important. It is a method of rebalancing an asset according to objectives. This is done by adjusting the weight of assets in a portfolio to achieve objectives such as reducing risk and increasing returns. As a rule, this process is carried out at specific times. However, when applied to virtual currencies, special requirements must be met, as the behaviour of this market is very particular in that it lacks control and rapid feedback (Shankar Raja M. et al., 2022; Colombo et al., 2021).

Many studies suggest that the introduction of Machine Learning (ML) can improve decision-making in cryptocurrency portfolio management. ML can identify patterns in large amounts of data, even those that are not obvious at first glance (Zhang, Zohren & Roberts, 2020). The application of ML to portfolio optimisation can improve risk management and profit optimisation, especially in long-term strategies (Sebastião & Godinho, 2021).

Some studies on cryptocurrency portfolio management focus on the major cryptocurrencies such as BTC and ETH (Liu & Tsyvinski, 2020; Sahu et al., 2024). The impact of smaller cryptocurrencies has been largely overlooked, thus failing to provide a complete picture of lesser-known currencies (Sahu et al., 2024). In addition, short-term strategies such as weekly updates require significant trading capital and do not adequately control long-term risk in volatile markets. Finally, there is not yet enough research comparing different types of ML models in a given situation.

The main goal of this study is to improve decision-making based on the rebalancing strategy of cryptocurrencies using ML. This approach can help manage risk, mitigate frequent trading costs, and improve long-term profitability potential. To this end, the following objectives are set: 1) evaluate ML-based strategies to optimize portfolio rebalancing, 2) analyse the effectiveness of different ML models to manage risk and maximize returns, 3) evaluate the impact of integrating smaller cryptocurrencies on diversification, and 4) provide insights on the advantages of long-term rebalancing strategies in volatile cryptocurrency markets.

This work provides one of the first comparative evaluations of multiple ML models specifically applied to rebalancing decisions rather than price forecasting or short-term trading.

The organization of this study is as follows: Section 2 describes the methodology used in this study, including data collection, preprocessing, model selection, and evaluation metrics; Section 3 presents the results and discussions of the results; and conclusions are drawn in Section 4.

Methodology

This study aims to improve decision-making in the management and rebalancing of cryptocurrency assets. The model is based on ML methods. Four models were specifically used, namely logistic regression, decision tree (DT), K-nearest neighbours (KNN), and Gradient Boosting. These models were selected for their ability to detect trends in complex data such as cryptocurrencies.

Dataset Collection and Preprocessing

Historical data was used, taken from CoinMarketCap and Kaggle. This data spans from 2013 to 2021, with daily updates for thousands of cryptocurrencies. The dataset includes two main tables, one historical over 4.4 million rows and 19 columns of daily market data such as date, coin_id, cmc_rank, market_cap, price, open, high, low, close, time_high, time_low, volume_24h, percent_change_1h, percent_change_24h, percent_change_7d, circulating supply, total supply, max_supply, num_market_pairs, and coins table which contains only metadata for cryptocurrencies, including name, symbol, category, platform, and launch date. A summary of the main features used in the analysis is provided in Table 1.

Table 1. Summary of Dataset Features

Feature	Description
Date	Daily timestamp of the record
coin_id	Internal identifier for each cryptocurrency from the coins table
cmc_rank	Ranking by market capitalization
market_cap	Total market capitalisation in USD
Price	Daily closing price of the coin in USD
volume_24h	Trading volume over the past 24 hours
percent_change_*	Percentage price change over the past (1hour, 24 hours, 7 days)
circulating_supply	Number of coins currently in circulation
total_supply	Total coins mined
max_supply	The maximum possible supply of the coin

The analysis focuses on the top cryptocurrencies per month. Factors analysed include price, market capitalisation, trading volume volume_24h, and ranking. Once extraction was complete, the data was cleaned and checked. First, incomplete or missing values were removed from components such as market capitalisation and volume. The replacement method with the same value as the previous one and the median was applied (Lin & Tsai, 2019). Then, values with large differences in weights, such as price and market capitalisation, were rescaled. StandardScaler was used to facilitate model learning (Lin et al., 2021). Dates were also separated into year, month, and day formats to capture temporal trends in trading activity (Passalis et al., 2021). Finally, the data had been prepared, and an exploratory analysis of the data was carried out. The price trends of the top 5 cryptocurrencies were analysed, as they have the highest value and the most complete data.

Feature Engineering

New features were created to improve the model's performance. This includes volatility, which is measured by the standard deviation of trades over seven consecutive days. The 7- and 30-day moving averages for price and market capitalisation have also been included (Poudel et al., 2023; Almeida & Gonçalves, 2022). These new features are designed to contribute to predictability and reduce the impact of sudden changes. A summary of the engineered features used in the analysis is provided in Table 2.

Table 2. Engineered Features Used

Engineered Feature	Based on	Description
price_volatility_7d	Price	Standard deviation of price over a 7-day rolling window
price_ma_*	Price	7, 30-day moving average of price
market_cap_ma_*	market_cap	7, 30-day moving average of market_cap

Target Variable Construction

The dependent variable is a binary label: rebalance (0) and hold (1). This label is computed using a momentum-based rule: if the closing price 30 days later is higher than the current price, the model assigns hold; otherwise, it assigns rebalance. This approach differs from traditional rebalancing strategies based on allocation drift, and instead uses future momentum as the decision trigger.

Model Selection

The selection of models used in this study was based on their ability to accurately predict and distinguish complex events such as the cryptocurrency market. Four main models were used, each with its own unique approach and characteristics. Logistic regression is a simple model suitable for predicting data with a uniform trend. It is suitable for data with linear relationships, but has limitations when dealing with data with complex relationships (Kumar, 2024).

The decision tree is a model capable of detecting complex trends through logical division. It has the ability to detect non-linear trends, making it a powerful option for poorly structured data (Kotsiantis, 2011).

K-Nearest Neighbors, on the other hand, relies on the density of the surrounding data, making it suitable for data of different dimensions. It is a simple but robust model when the data are well correlated, but it becomes unstable if the structure of the data is too variable (Ozturk Kiyak et al., 2023).

Finally, Gradient Boosting is a system that combines several simple models with a step-by-step rule to correct previous errors. It is able to progressively correct learning errors, leading to highly accurate and robust predictions (Zhang et al., 2019).

These models have been selected because they each have different perspectives and approaches. They meet the need for evaluation and alignment with market realities. They were also chosen because they are familiar with the financial sector and forecasting work based on complex data. By analysing their capabilities, it is possible to distinguish which of them is best suited to making portfolio decisions in volatile markets.

Training and Hyperparameter Tuning

After feature engineering, we trained and tested the four models. The dataset was split into 80% training and 20% testing (Pedregosa et al., 2011). GridSearchCV was used to fit all hyperparameters. This method performs an exhaustive search over a predefined set of hyperparameters. It trains the model with all possible combinations of parameters and evaluates each one using cross-validation (Pedregosa et al., 2011), which helps reduce overfitting (Hastie et al., 2001). As with logistic regression, the C value was tested. For the decision tree, the tree depth and leaf sample size were set. In KNN, the number of neighbours and their weights were tested. And for Gradient Boosting, the number of trees, learning rate, and tree depth were selected.

All experiments were conducted in Python, on a machine equipped with an Apple M3 Pro processor and 18 GB of unified memory. Hyperparameter tuning was performed using GridSearchCV with three-fold cross-validation.

Evaluation Metrics

Finally, the performance of the models was verified using measures such as accuracy, precision, recall, F1 score, and ROC-AUC. These figures contributed to the overall assessment of accuracy, discernment, and the ability to identify when rebalancing is required. These results determine which models are most effective for analysing and making decisions in cryptocurrency portfolio management (Naidu et al., 2023).

Results and Discussion

Once the model had been trained and fine-tuned, its performance was tested. Parts of the data that were not included during training were used. The aim was to see whether the models were capable of accurately predicting the movements that should be made in cryptocurrencies.

Model Performance Results

The model performance was measured using different evaluation metrics: accuracy, precision, recall, F1-score, and ROC-AUC. These metrics help to understand how well the prediction task was handled. Table 3 shows how each model performed.

Table 3. Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.5465	0.0000	0.0000	0.0000	0.5152
DT	0.8338	0.8211	0.8099	0.8154	0.8913
KNN	0.7054	0.6866	0.6447	0.6650	0.7657
Gradient Boosting	0.7571	0.7546	0.6881	0.7198	0.8411

The DT achieved the highest performance with an accuracy of 83.38% and ROC-AUC of 0.8913. This shows that the model can make a clear difference between rebalance and hold actions. Gradient Boosting comes next. It gives stable and close scores for all metrics. KNN gives average results. Logistic Regression gives very poor results and does not learn the patterns from the data.

Financial Interpretation

From a financial perspective, precision and recall are very important in a rebalancing decision. A low recall means the model misses moments where a rebalance is needed. This can increase the risk in the portfolio. Low precision means the model sends too many incorrect predictions. This can cause many unnecessary trades and higher costs. The DT and Gradient Boosting show good precision and recall. They detect useful moments for action and avoid many false alerts.

The strong results of the tree-based models come from their ability to read complex data. Cryptocurrency prices do not follow simple trends. They move in sudden and irregular ways. Tree models can handle this. They create rules that match these changes. They can also read how features like moving averages, volatility, and market cap work together. In contrast, Logistic Regression assumes linear separability and is therefore unable to capture structural complexity in the dataset.

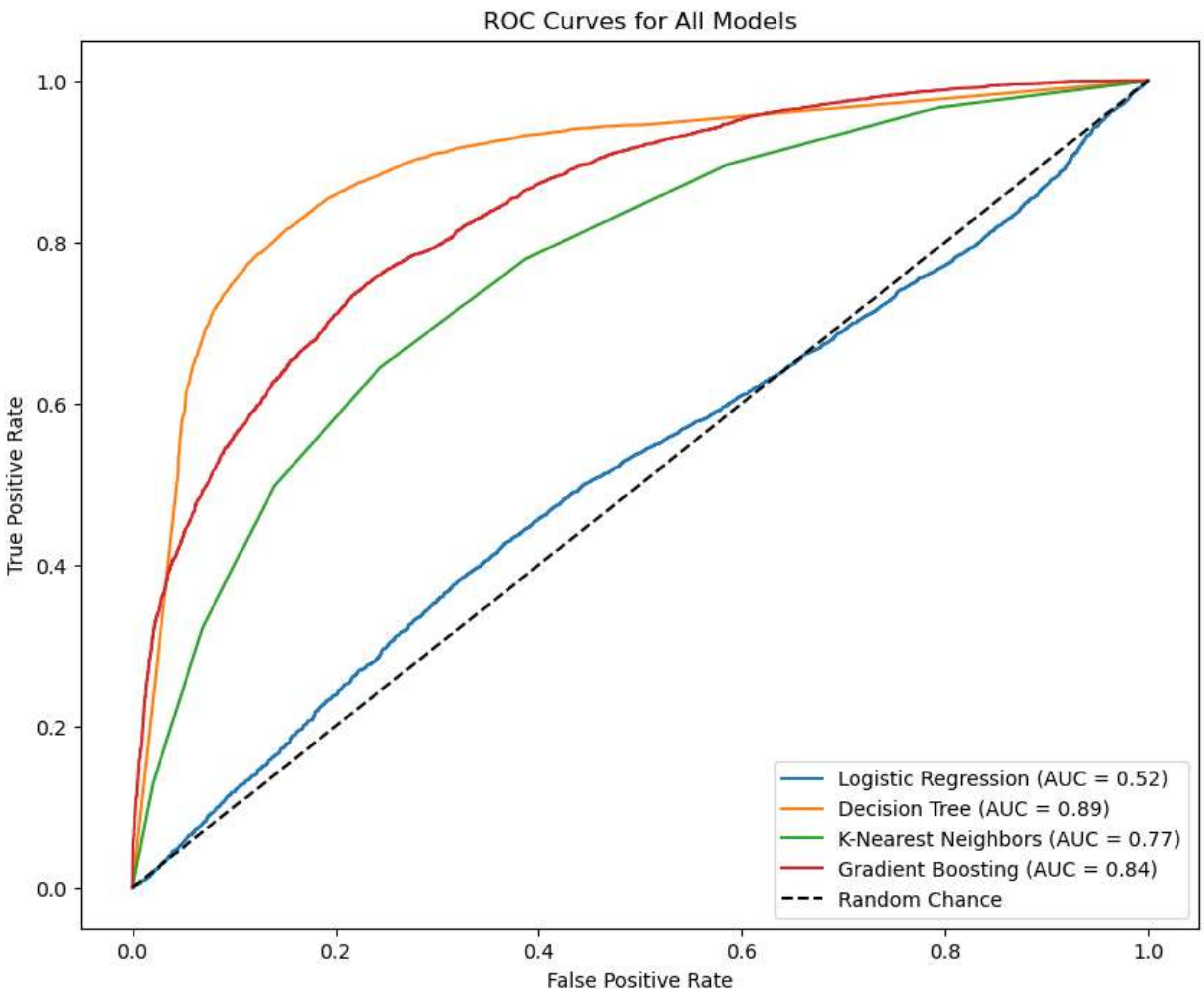

Figure 1. ROC-AUC Curves for All Models

Figure 1 shows the ROC curves of all the tested models. The curves confirm that Decision Tree and Gradient Boosting give the best separation. Their lines stay higher on the graph, which means better detection of correct decisions.

These results also show how the model's prediction can help the portfolio. Accurate and consistent predictions can guide the portfolio during fast market changes. It can help the portfolio avoid large losses in a negative trend and stay invested during a positive trend. High-quality predictions with fewer mistakes also reduce extra trades, so the portfolio avoids high transaction costs. For these reasons, the DT and Gradient Boosting models can support better risk control and smoother growth over time.

The main contribution of this study is the comparative evaluation of multiple ML models for identifying optimal rebalancing moments in cryptocurrency portfolios. This approach enables portfolios to adjust dynamically to rapid market changes. The results show that momentum-based ML models can effectively support portfolio rebalancing decisions, providing a more adaptive alternative to fixed monthly rules that do not react to sudden market movements.

Conclusion

This study showed that the use of ML can improve decisions in cryptocurrency portfolio management by identifying optimal rebalancing moments, whether an asset should be held or rebalanced using a 30-day momentum-based indicator. Decision Tree and Gradient Boosting models provided the strongest performance. This demonstrates their ability to capture the non-linear and irregular behaviour of cryptocurrency markets.

The study is limited by the use of historical data only and the absence of transaction cost modelling, external market indicators, or sentiment-based features. These factors may influence real portfolio performance.

Future work should incorporate real-time indicators, macroeconomic variables, and full portfolio-level back testing to evaluate the financial impact of ML-driven rebalancing decisions more accurately. Such improvements may strengthen the role of machine learning in long-term portfolio management under volatile market conditions.

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