

RESEARCH ARTICLE

A machine learning framework for multi-market portfolio optimization: Evidence from U.S. stocks and cryptocurrencies

Pejman Peykani^{1*}, Daniyal Sabour¹, and Cristina Tanasescu²

¹Department of Industrial Engineering, Faculty of Engineering, Khatam University, Tehran, Iran

²Faculty of Economic Sciences, Lucian Blaga University of Sibiu, Sibiu, Romania
p.peykani@khatam.ac.ir, daniyalsabour@gmail.com, cristina.tanasescu@ulbsibiu.ro

ARTICLE INFO

Article History:

Received: June 9, 2026

Revised: July 9, 2026

Accepted: July 13, 2026

Published Online: August 3, 2026

Keywords:

Portfolio optimization

Machine learning

XGBoost

Mean-variance

Semi-variance

Absolute deviation

Cryptocurrency

AMS Classification 2010:

90C05; 90C08; 90C70; 90C90

ABSTRACT

This study presents an integrated framework for multi-market portfolio optimization that integrates machine-learning-based return forecasting with classical and downside-oriented risk models. Using daily data for Bitcoin, Ethereum, BNB, Microsoft, and Tesla, the XGBoost algorithm is employed to predict short-term returns, after which the forecasts are used to construct optimal portfolios under the Mean-Variance (MV), Mean-Semi-Variance (MSV), and Mean-Absolute Deviation (MAD) models. A naïve equal-weighted portfolio is included as a benchmark. The results show that the predictive models provide useful signals for portfolio construction, with all optimized strategies achieving markedly lower risk than the naïve portfolio for the same expected return level. Tangency portfolios, particularly the Maximum Sortino and Maximum Sharpe-AD configurations, delivered the highest efficiency gains and the strongest performance on out-of-sample data. Overall, the findings demonstrate that combining machine learning with risk-sensitive optimization tools can improve decision-making in markets characterized by volatility and mixed asset dynamics.



1. Introduction

Portfolio management encompasses the processes of identifying, selecting, and supervising a collection of investments through asset evaluation, capital allocation, performance assessment, and periodic rebalancing. A central challenge lies in determining the most effective portfolio composition, a task commonly addressed through portfolio optimization.¹ In modern financial markets, investors utilize a wide array of instruments, ranging from individual stocks and Exchange-Traded Funds (ETFs) to mutual and index funds. Portfolio optimization serves as the primary mechanism for managing the risk-return trade-off aiming either to maximize returns for a given risk level or to minimize risk for a target return.^{2,3}

Historically, the Mean-Variance (MV) model established the foundation for quantitative risk management by using variance to capture risk. Since its introduction, advances in computational power and algorithms have led to extensive refinements, with researchers adapting the model to real-world conditions and testing its variants across different datasets and performance measures.^{1,4,5}

Markowitz⁶ later introduced the Mean-Semi-Variance (MSV) model as an alternative. Semi-variance measures downside risk by focusing on the dispersion of returns below the expected value or a target return, ignoring values above it. This approach provides a more realistic assessment of potential losses, making it especially useful for risk-averse investors.^{7,8}

*Corresponding Author

Konno and Yamazaki⁹ introduced the Mean-Absolute Deviation (MAD) model, which replaces variance with absolute deviation as the measure of portfolio risk. This approach was proposed as an alternative to the MV framework, which relies on the assumption that asset returns follow a normal distribution.¹⁰

In practice, portfolio optimization must account for the real-world characteristics of the assets involved, including correlations and dependencies, market risks, and practical constraints. These may include quantity limits restricting the number of assets, weight allocation caps, and transaction costs. Incorporating such factors often makes the optimization problem too complex for conventional analytical methods, necessitating alternative techniques such as heuristic or metaheuristic algorithms.^{11–13}

Effective risk management relies heavily on portfolio diversification. When constructing an efficient portfolio, market participants draw from an expanding universe of asset classes. While traditional allocations typically involve stocks, bonds, and commodities, digital instruments such as cryptocurrencies now frequently appear in modern investment strategies.^{14–16}

Cryptocurrencies represent a new type of financial asset, with rapidly increasing market capitalization and growing investor attention. They offer advantages over traditional currencies, including reliable and anonymous transactions at lower costs, enabled by blockchain technology. However, they also carry significant risks, as they are not backed by central banks or monetary authorities, making them highly sensitive to real economic events, such as the COVID-19 pandemic, and fueling global calls for regulatory oversight.^{17–19}

While interest in cryptocurrencies as viable investment assets continues to grow, access to cryptocurrency markets remains restricted in many countries. One common approach investors use to overcome this limitation is through cryptocurrency ETFs, which offer indirect exposure to digital assets. Despite these developments, the cryptocurrency market remains highly complex and rapidly evolving, requiring investors to approach it with caution and careful analysis.^{18,20}

The financial services sector increasingly depends on advanced computational methods, with artificial intelligence and machine learning transforming the development of trading and investment strategies. Accurate asset forecasting remains essential for informed decision-making and sustainable long-term growth. Although the efficient market hypothesis suggests that financial asset prices are inherently unpredictable, empirical research

has demonstrated that price movements and returns can, to some extent, be anticipated.^{21–23}

Within machine learning, ensemble algorithms are designed to reduce bias and variance, thereby enhancing predictive accuracy. Among these methods, eXtreme Gradient Boosting (XGBoost) has gained prominence due to its high performance, computational efficiency, and versatility across both classification and regression tasks.^{21,24}

Despite growing interest in combining machine learning with portfolio optimization, most existing studies remain limited to MV frameworks and rarely incorporate downside-focused risk measures such as semi-variance. Moreover, when machine learning techniques are employed, they are typically applied to pure cryptocurrency portfolios rather than mixed portfolios spanning both digital assets and traditional equities. This represents a notable gap in the literature, as heterogeneous, multi-market portfolios are increasingly relevant to real-world investors navigating both asset classes simultaneously.

This study introduces an integrated framework linking XGBoost-based return forecasting with three distinct optimization models: MV, MSV, and MAD. The analysis applies these models jointly to a mixed portfolio containing both U.S. equities and cryptocurrencies. Specifically, XGBoost forecasts the daily returns of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Microsoft (MSFT), and Tesla (TSLA). These forecasts are then used to construct optimal portfolios under the MV, MSV, and MAD frameworks, benchmarking them against an equal-weighted baseline. Comparing these methods clarifies how machine-learning forecasts influence portfolio efficiency and risk management across heterogeneous asset classes.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on cryptocurrency and mixed-asset portfolio optimization. Section 3 presents the theoretical background of XGBoost, Bayesian optimization, and the MV, MSV, and MAD optimization models. Section 4 describes the data, input features, and the overall research methodology. Section 5 presents the experimental results, including return prediction performance and portfolio optimization outcomes. Section 6 concludes the paper and outlines directions for future research.

2. Literature review

The integration of digital assets into mainstream finance has motivated extensive research into cryptocurrency portfolio optimization. Early investigations frequently relied on standard frameworks,

such as Mean-Variance (MV) and Global Minimum Variance (GMV), to evaluate risk-return profiles and diversification potential. Subsequent literature introduced advanced methodologies, including GARCH and Copula models, alongside a gradual adoption of machine learning tools to capture non-linear dependencies and volatility shifts. A recurring theme across this body of work involves testing whether blending cryptocurrencies with traditional equities actually stabilizes and enhances overall portfolio performance.

Several studies have explored portfolio optimization by integrating cryptocurrencies with traditional financial assets. Eisl *et al.*²⁵ constructed mixed portfolios containing Bitcoin and traditional assets, employing Conditional Value-at-Risk (CVaR) as the risk measure within the Mean-CVaR framework, using an equally weighted portfolio as a benchmark. Their results showed that adding Bitcoin improved the overall return-risk profile.

Brauneis and Mestel²⁶ compared Mean-Variance, Global Minimum Variance (GMV), and Maximum Sharpe (Tangency) models against the Naïve portfolio, finding that the simple equal-weighted approach produced the best performance.

Estalayo *et al.*²⁷ applied a multi-objective optimization strategy for seven cryptocurrencies, seeking to maximize return, minimize volatility, and enhance diversification, using return forecasts from a Gated Recurrent Unit (GRU) model.

Hrytsiuk & Babych²⁸ examined cryptocurrency portfolio optimization under non-normal return distributions using a modified Markowitz framework. Analyzing major cryptocurrencies alongside selected stocks, they found that the Laplace distribution captured return behavior more accurately than the Cauchy or normal models. Their results showed that portfolios combining cryptocurrencies with traditional assets, particularly Amazon and USDT, achieved higher returns with lower risk, highlighting the Laplace model's effectiveness in evaluating cryptocurrency risk dynamics.

Ma *et al.*²⁹ developed a tangency portfolio by maximizing the Sharpe ratio and observed that including cryptocurrencies significantly improved portfolio efficiency relative to the Naïve benchmark.

Bakry *et al.*³⁰ used Global Minimum Variance, Maximum Sharpe, and risk parity methods under boundary constraints and found that portfolios containing Bitcoin performed better overall, though allocations to Bitcoin remained small due to its high volatility.

Bedoui *et al.*³¹ proposed a hybrid approach for multi-asset portfolio optimization that integrates GARCH, Extreme Value Theory (EVT), and Vine Copula models within a Conditional Value-at-Risk (CVaR) framework. Using daily data from 2013 to 2022 across cryptocurrencies, commodities, and stock indices, the study rejected the assumption of normality and modeled volatility and tail dependence through C-Vine copulas. The Mean-CVaR model, optimized via an improved NSGA-II genetic algorithm, outperformed traditional Mean-Variance and Mean-Absolute Deviation methods by focusing on downside risk. Results showed that assets like Bitcoin and oil were excluded from the minimum-risk portfolio, while gold and the S&P 500 received the highest allocations. Overall, the C-Vine Copula-GARCH-EVT-CVaR model provided a more accurate and robust framework for managing extreme risks and interdependencies in diversified portfolios.

Zhou *et al.*³² used Support Vector Machines (SVM) to forecast cryptocurrency prices and applied various optimization approaches including Mean-Variance, Global Minimum Variance, and Sharpe ratio maximization, showing that portfolios based on predicted data yielded superior results.

Jeleskovic *et al.*³³ examined the impact of integrating cryptocurrencies into traditional portfolios using an enhanced GARCH-Copula-Markowitz framework. By modeling volatility and non-linear dependencies through GARCH and Vine Copula techniques, the study compared traditional, crypto-only, and mixed portfolios. Results showed that portfolios including cryptocurrencies achieved higher risk-adjusted returns and greater stability, while pure crypto portfolios remained more volatile. Overall, the findings suggest that combining cryptocurrencies with traditional assets can enhance diversification and improve portfolio performance.

Abbas & Usman³⁴ examined portfolio optimization in the Pakistani financial market to assess how integrating cryptocurrencies with traditional assets affects performance and diversification. Using daily data from 2018 to 2023, the study compared traditional and crypto-inclusive portfolios across four optimization strategies: Naïve Equal Weighting, Maximum Return, Maximum Sharpe Ratio, and Minimum Variance. The findings showed that adding cryptocurrencies reduced overall volatility and improved risk-adjusted performance, with the Maximum Sharpe Ratio portfolio delivering the most balanced results. Overall, the inclusion

of digital assets enhanced portfolio stability and diversification within an emerging market context.

Moreover, studies employing GARCH-based return modeling have consistently shown that integrating volatility dynamics into portfolio construction enhances overall performance.³⁵⁻³⁷

Existing literature predominantly relies on standard Mean-Variance models, rarely exploring downside-focused risk measures such as semi-variance. Furthermore, empirical modeling predominantly utilizes traditional econometric techniques, leaving machine learning implementations relatively scarce. Even when researchers deploy machine learning algorithms, they generally test them on isolated cryptocurrency portfolios rather than heterogeneous structures containing both digital assets and traditional equities. This research directly targets that specific gap.

3. Research background

The following theoretical framework outlines the primary methodologies driving this analysis: XGBoost for forecasting returns, Bayesian optimization for hyperparameter tuning, and the MV, MSV, and MAD models for portfolio construction.

3.1. XGBoost

XGBoost was introduced by Chen in 2016 as an enhanced version of Gradient Boosting Decision Trees (GBDT). The method optimizes an objective function that combines a loss term with a regularization term, where the latter helps control variance and reduce the risk of overfitting.^{21,24}

3.2. Bayesian optimization

Bayesian optimization is a global search method that seeks to minimize a function $f(x)$ over a bounded domain. It builds a probabilistic model to guide evaluations by balancing exploration and exploitation through an acquisition function. This approach is effective for expensive, non-convex problems such as tuning machine learning models, as it requires fewer evaluations than traditional methods.^{38,39}

3.3. Mean-Variance optimization

Under the Mean-Variance model, investors seek to maximize expected returns for a given risk level or minimize overall risk for a target return. The model uses variance (or standard deviation) as its primary risk measure, producing an efficient frontier that maps optimal risk-return combinations. However, MV frameworks assume normally

distributed asset returns and linear, stable correlations. While this ensures mathematical tractability, these conditions rarely align with actual financial markets, which consistently exhibit fat-tailed distributions, volatility clustering, and asymmetry.^{4,40,41}

In the MV framework, an investor allocates wealth among n available securities to achieve an optimal balance between expected return and risk. The portfolio is represented by a vector of asset weights:

$$\mathbf{X} = [x_1, x_2, \dots, x_n] \quad (1)$$

where x_j , ($j = 1, 2, \dots, n$) denotes the proportion of total investment allocated to the j th asset.

The expected portfolio return (E_P) and portfolio variance (V_P), which serves as the risk measure, are given by:

$$E_P = \mathbf{X}' \boldsymbol{\mu} = \sum_{j=1}^n x_j \mu_j \quad (2)$$

$$V_P = \mathbf{X}' \mathbf{C} \mathbf{X} \quad (3)$$

where $\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_n)'$ is the vector of expected returns for the individual assets, $\mathbf{C}$ is the $n \times n$ covariance matrix of asset returns, and $\mathbf{X}'$ denotes the transpose of $\mathbf{X}$.

The portfolio optimization problem aims to minimize overall risk (variance) for a given target return R :

$$\min V_P = \mathbf{X}' \mathbf{C} \mathbf{X} \quad (4)$$

$$\sum_{j=1}^n x_j \mu_j = R \quad (5)$$

$$\sum_{j=1}^n x_j = 1 \quad (6)$$

$$x_j \geq 0 \quad \forall j. \quad (7)$$

Equations (6) and (7) specify that the portfolio weights are non-negative and sum to one, ensuring full investment without short-selling.

3.4. Mean-Semi-Variance optimization

To strictly isolate downside risk, Semi-Variance (SV) measures the expected squared deviations of returns below a target or expected threshold, intentionally ignoring positive deviations. Rather than requiring a traditional covariance matrix, SV relies on the joint distribution of the underlying securities. This design actively minimizes the probability of falling short of return targets. When return distributions are perfectly symmetric, the SV and variance models generate identical efficient portfolios.^{6,40}

The Mean-Semi-Variance portfolio optimization problem can be formulated as follows:

$$\min \frac{1}{s} \sum_{i=1}^s y_i^2 \quad (8)$$

$$S.t. \ y_i \geq \sum_{j=1}^n [R - x_j r_{ij}] \quad \forall i \quad (9)$$

$$\sum_{j=1}^n x_j \mu_j = R \quad (10)$$

$$\sum_{j=1}^n x_j = 1 \quad (11)$$

$$x_j \geq 0 \ \forall j, \ y_i \geq 0 \ \forall i. \quad (12)$$

In this formulation, when an observed return falls below the expected return, the corresponding y_i variable becomes strictly positive. Minimizing the sum of y_i^2 ensures that y_i equals the exact shortfall between the expected and observed return. Conversely, if the observed return exceeds the expected return, y_i would be negative, but the non-negativity constraint forces it to zero. As the objective minimizes y_i^2 , the optimal y_i is zero in that case.

3.5. Mean-Absolute deviation optimization

The Mean-Absolute Deviation framework quantifies risk as the average absolute deviation of returns from their mean, focusing on the scale of fluctuations rather than their squared magnitudes. This structural shift converts portfolio optimization into a linear programming problem, which significantly reduces computational load and mitigates estimation errors associated with the MV model. Furthermore, MAD operates effectively without assuming normal return distributions, producing highly stable risk assessments in skewed or erratic markets. Even though MV and MAD outputs align under normal distribution conditions, the MAD approach consistently constructs more resilient portfolios in the presence of real-world market irregularities.^{9,40}

Absolute deviation is defined as the expected value of the absolute difference between the observed return and its expected return. It can be expressed as follows:

$$|R - E| = \begin{cases} R - E & \text{if } R > E \\ E - R & \text{if } R \leq E. \end{cases} \quad (13)$$

The portfolio optimization problem under the MAD framework can be formulated as the following linear program:

$$\min \frac{1}{s} \sum_{i=1}^s y_i, \quad (14)$$

$$S.t. \ y_i \geq \sum_{j=1}^n [R - x_j r_{ij}] \quad \forall i \quad (15)$$

$$y_i \geq \sum_{j=1}^n [x_j r_{ij} - R] \quad \forall i \quad (16)$$

$$\sum_{j=1}^n x_j \mu_j = R \quad (17)$$

$$\sum_{j=1}^n x_j = 1 \quad (18)$$

$$x_j \geq 0 \ \forall j, \ y_i \geq 0 \ \forall i. \quad (19)$$

When the observed return for a given scenario exceeds the expected return, the first constraint ensures that y_i remains zero; when the observed return falls below the expected return, the second constraint activates, making y_i positive. Since y_i is constrained to be non-negative and the objective minimizes their sum, y_i precisely captures the absolute difference between the realized and expected returns. This formulation thus provides an exact and computationally efficient solution for portfolio selection under the MAD criterion.

4. Data and methodology

The empirical analysis relies on historical asset pricing and specific technical indicators for the initial forecasting phase. Subsequent steps encompass data prediction, simulation mechanics, optimal portfolio construction, and the evaluation criteria used to measure overall performance.

4.1. Data

Candlestick price data for Bitcoin, Ethereum, BNB, Microsoft, and Tesla were collected from March 20, 2024, to July 14, 2025. These assets were selected to provide a representative and liquid cross-section of both cryptocurrency and U.S. equity markets, rather than to exhaust the full universe of investable assets. Similarly, the 30-day out-of-sample evaluation window was deliberately chosen to align with the single-period, short-horizon design of the proposed framework, reflecting the rapidly shifting return dynamics characteristic of cryptocurrency markets—longer evaluation windows risk conflating multiple market regimes within a single static model. This design choice, along with comparable short-horizon precedents in the recent literature, is discussed further in the limitations discussion in Section 6. Bitcoin

and Ethereum serve as benchmark cryptocurrencies due to their dominant market roles, while BNB represents a major exchange-linked digital asset with distinct market dynamics. Microsoft and Tesla were selected as large-cap U.S. equities with substantial market influence and contrasting risk-return characteristics.

This combination enables the evaluation of the proposed machine-learning-based portfolio optimization framework in a heterogeneous, multi-market setting. By combining digital assets with traditional equities, the analysis extends classical portfolio optimization models to assets with fundamentally different return distributions, volatility structures, and market microstructures, without focusing on asset-specific performance comparison.

Daily returns were used as prediction targets, and technical indicators were employed as input features to train the XGBoost model. Candlestick price data for all assets were obtained using the Yahoo Finance Python library.

4.2. Input features

Input features for this study included Relative Strength Index (RSI), Moving Average Convergence/Divergence (MACD) and its signal along with their difference, On-Balance Volume (OBV), Average Directional Movement Index (ADX) with its positive and negative components, Bollinger Bands, Parabolic SAR, and the stochastic oscillator with its signal. Additional features included the daily price range and the previous day's closing price. In addition to these technical indicators, the CBOE 13-week Treasury Bill Interest Rate Index (IRX), reflecting the daily short-term U.S. Treasury bill rate, was included as a macroeconomic input.

In total, 17 features were used to predict the daily return of each asset. After calculating these indicators, the final training and test datasets for each asset, excluding weekends, are shown in **Table 1**.

A strictly chronological design eliminates look-ahead bias and data leakage during processing and estimation. Calculations for technical indicators and macroeconomic variables rely solely on data available up to the specific observation date, ignoring any future pricing. The temporal split between training and test sets ensures that all machine-learning models, along with their hyperparameter tuning and model selection phases, are trained exclusively on training data. Consequently, test-period information never influences forecasting performance or model estimation.

4.3. Hyperparameter optimization

Bayesian optimization was used to tune the XGBoost hyperparameters. The procedure executed 100 iterations across the training sets to identify optimal values based on the search ranges detailed in **Table 2**.

This technique efficiently navigates high-dimensional parameter spaces without requiring exhaustive model evaluations. Model performance was measured exclusively on training data using cross-validated prediction error as the objective function. Keeping hyperparameter selection entirely separate from the test period prevents data leakage and prioritizes generalization over excessive in-sample fitting.

4.4. XGBoost forecasting and portfolio optimization

Following hyperparameter tuning, the XGBoost algorithm processed the training set to forecast daily returns for the final 30-day window. The MV, MSV, and MAD portfolio optimization models then incorporated these predictions in place of traditional expected returns, evaluating them against a naïve equal-weighted benchmark.

Because the framework operates in a static, single-period environment, it establishes portfolio positions via a single trade at the start of the 30-day holding block. This design eliminates the need for periodic rebalancing, restricting transaction costs to a one-time initiation fee rather than the compounded frictions associated with daily or weekly turnover.

In addition to minimum-risk portfolios, maximum-efficiency portfolios are constructed for each risk framework. The Maximum Sharpe portfolio maximizes the ratio of expected return to portfolio variance under the MV model. Analogously, the Maximum Sortino portfolio maximizes the ratio of expected return to portfolio semi-variance, treating downside risk asymmetrically by penalizing only negative deviations from the target return. Under the MAD framework, the Maximum Sharpe-AD portfolio maximizes the ratio of expected return to mean absolute deviation. These formulations follow directly from the corresponding risk definitions in Sections 3.3–3.5 and allow a consistent comparison of efficiency-maximizing portfolios under different notions of risk. For ratio-based portfolios, expected returns are defined in excess of the risk-free rate, ensuring consistency with the standard definitions of the Sharpe, Sortino, and Sharpe-AD performance measures.

Table 1. Dataset summary

Set	Date Range	Number of Days	Percentage
Train Set	2024/05/07 to 2025/05/29	266	90%
Test Set	2025/05/30 to 2025/07/14	30	10%

Table 2. XGBoost hyperparameters search ranges

Hyperparameter	Details	Search Range
max-depth	Maximum Depth of a Tree	{3, 4, ..., 10}
learning-rate	Step Size Shrinkage Used in Update	[0.01, 0.3]
n-estimators	Number of Trees	{100, 101, ..., 1000}
subsample	Subsample Ratio of the Training Instances	[0.6, 1]
colsample-bytree	Subsample Ratio of Features	[0.6, 1]
reg-alpha	L1 Regularization Term on Weights	[0.0, 5.0]
reg-lambda	L2 Regularization Term on Weights	[0.0, 5.0]
min-child-weight	Minimum Sum of Instance Weight (Hessian) Needed in a Child	[1.0, 10.0]

All assets are modeled in terms of daily returns, ensuring a common unit of measurement across cryptocurrencies and equities. Risk metrics including variance, semi-variance, and absolute deviation are computed at the portfolio level rather than normalized at the individual asset level. Asset-specific volatility differences are therefore naturally reflected through the optimized portfolio weights. This design allows highly volatile assets such as cryptocurrencies to contribute proportionally more to overall portfolio risk without imposing artificial scaling that could distort relative risk contributions.

Finally, **Figure 1** maps the complete operational pipeline, tracking the process from initial data collection and feature engineering through XGBoost prediction and portfolio evaluation.

5. Experimental results

This section presents the prediction results and evaluates portfolio performance using the proposed approaches.

5.1. Prediction results

The performance of XGBoost is evaluated using Root Mean Squared Error (RMSE), R^2 , and directional (trend) accuracy. While RMSE and R^2 assess the accuracy of return-level predictions, trend accuracy measures the model’s ability to correctly predict the direction of daily returns, which is particularly relevant for portfolio allocation decisions. **Table 3** summarizes the prediction results for each asset.

As shown in **Table 3**, R^2 values exceed 0.65 for all cryptocurrencies and are above 0.55 for all assets. XGBoost performs better on cryptocurrencies than on stocks in terms of the predictability

of return levels. Meanwhile, the model achieves consistently high trend accuracy across all assets, exceeding 70% in every case and reaching above 80% for Ethereum, Microsoft, and Tesla. Notably, for assets such as Tesla, directional accuracy remains strong despite relatively lower R^2 or higher RMSE values, indicating that while precise return magnitudes are harder to predict, the model effectively captures the dominant direction of price movements.

Table 3. XGBoost forecasting performance with Bayesian-Optimized hyperparameters

Asset	RMSE	R^2	Trend Accuracy
Bitcoin	0.0114	0.65	70%
Ethereum	0.0177	0.76	83%
Binance Coin	0.0090	0.66	73%
Microsoft	0.0044	0.60	83%
Tesla	0.0284	0.55	80%

To assess the sensitivity of the forecasting performance to hyperparameter optimization, we additionally evaluate the XGBoost model under a baseline configuration without Bayesian hyperparameter optimization. **Table 4** reports the corresponding RMSE, R^2 , and trend accuracy metrics for each asset, allowing a direct comparison with the optimized results reported in **Table 3**.

As shown in **Table 4**, without hyperparameter tuning, predictive performance in terms of RMSE and R^2 generally weakens for most assets, with Bitcoin being the primary exception. In particular, the optimized model reported in **Table 3** exhibits consistently lower prediction errors and higher explanatory power across both cryptocurrencies and equities. While directional accuracy

remains comparable for some assets, the improvements achieved through Bayesian hyperparameter optimization are more pronounced in return-level metrics. These results underscore the role of systematic hyperparameter tuning in improving forecast precision and stabilizing model performance in heterogeneous and volatile markets. **Figures 2–6** illustrate the comparison between actual and predicted values, with the red line for predictions and the blue line for the true test data.

Table 4. XGBoost performance without hyperparameter tuning

Asset	RMSE	R^2	Trend Accuracy
Bitcoin	0.0086	0.80	80%
Ethereum	0.0206	0.68	83%
Binance Coin	0.0097	0.61	67%
Microsoft	0.0052	0.43	80%
Tesla	0.0321	0.43	77%

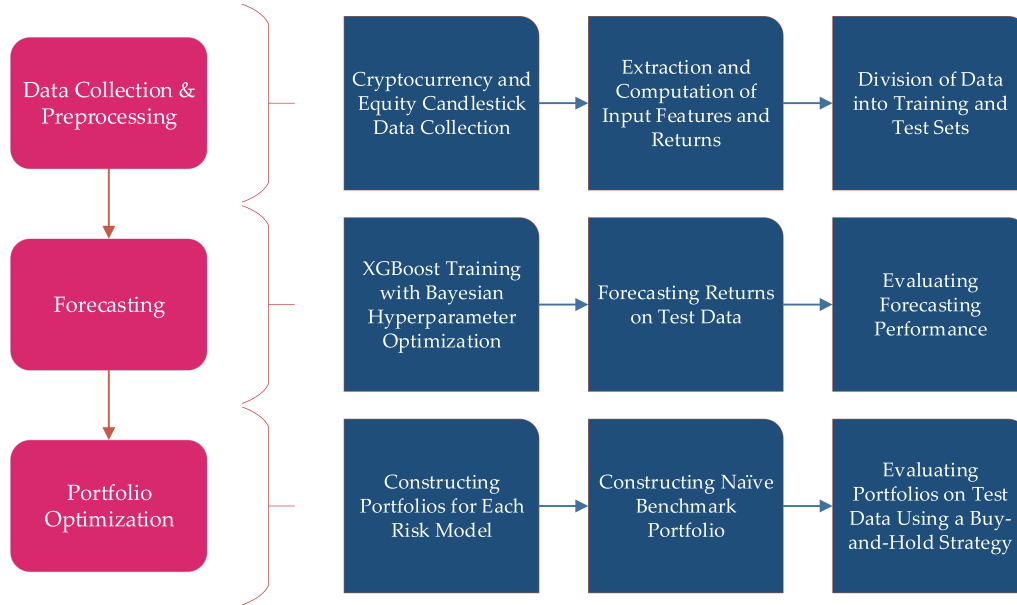


Figure 1. Overview of the proposed machine learning-based forecasting and portfolio optimization framework

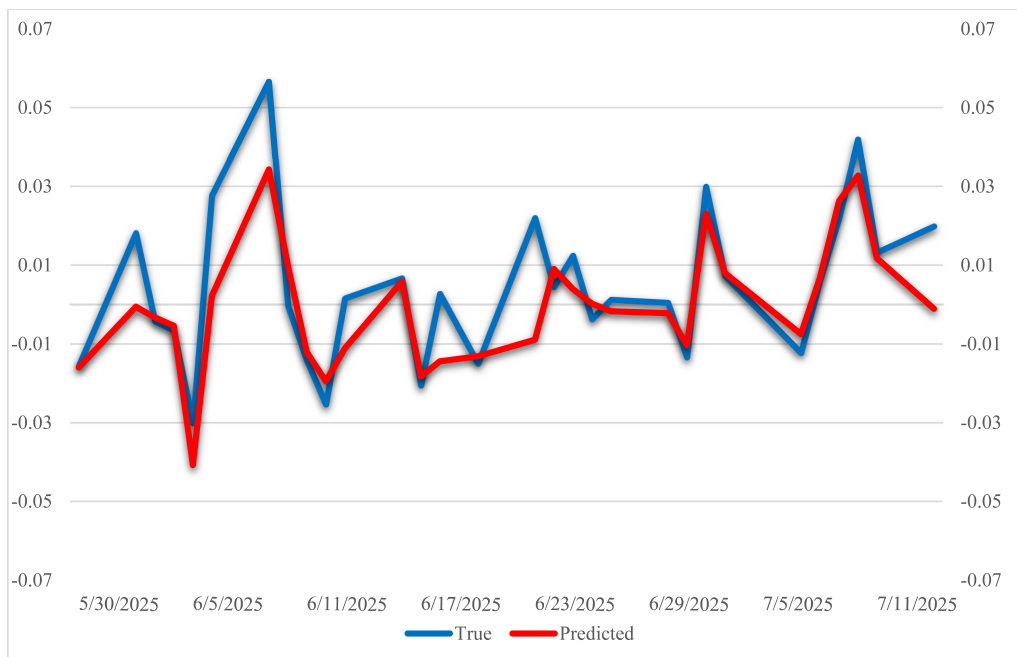


Figure 2. XGBoost forecasted vs. actual daily returns on the test set: bitcoin

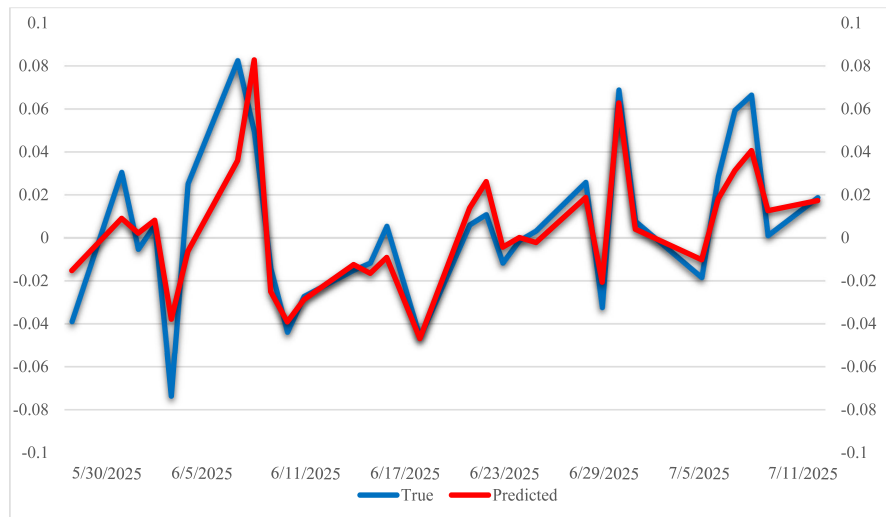


Figure 3. XGBoost forecasted vs. actual daily returns on the test set: ethereum

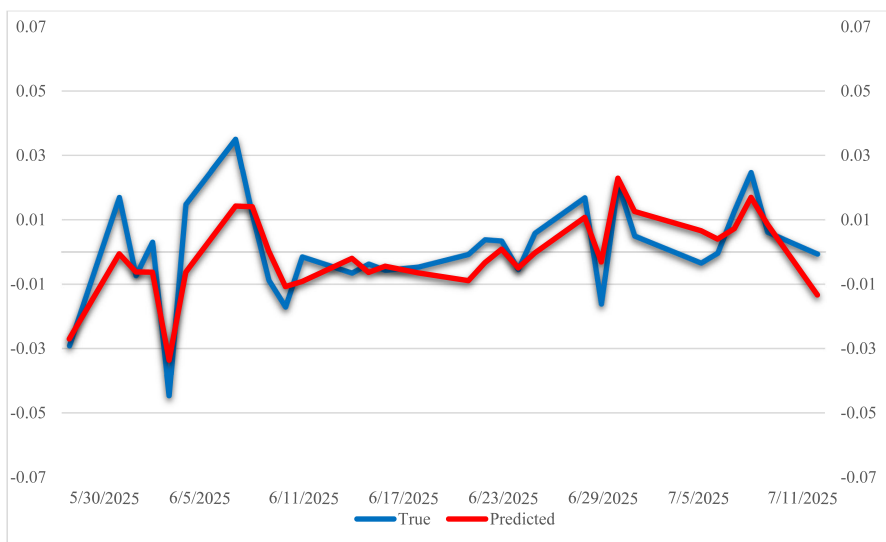


Figure 4. XGBoost forecasted vs. actual daily returns on the test set: BNB

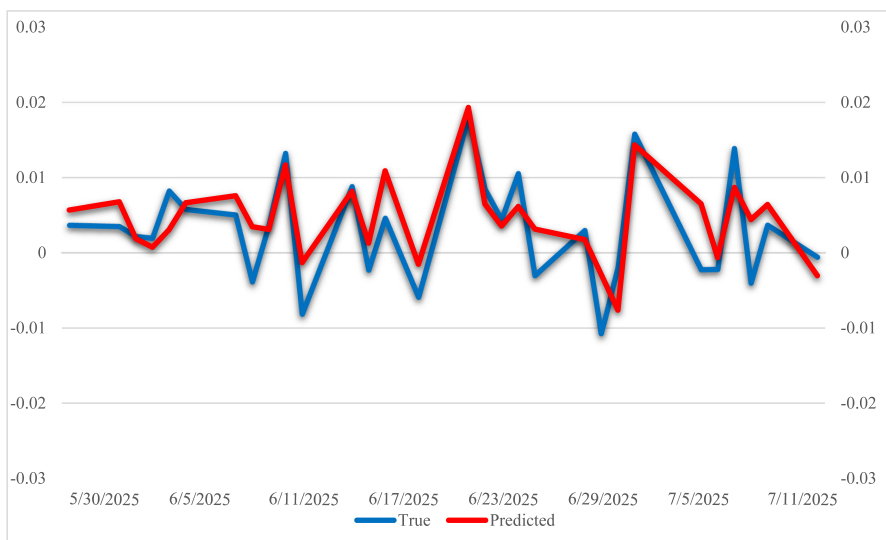


Figure 5. XGBoost forecasted vs. actual daily returns on the test set: Microsoft

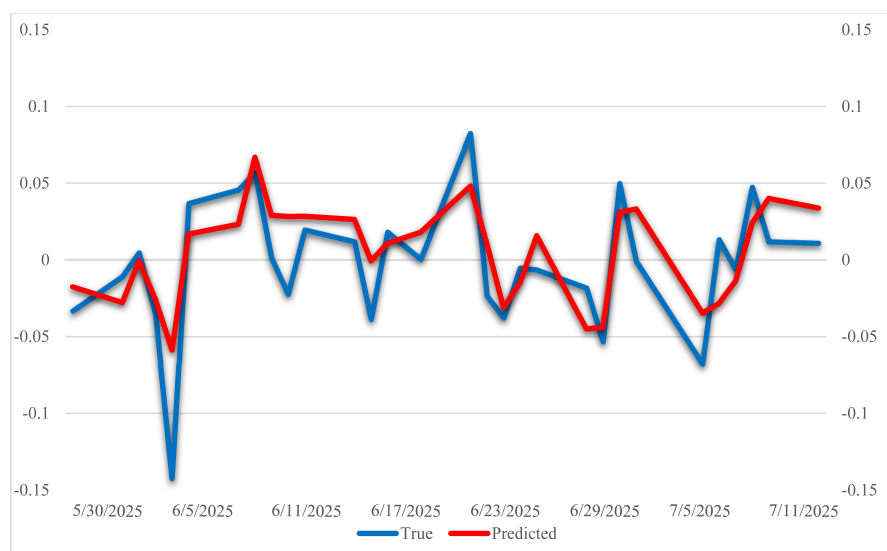


Figure 6. XGBoost forecasted vs. actual daily returns on the test set: Tesla

The figures show that XGBoost captures major market shocks reasonably well. However, challenges arise for assets such as Tesla, as shown in **Figure 6**, where large shocks and high volatility contributed to lower predictive performance. The results also indicate that while the model performs well overall, its accuracy tends to weaken over time for certain assets such as Microsoft.

5.2. Portfolio optimization

Optimal portfolios are constructed based on predictions using MV, MSV, and MAD methods. Boundary constraints are imposed to reflect real-world market conditions, ensuring that asset allocations

remain between 0.1 and 0.4. Maximum Sharpe ratio, maximum Sortino ratio, and maximum Sharpe-AD ratio portfolios are also constructed. **Figures 7–9** present the efficient frontier along with the tangency portfolio for each of the three methods. We assume a daily risk-free rate of 0.0174% based on data from the U.S. Department of the Treasury.

The naïve portfolio, used as the benchmark, is evaluated alongside the tangency portfolios and the portfolios constructed to match its return level. **Tables 5–7** report the performance outcomes for all portfolio configurations. The performance of each portfolio on the actual test data with a one-month buy-and-hold strategy is also shown in **Table 8**.

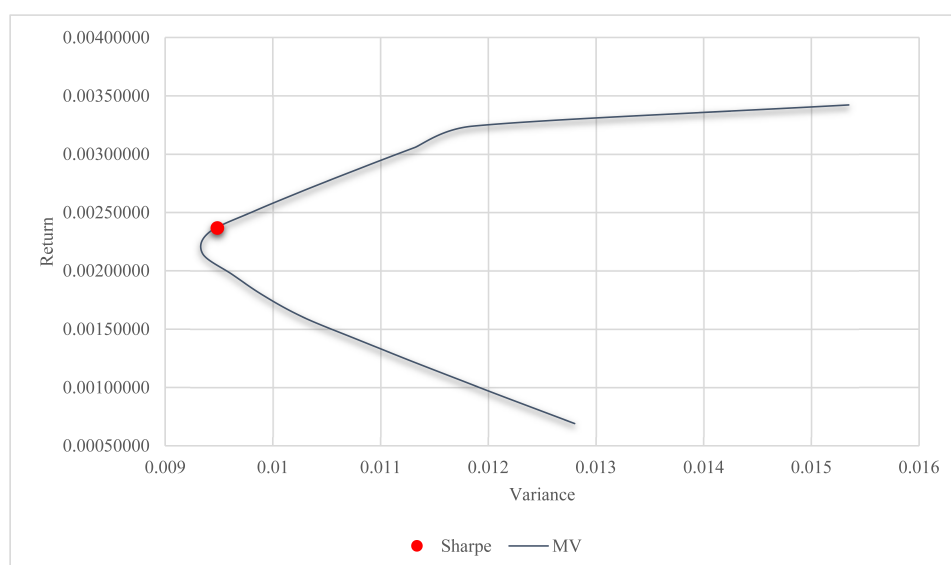


Figure 7. Efficient frontier and tangency portfolio for mean-variance model

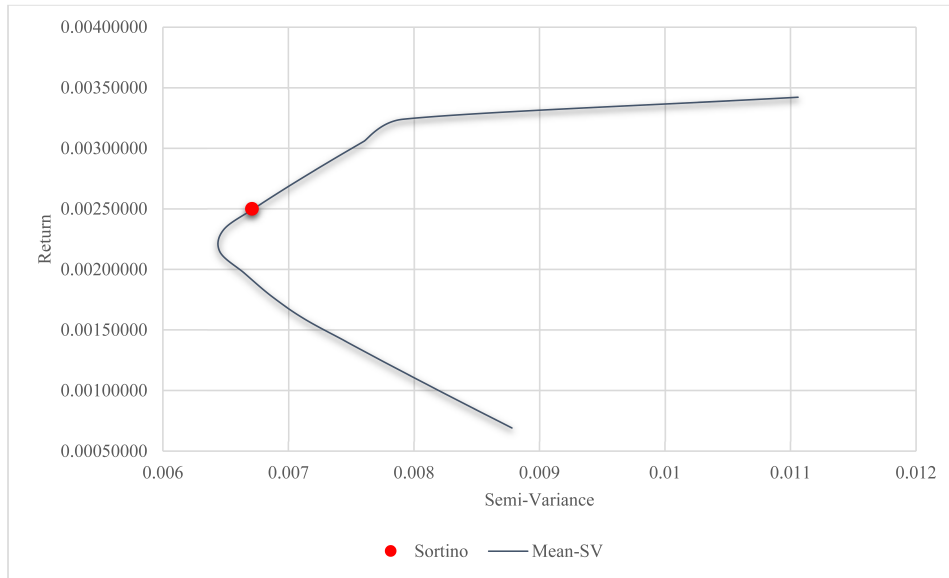


Figure 8. Efficient frontier and tangency portfolio for mean-semi-variance model

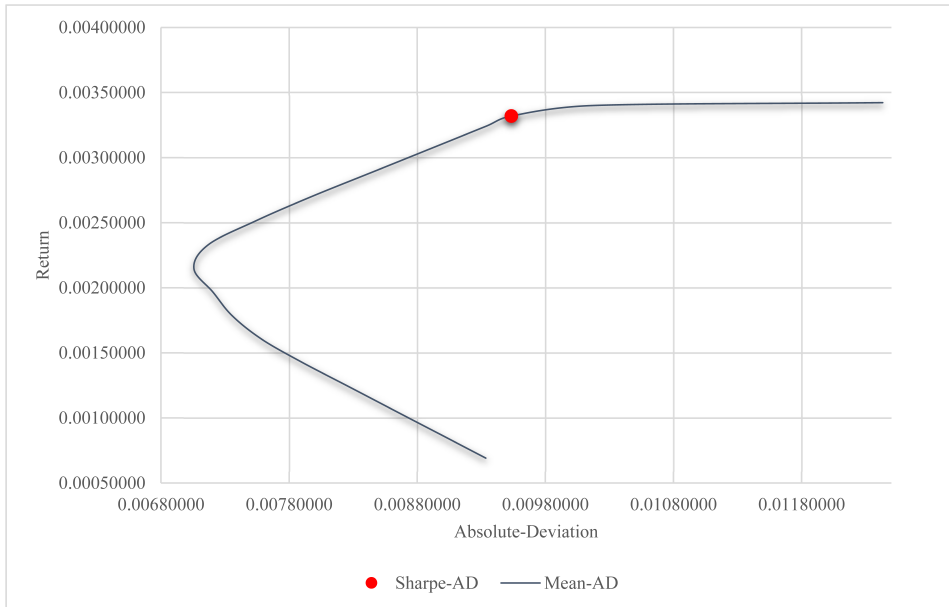


Figure 9. Efficient frontier and tangency portfolio for mean-absolute deviation model

The empirical results indicate that integrating machine-learning predictions with downside-focused optimization yields noticeable improvements over the baseline naïve portfolio. Across the evaluated optimization frameworks, the targeted strategies successfully lowered risk—measured by variance, semi-variance, and absolute deviation—while maintaining or exceeding benchmark returns. The maximum-ratio configurations, particularly the Maximum Sharpe-AD and Maximum Sortino models, exhibited the most substantial efficiency gains and consistently outperformed both their minimum-risk counterparts and the equal-weighted baseline.

When evaluated on real out-of-sample data using a one-month buy-and-hold strategy (**Table 8**), the superiority of the optimized strategies remained evident. The naïve portfolio generated a cumulative return of 6.6%, while all optimization methods produced higher returns, with the Maximum Sharpe (7.2%), Maximum Sortino (7.6%), and especially the Maximum Sharpe-AD portfolio (10.2%) delivering the strongest performance. These results highlight the advantage of incorporating both predictive signals and risk-sensitive models in volatile asset environments.

Table 5. Performance of mean-variance portfolios

Portfolio	Return	Variance	Sharpe
Naïve	0.22%	0.0139	0.148
Mean-Variance	0.22%	0.0092	0.224
Maximum Sharpe	0.24%	0.0095	0.231

Table 6. Performance of mean-semi-variance portfolios

Portfolio	Return	SV	Sortino
Naïve	0.22%	1.23	0.002
Mean-SV	0.22%	0.0064	0.324
Maximum Sortino	0.25%	0.0067	0.347

Table 7. Performance of mean-absolute deviation portfolios

Portfolio	Return	AD	Sharpe-AD
Naïve	0.22%	0.01076963	0.1915
Mean-AD	0.22%	0.00699486	0.2959
Maximum Sharpe-AD	0.33%	0.00953435	0.3299

Table 8. Out-of-sample portfolio performance (30-day buy-and-hold)

Portfolio	Cumulative Return
Naïve	6.6%
Mean-Variance	6.8%
Maximum Sharpe	7.2%
Mean-SV	6.8%
Maximum Sortino	7.6%
Mean-AD	6.8%
Maximum Sharpe-AD	10.2%

The optimized portfolio weights further reinforce these patterns. Across the different models, the tangency portfolios consistently shifted capital toward assets with stronger predicted performance and more favorable risk characteristics. In most solutions, Microsoft (MSFT) and Tesla (TSLA) received meaningful allocations, reflecting their stability relative to the highly volatile cryptocurrencies. Meanwhile, cryptocurrency allocations adjusted sharply across methods: BNB frequently appeared with high weights under different optimization methods except maximum Sharpe-AD, while ETH and BTC saw moderated exposure de-

pending on the specific risk measure. These patterns indicate that the optimization frameworks effectively balanced the trade-off between exploiting high predictive returns and mitigating asset-specific volatility.

Taken together, these results confirm that combining XGBoost-based return forecasting with MV, MSV, and MAD optimization provides consistent improvements in both risk control and realized performance. The findings also underscore that more flexible downside or absolute deviation-based risk measures yield stronger practical outcomes than variance alone, especially in markets characterized by asymmetry, heavy tails, and structural volatility.

From a numerical perspective, the magnitude of the performance improvements observed in this study is broadly comparable to those reported in recent related works. For example, Zhou *et al.*³² document notable out-of-sample Sharpe and Sortino ratio improvements for machine-learning-informed cryptocurrency portfolios relative to naïve benchmarks. Bedoui *et al.*³¹ report substantial reductions in downside risk using CVaR-based optimization frameworks. Similar efficiency gains are also reported by Ma *et al.*²⁹ and Bakry *et al.*³⁰, who show that optimized portfolios incorporating cryptocurrencies outperform equal-weighted strategies in terms of risk-adjusted returns. In our case, the Maximum Sortino and Maximum Sharpe-AD portfolios achieve notable improvements in realized performance and downside risk mitigation relative to the naïve benchmark, despite relying on simpler downside risk measures and a different forecasting-optimization architecture. This suggests that the benefits of integrating predictive signals into portfolio construction are robust across asset classes, risk measures, and modeling choices.

While the empirical results consistently show superior risk-adjusted performance of the optimized portfolios relative to the naïve benchmark, formal statistical hypothesis testing of performance differences (e.g., Sharpe or Sortino ratio tests) was not conducted in this study. Given the relatively short out-of-sample evaluation window, the analysis focuses on economic significance and robustness of performance patterns across multiple risk measures and portfolio constructions. The observed dominance of the Maximum Sortino and Maximum Sharpe-AD portfolios across both return and downside risk metrics provides consistent evidence of practical improvement rather than isolated statistical artifacts. Incorporating formal

statistical tests or bootstrap-based confidence intervals is left for future research, particularly in longer-horizon or rolling evaluation settings.

5.3. Managerial insights and implications

The empirical findings present distinct operational strategies for market participants managing mixed cryptocurrency-equity portfolios. The consistent advantage of machine-learning-informed allocations over the equal-weighted benchmark demonstrates that accessible forecasting models like XGBoost provide reliable signals for short-horizon asset allocation. This finding holds particular value for practitioners seeking model transparency, interpretability, and lower computational demands compared to complex deep learning architectures.

The selection of the underlying risk measure also demonstrates substantial practical impact. Because the Maximum Sortino and Maximum Sharpe-AD configurations generated stronger risk-adjusted and realized returns than the Mean-Variance model, practitioners navigating asymmetric or fat-tailed return distributions, common in cryptocurrency markets, stand to benefit from downside-focused or absolute deviation frameworks instead of relying solely on variance. Asset allocation behaviors observed in the optimized weights provide further structural guidance. The models consistently directed capital toward established equities like Microsoft and Tesla, balancing this stability with targeted cryptocurrency exposure to capture higher expected returns. Over short evaluation horizons, this specific weighting pattern suggests that mixed-asset diversification provides a more measured entry into digital asset markets compared to concentrated cryptocurrency holdings. However, due to inherent asset volatility and the short evaluation window, this observation remains context-specific and does not constitute a broad investment recommendation.

Structurally, the single-period design of this framework aligns best with tactical, short-term allocation adjustments, such as monthly rebalancing, rather than long-term buy-and-hold investing. Extending the holding period without adapting the model risks degrading forecast accuracy due to rapidly shifting market dynamics. Consequently, applying this framework over extended horizons requires a rolling or periodically retrained forecasting mechanism rather than a static evaluation window. Implementation strategies must also account for constraints related to the asset universe, sample size, and the absence of transaction cost modeling, as detailed in the concluding section.

6. Conclusions and future research directions

This research investigated the integration of machine-learning return forecasts into multi-market portfolio optimization, specifically comparing the Mean-Semi-Variance and Mean-Absolute Deviation models against the standard Mean-Variance framework. Feeding XGBoost predictions into the MV, MSV, and MAD models consistently outperformed the equal-weighted benchmark. Across all three optimization categories, the minimum-risk configurations matched the benchmark's return at a substantially lower risk level, while the maximum-ratio designs generated superior expected returns and risk-adjusted metrics. Out-of-sample testing confirmed these advantages, as the Maximum Sortino and Maximum Sharpe-AD portfolios delivered the highest realized returns over a one-month buy-and-hold period. Furthermore, the resulting asset weights demonstrate that these optimization models successfully merged predictive signals with risk management, shifting capital toward assets with more stable or favorable expected trajectories. The forecasting phase also maintained high directional accuracy across the asset pool, confirming the model's capacity to identify market trends even when precise point-wise predictions fluctuated.

These empirical results align with recent literature demonstrating that pairing machine-learning forecasts with risk-aware optimization models elevates portfolio efficiency. While previous research often prioritizes complex risk modeling or pure cryptocurrency portfolios, this analysis shows that semi-variance and absolute deviation measures achieve similar performance gains in a mixed cryptocurrency-equity environment. This adaptability highlights the practical utility of the proposed framework across different market scenarios. However, the research scope involves specific constraints. The analysis uses a short sample period and a restricted asset pool to align with the framework's single-period, short-horizon design. This configuration focuses on tactical allocation rather than long-term strategic investment, meaning it may not fully capture prolonged market phases, such as extended bear markets or severe structural shifts.

It is also worth noting that the length of the empirical sample is comparable to that used in several recent studies. For example, Zhou *et al.*³² employ a sample of approximately six months, while Hrytsiuk & Babych²⁸ consider a horizon of about 2.5 years, which is close to the period analyzed in this study. More directly comparable to

the present design, Lorenzo and Arroyo⁴² evaluate crypto-asset portfolio allocation using a 30-day holding period, and Huang *et al.*⁴³ construct and evaluate mixed-asset portfolios over short, rolling evaluation windows within the M6 forecasting competition framework. In the context of cryptocurrency markets, extending the sample far beyond recent years may introduce additional challenges, as return dynamics and volatility structures can change markedly across regimes. Using a more recent and relatively homogeneous period helps ensure that the forecasting model is trained on data that remain relevant for current market conditions, rather than averaging across structurally different phases. Given the short out-of-sample window, formal statistical inference would have limited power and may produce unreliable conclusions. Extending the evaluation to longer or multiple test windows would require the forecasting model to remain accurate over a longer span, which the current static, single-period training is not well suited to achieve; this motivates the rolling or expanding forecast window approach identified in the future research directions below.

Moreover, the modelling framework assumes static relationships during the test window, an assumption that may not fully capture the dynamics of rapidly changing markets, particularly for cryptocurrencies.

In addition, the downside-oriented risk measures employed in this study depend on the return distributions implied by the forecasting and optimization framework. During periods of abrupt regime shifts or extreme market stress, such distributions may change rapidly, potentially limiting the ability of semi-variance and absolute deviation to fully capture tail risk. As a result, downside risk may be underestimated in environments characterized by structural breaks or unprecedented shocks.

Furthermore, the empirical results may be sensitive to modeling choices at both the forecasting and optimization stages. Although Bayesian optimization is employed to tune XGBoost hyperparameters, predictive performance can still vary under alternative parameter configurations. The stability of the resulting optimal portfolio weights was also not formally examined and may be affected by small changes in forecasts or estimation inputs. In addition, the analysis relies on a fixed 30-day forecast horizon, and alternative window lengths could lead to different risk-return trade-offs. A formal sensitivity and robustness analysis along these dimensions is therefore left for future research. As well, a comparison with non-optimized forecasting specifications indicates

that hyperparameter tuning plays an important role in improving predictive accuracy, particularly in terms of error reduction and explanatory power, highlighting another dimension of model sensitivity.

Also, the empirical analysis adopts a single-period portfolio optimization framework and therefore abstracts from transaction costs, turnover, and dynamic rebalancing. While these frictions are critical for real-world implementation and would likely attenuate realized performance gains, their omission allows a clean assessment of the interaction between machine-learning-based return forecasts and alternative risk measures.

Regarding the potential impact of transaction costs, it is worth noting that every portfolio evaluated in this study, including the Naïve benchmark, is implemented as a single-period buy-and-hold strategy requiring only one initial allocation trade and one terminal liquidation, rather than repeated rebalancing over the holding period. Transaction costs and bid-ask spreads would therefore be incurred on a comparable, one-time basis across all strategies rather than compounding differentially between them. Since these costs apply broadly across the naïve and optimized portfolios alike, they are unlikely to systematically favor one approach over another or to reverse the relative performance ordering observed in this study. Nonetheless, a more rigorous treatment incorporating asset-specific fee structures, bid-ask spreads, and slippage, particularly under a dynamic, multi-period rebalancing framework, is identified as an important direction for future research.

Future work can address these limitations in several ways. First, rolling or expanding forecast windows could be used to better capture time-varying dependencies and would directly address the limitation of the current fixed 30-day evaluation window by allowing the model to be periodically retrained as new data becomes available, rather than requiring a longer static test period that risks degrading forecast relevance in fast-moving markets. Second, the predictive stage could be enhanced with recurrent neural networks, transformers, or different deep learning models capable of learning longer-horizon patterns. In addition, future research could explore alternative hyperparameter optimization strategies, such as metaheuristic algorithms (e.g., particle swarm optimization or genetic algorithms), to further assess the robustness and efficiency of the forecasting stage. Incorporating macroeconomic variables, sentiment indicators, or blockchain-level metrics may also strengthen predictive accuracy.^{21,44,45}

Extending the framework to a multi-period setting with explicit trading costs and rebalancing constraints also represents an important direction for future research. The optimization process could be extended to include transaction costs, liquidity constraints, leverage rules, tax considerations, and dynamic rebalancing frequencies to better reflect realistic trading conditions.^{8,13,46,47}

A further important direction concerns the explicit treatment of uncertainty in the forecasting-optimization pipeline. In the present study, XGBoost forecasts are treated as fixed point estimates when constructing the MV, MSV, and MAD portfolios, and the optimization models themselves do not explicitly account for the estimation error inherent in machine-learning-based return predictions. This may understate the true uncertainty surrounding the resulting portfolio weights, particularly for highly volatile assets such as cryptocurrencies, where forecast errors can be substantial even when directional accuracy is high. Incorporating uncertainty-modeling frameworks such as fuzzy formulations,^{48–52} robust optimization,^{41,53–55} or stochastic programming^{56–59} could help address this limitation by explicitly representing the imprecision or variability of forecasted returns, rather than treating them as deterministic inputs. Integrating any of these approaches with the machine-learning-based forecasting stage employed in this study could yield portfolios that are more resilient to prediction error and better suited to the uncertain, fast-moving conditions characteristic of mixed cryptocurrency-equity markets.

Future research could also explore alternative optimization techniques, such as evolutionary algorithms or machine-learning-based optimization procedures, to assess their performance relative to traditional approaches. In addition, evaluating a broader set of risk measures, including Conditional Value-at-Risk (CVaR), downside risk metrics, or drawdown-based criteria, may improve the framework's ability to capture different dimensions of risk. Finally, applying the model to longer horizons or stress-period simulations would help assess its robustness under extreme market environments.^{31,60–62}

Integrating these methodological adjustments promises to generate highly adaptive portfolio models capable of processing the structural complexities and rapid shifts inherent in modern financial environments.

Acknowledgements

None.

Funding

None.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Conceptualization: All authors

Data curation: Pejman Peykani, Daniyal Sabour

Formal analysis: All authors

Investigation: Pejman Peykani, Daniyal Sabour

Methodology: All authors

Project administration: All authors

Resources: All authors

Software: Pejman Peykani, Daniyal Sabour

Supervision: Pejman Peykani, Cristina Tanasescu

Validation: All authors

Visualization: Pejman Peykani, Daniyal Sabour

Writing - original draft: Pejman Peykani, Daniyal Sabour

Writing - review & editing: All authors

Availability of data

All data generated or analyzed during this study are available from the corresponding author upon reasonable request.

AI tools statement

During the preparation of this work, the authors used Generative AI and AI-assisted technologies to improve the readability and language of the manuscript. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

References

1. Salo A, Doumpos M, Liesiö J, Zopounidis C. Fifty years of portfolio optimization. *Eur J Oper Res.* 2024;318(1):1-18. <https://doi.org/10.1016/j.ejor.2023.12.031>
2. Das JD, Bowala S, Thulasiram RK, Thavaneswaran A. Hybrid Data-Driven and Deep Learning Based Portfolio Optimization. *J Math Financ.* 2024;14(03):271-310. <https://doi.org/10.4236/jmf.2024.143016>
3. Peykani P, Namakshenas M, Nouri M, Kavand N, Rostamy-Malkhalifeh M. A Possibilistic Programming Approach to Portfolio Optimization Problem Under Fuzzy Data. In: *Advances in*

- Econometrics, Operational Research, Data Science and Actuarial Studies: Techniques and Theories*. Cham: Springer International Publishing; 2022:377-387.
https://doi.org/10.1007/978-3-030-85254-2_23
4. Markowitz H. Portfolio Selection. *J Finance*. 1952;7(1):77-91.
<https://doi.org/10.2307/2975974>
5. Kalayci CB, Ertenlice O, Akbay MA. A comprehensive review of deterministic models and applications for mean-variance portfolio optimization. *Expert Syst Appl*. 2019;125:345-368.
<https://doi.org/10.1016/j.eswa.2019.02.011>
6. Markowitz H. *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons; 1959. <https://doi.org/10.1017/S0020268100019831>
7. Cheng G, Ahmadzade H, Farahikia M, Yarmohammadi M. Uncertain random portfolio optimization via semi-variance. *Int J Mach Learn Cybern*. 2022;13(9):2533-2543.
<https://doi.org/10.1007/s13042-022-01542-6>
8. Yan W, Miao R, Li S. Multi-period semi-variance portfolio selection: Model and numerical solution. *Appl Math Comput*. 2007;194(1):128-134.
<https://doi.org/10.1016/j.amc.2007.04.036>
9. Konno H, Yamazaki H. Mean-Absolute Deviation Portfolio Optimization Model and Its Applications to Tokyo Stock Market. *Manage Sci*. 1991;37(5):519-531.
<https://doi.org/10.1287/mnsc.37.5.519>
10. Moon Y, Yao T. A robust mean absolute deviation model for portfolio optimization. *Comput Oper Res*. 2011;38(9):1251-1258.
<https://doi.org/10.1016/j.cor.2010.10.020>
11. Mba JC, Mai MM. A Particle Swarm Optimization Copula-Based Approach with Application to Cryptocurrency Portfolio Optimisation. *J Risk Financ Manag*. 2022;15(7).
<https://doi.org/10.3390/jrfm15070285>
12. Tenkam HM, Mba JC, Mwambi SM. Optimization and Diversification of Cryptocurrency Portfolios: A Composite Copula-Based Approach. *Appl Sci*. 2022;12(13).
<https://doi.org/10.3390/app12136408>
13. Peykani P, Nouri M, Eshghi F, Khamechian M, Farrokhi-Asl H. A Novel Mathematical Approach for Fuzzy Multi-Period Multi-Objective Portfolio Optimization Problem under Uncertain Environment and Practical Constraints. *J Fuzzy Ext Appl*. 2021;2(3):191-203.
<https://doi.org/10.22105/jfea.2021.287429.1150>
14. Alidaee B, Wang H, Wang W. Comparative Study of Portfolio Optimization Models for Cryptocurrency and Stock Markets. *IEEE Access*. 2025;13(March):49861-49873.
<https://doi.org/10.1109/ACCESS.2025.3551628>
15. Boido C, Aliano M. the Contribution of Cryptocurrencies To Portfolio Diversification. *Invest Manag Financ Innov*. 2025;22(2):26-35.
[https://doi.org/10.21511/imfi.22\(2\).2025.03](https://doi.org/10.21511/imfi.22(2).2025.03)
16. Pho KH, Ly S, Lu R, Hoang TH Van, Wong WK. Is Bitcoin a better portfolio diversifier than gold? A copula and sectoral analysis for China. *Int Rev Financ Anal*. 2021;74(January):101674.
<https://doi.org/10.1016/j.irfa.2021.101674>
17. Nakamoto S. Bitcoin: A peer-to-peer electronic cash system. *SSRN*. 2008.
<https://doi.org/10.2139/ssrn.3440802>
18. Chernova N, Serhiienko O, Bril M, Bilotserkivskiy O, Kochorba V. Investigation of Modern Investment Opportunities With Cryptocurrency Market: Optimization Approach. *Intellect Econ*. 2024;18(1):80-105.
<https://doi.org/10.13165/IE-24-18-1-04>
19. Kurosaki T, Kim YS. Cryptocurrency portfolio optimization with multivariate normal tempered stable processes and Foster-Hart risk. *Financ Res Lett*. 2022;45:1-15.
<https://doi.org/10.1016/j.frl.2021.102143>
20. Zarezade R, Ghousi R, Mohammadi E, Ghanbari H. Chance-constrained programming for Cryptocurrency portfolio optimization using Conditional Drawdown at Risk. *J Ind Syst Eng*. 2024;16(2):130-153.
https://www.jise.ir/article_206753_6afd783361e500ef3ccd24fccd3221ff.pdf
21. Chen W, Zhang H, Mehlaawat MK, Jia L. Mean-variance portfolio optimization using machine learning-based stock price prediction. *Appl Soft Comput*. 2021;100:106943.
<https://doi.org/10.1016/j.asoc.2020.106943>
22. Jensen MC. Some anomalous evidence regarding market efficiency. *J Financ Econ*. 1978;6(2-3):95-101.
[https://doi.org/10.1016/0304-405X\(78\)90025-9](https://doi.org/10.1016/0304-405X(78)90025-9)
23. Goodell JW, Kumar S, Lim WM, Pattnaik D. Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *J Behav Exp Financ*. 2021;32:100577.
<https://doi.org/10.1016/j.jbef.2021.100577>
24. Chen T, Guestrin C. XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. August 13-17, 2016: San Francisco, CA.
<https://doi.org/10.1145/2939672.2939785>
25. Eisl A, Gasser SM, Weinmayer K. Caveat Emptor: Does Bitcoin Improve Portfolio Diversification?

- SSRN Electron J. 2015;1-21.
<https://doi.org/10.2139/ssrn.2408997>
26. Brauneis A, Mestel R. Cryptocurrency-portfolios in a mean-variance framework. *Financ Res Lett*. 2019;28:259-264.
<https://doi.org/10.1016/j.frl.2018.05.008>
27. Estalayo I, Ser J Del, Osaba E, et al. Return, Diversification and Risk in Cryptocurrency Portfolios using Deep Recurrent Neural Networks and Multi-Objective Evolutionary Algorithms. In: *IEEE Congress on Evolutionary Computation (CEC)*. Piscataway, NJ: IEEE; 2019;(DI):755-761.
<https://doi.org/10.1109/CEC.2019.8790121>
28. Hrytsiuk P, Babych T. The cryptocurrencies risk measure based on the Laplace distribution. *CEUR Workshop Proc*. 2020;2713(July):261-276.
<https://doi.org/10.55056/ceur-ws.org%2Fvol-2713%2Fpaper25.pdf>
29. Ma Y, Ahmad F, Liu M, Wang Z. Portfolio optimization in the era of digital financialization using cryptocurrencies. *Technol Forecast Soc Change*. 2020;161:120265.
<https://doi.org/10.1016/j.techfore.2020.120265>
30. Bakry W, Rashid A, Al-Mohamad S, El-Kanj N. Bitcoin and Portfolio Diversification: A Portfolio Optimization Approach. *J Risk Financ Manag*. 2021;14(7).
<https://doi.org/10.3390/jrfm14070282>
31. Bedoui R, Benkraiem R, Guesmi K, Kedidi I. Portfolio Optimization through Hybrid Deep Learning and Genetic Algorithms Vine Copula-GARCH-EVT-CVaR Model. *Technol Forecast Soc Change*. 2023;197:122887.
<https://doi.org/10.1016/j.techfore.2023.122887>
32. Zhou Z, Song Z, Xiao H, Ren T. Multi-source data driven cryptocurrency price movement prediction and portfolio optimization. *Expert Syst Appl*. 2023;219:119600.
<https://doi.org/10.1016/j.eswa.2023.119600>
33. Jeleskovic V, Latini C, Younas ZI, Al-Faryan MAS. Cryptocurrency portfolio optimization: Utilizing a GARCH-copula model within the Markowitz framework. *J Corp Account Financ*. 2024;(March):139-155.
<https://doi.org/10.1002/jcaf.22721>
34. Abbas SF, Usman M. Optimizing portfolios in digital finance: an integration of cryptocurrencies with conventional assets. *Crit Rev Soc Sci Stud*. 2025;3(1):2894-2913.
<https://doi.org/10.69565/jems.v3i3.338>
35. Osman M Ben, Hamdi H, Naoui K, Galariotis E, Guesmi K. Diversification in financial and crypto markets. *Int Rev Financ Anal*. 2023;89:102785.
<https://doi.org/10.1016/j.irfa.2023.102785>
36. Som A, Kayal P. A multicountry comparison of cryptocurrency vs gold: Portfolio optimization through generalized simulated annealing. *Blockchain Res Appl*. 2022;3(3):100075.
<https://doi.org/10.1016/j.bcra.2022.100075>
37. Johansson K, Boyd S. Simple and Effective Portfolio Construction with Crypto Assets. *arXiv*. 2024;1-27.
<https://doi.org/10.48550/arXiv.2412.02654>
38. Klein A, Falkner S, Bartels S, Hennig P, Hutter F. Fast Bayesian optimization of machine learning hyperparameters on large datasets. In: *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*. 2017;54:528-536. <https://proceedings.mlr.press/v54/klein17a.html>
39. Snoek J, Larochell H, Adams RP. Practical Bayesian Optimization of Machine Learning Algorithms. In: *Advances in Neural Information Processing Systems 25*. 2012:2951-2959.
<https://doi.org/10.1163/15685292-12341254>
40. Kandasamy H. *Portfolio Selection Under Various Risk Measures*. Dissertation. Clemson University; 2008. <https://open.clemson.edu/cgi/viewcontent.cgi?article=1235&context=all.dissertations>
41. Peykani P, Mohammadi E, Jabbarzadeh A, Rostamy-Malkhalifeh M, Pishvae MS. A Novel Two-Phase Robust Portfolio Selection and Optimization Approach under Uncertainty: A Case Study of Tehran Stock Exchange. 2020;15.
<https://doi.org/10.1371/journal.pone.0239810>
42. Lorenzo L, Arroyo J. Online Risk-Based Portfolio Allocation on Subsets of Crypto Assets Applying a Prototype-Based Clustering Algorithm. *Financ Innov*. 2023;9:25.
<https://doi.org/10.1186/s40854-022-00438-2>
43. Huang X, Newton DP, Platanakis E, Sutcliffe C. Single-stage Portfolio Optimization with Automated Machine Learning for M6. *Int J Forecast*. 2025;41(4):1450-1460.
<https://doi.org/10.1016/j.ijforecast.2024.08.004>
44. Viéitez A, Santos M, Naranjo R. Machine learning Ethereum cryptocurrency prediction and knowledge-based investment strategies. *Knowledge-Based Syst*. 2024;299.
<https://doi.org/10.1016/j.knosys.2024.112088>
45. Akyildirim E, Goncu A, Sensoy A. Prediction of cryptocurrency returns using machine learning. *Ann Oper Res*. 2021;297(1-2):3-36.
<https://doi.org/10.1007/s10479-020-03575-y>
46. Peykani P, Nouri M, Pishvae MS, Oprean-stan C, Mohammadi E. Credibilistic Multi-Period Mean-Entropy Rolling Portfolio Optimization Problem Based on Multi-Stage Scenario Tree. *Mathematics*. 2023;11(18):3889.
<https://doi.org/10.3390/math11183889>

47. Li X, Uysal AS, Mulvey JM. Multi-Period Portfolio Optimization using Model Predictive Control with Mean-Variance and Risk Parity Frameworks. *Eur J Oper Res.* 2022;299(3):1158-1176. <https://doi.org/10.1016/j.ejor.2021.10.002>
48. Mahmoodirad A, Pamucar D, Niroomand S, Simic V. A novel hybrid neutrosophic-fuzzy-uncertain data envelopment analysis model for assessment of wind farm locations. *Energy Nexus.* 2026;100704. <https://doi.org/10.1016/j.nexus.2026.100704>
49. Ghanbari H, Mohammadi E, Fooeik AML, Kumar RR, Stauvermann PJ, Shabani M. Cryptocurrency Portfolio Allocation under Credibilistic CVaR Criterion and Practical Constraints. *Risks.* 2024;12(10). <https://doi.org/10.3390/risks12100163>
50. Li X, Qin Z, Kar S. Mean-variance-skewness model for portfolio selection with fuzzy returns. *Eur J Oper Res.* 2010;202(1):239-247. <https://doi.org/10.1016/j.ejor.2009.05.003>
51. Carlsson C, Fullér R, Majlender P. A possibilistic approach to selecting portfolios with highest utility score. *Fuzzy Sets Syst.* 2002;131(1):1-21. [https://doi.org/10.1016/S0165-0114\(01\)00251-2](https://doi.org/10.1016/S0165-0114(01)00251-2)
52. Mirzaei N, Mahmoodirad A, Niroomand S, Nowzari R. A sustainable intuitionistic fuzzy Z-number multi-objective model for optimizing electric vehicle charging infrastructure in the European side of Istanbul. *Sustain Cities Soc.* 2026;107391. <https://doi.org/10.1016/j.scs.2026.107391>
53. Kovalenko I, Conlon T, Cotter J. Active portfolio management using robust optimization. *Ann Oper Res.* 2025. <https://doi.org/10.1007/s10479-025-06757-8>
54. Peykani P, Mohammadi E, Farzipoor Saen R, Sadjadi SJ, Rostamy-Malkhalifeh M. Data envelopment analysis and robust optimization: A review. *Expert Syst.* 2020;37(4). <https://doi.org/10.1111/exsy.12534>
55. Niroomand S, Saleh H, Shafiee M, Pamucar D, Mahmoodirad A. Optimizing subgroup selection in petrochemical industries : A robust data envelopment analysis approach for uncertainty management. *An Int J Optim Control Theor Appl.* 2026;16(1):246-264. <https://doi.org/10.36922/IJOCTA025310138>
56. Consigli G, Dempster MAH. Dynamic stochastic programming for asset – liability management. *Ann Oper Res.* 1998;81(0):131-161. <https://doi.org/10.1023/A:1018992620909>
57. Huang X. Fuzzy chance-constrained portfolio selection. *Appl Math Comput.* 2006;177(2):500-507. <https://doi.org/10.1016/j.amc.2005.11.027>
58. Masmoudi M, Ben F. A chance constrained recourse approach for the portfolio selection problem. *Ann Oper Res.* 2017;251(1):243-254. <https://doi.org/10.1007/s10479-015-1844-2>
59. Peykani P, Mohammadi E, Emrouznejad A. An Adjustable Fuzzy Chance-Constrained Network DEA Approach with Application to Ranking Investment Firms. *Expert Syst Appl.* 2021;166:113938. <https://doi.org/10.1016/j.eswa.2020.113938>
60. Sun R, Stefanidis A, Jiang Z, Su J. Combining Transformer based Deep Reinforcement Learning with Black-Litterman Model for Portfolio Optimization. *Neural Comput Appl.* 2024;36(32):20111-20146. <https://doi.org/10.1007/s00521-024-09805-9>
61. Cao X, Shuai L. Neural Networks for Portfolio Analysis With Cardinality Constraints. *IEEE Trans Neural Networks Learn Syst.* 2023;35(12):17674-17687. <https://doi.org/10.1109/TNNLS.2023.3307192>
62. Cui T, Du N, Yang X, Ding S. Multi-period portfolio optimization using a deep reinforcement learning hyper-heuristic approach. *Technol Forecast Soc Change.* 2024;198(2023):122944. <https://doi.org/10.1016/j.techfore.2023.122944>

Pejman Peykani is a faculty member in the Department of Industrial Engineering at Khatam University, Iran. He earned his Postdoctoral and Ph.D. in Industrial Engineering from Iran University of Science and Technology and holds an M.Sc. in Financial Engineering from K. N. Toosi University of Technology. His research interests include performance assessment, productivity management, data envelopment analysis (DEA), uncertainty programming, robust optimization, fuzzy optimization, stochastic optimization, portfolio selection and optimization, capital markets (mutual funds, stock exchanges), money markets (banking, insurance), financial modeling, and multi-criteria decision-making (MCDM) problems.

 <https://orcid.org/0000-0001-7486-6796>

Daniyal Sabour is an M.Sc. student in Financial Engineering at Khatam University, Iran. He received his B.Sc. in Industrial Engineering from Amirkabir University of Technology. His research interests include machine learning, financial analysis, quantitative finance, portfolio optimization, financial modeling, market analysis, and financial data analysis. His work focuses on the application of computational and analytical methods in financial markets and investment decision-making, with particular emphasis on cryptocurrency markets and digital financial assets. His recent work involves the use of machine learning and data-driven approaches for financial asset analysis, return prediction, and portfolio management.

 <https://orcid.org/0009-0007-4328-3900>

Cristina Tanasescu is a Professor at the Faculty of Economic Sciences, Lucian Blaga University of Sibiu, Romania. Her main research interests include theoretical economics, the philosophy and methodology of economics, economic epistemology, economic and

institutional modeling, and financial markets. She is a member of national and international scientific associations and serves as an Associate Editor for the journal *Management of Sustainable Development*.
<https://orcid.org/0000-0001-8347-4014>

 <https://orcid.org/0000-0001-8347-4014>

An International Journal of Optimization and Control: Theories & Applications (<https://accscience.com/journal/ijocta>)



This work is licensed under a Creative Commons Attribution 4.0 International License. The authors retain ownership of the copyright for their article, but they allow anyone to download, reuse, reprint, modify, distribute, and/or copy articles in IJOCTA, so long as the original authors and source are credited. To see the complete license contents, please visit <http://creativecommons.org/licenses/by/4.0/>.