

Evaluation of traditional and machine learning-based investment strategies on cryptocurrency portfolio management

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Abstract

With the popularity of cryptocurrencies increasing, investors are becoming more interested in developing investment portfolios based on or including cryptocurrencies. This often involves using traditional econometric or statistical tools used in more established markets. Yet due to the highly volatile nature of cryptocurrency markets, researchers have been working towards optimised algorithms for incorporating cryptocurrencies into portfolios, often based on machine learning algorithms. Comparisons about the performance of machine learning algorithms and econometrics is however lacking. This study evaluates various portfolio development strategies through backtesting on historical data of 134 cryptocurrencies obtained from online exchange markets. It contributes to understanding about cryptocurrency market behaviour, and how to optimise strategies for incorporating cryptocurrencies within investment portfolios.

Introduction

Cryptocurrencies are digital currencies protected by cryptography, making them extremely difficult to counterfeit or double-spend. Most cryptocurrencies operate on decentralized networks using blockchain technology—a distributed ledger maintained by a network of computers. This decentralisation makes them theoretically resistant to government control or manipulation. A blockchain is a series of interconnected blocks of data on an online ledger. Each block contains a set of transactions that have been independently verified by validators within the network.

Cryptocurrencies have evolved from a niche asset to a popular investment choice, driven by millennials' growing interest, increased risk tolerance, perceived profitability, and the wider acceptance of cryptocurrencies as a viable investment option. In recent years, the prediction of cryptocurrency prices has garnered significant interest from investors, researchers, and industry professionals. Prediction of cryptocurrency prices is important for building trading strategies, risk management, price discovery, market sentiment analysis and business applications. Predicting cryptocurrency prices is widely regarded as one of the most challenging tasks in the financial domain (Livieris et al., 2021). The challenges, complexity, and interpretability of these models have been identified as key issues in time series forecasting.

While first studies mostly paid attention to cryptocurrency market efficiency and volatility, recent interests have evolved towards the incorporation of cryptocurrencies in investment portfolios. These studies have looked at traditional tools for portfolio management such as the relative strength index (RSI) or moving average crossovers (Cheah, 2024). Other studies have used machine learning algorithms for incorporating cryptocurrencies into portfolios, including Classification Learners (e.g. support vector machines, k-means clustering), Long Short-Term Memory (LSTM)-based artificial neural networks, Convolutional Neural Networks (CNN), and Attention-based neural networks. While many of these studies show good accuracy in prediction of cryptocurrency markets, a comparison amongst the various tools available is currently lacking. This study investigates the ability of various econometric, statistical, and machine-learning approaches on developing cryptocurrency portfolios. Performance of each approach will be evaluated through backtesting on historical cryptocurrency prices taken from global cryptocurrency exchange markets.

Background

Investors are primarily focused on uncertainty when allocating their funds in financial markets. This uncertainty is more pronounced than ever due to technological advancements and globalization, which have radically altered our lives and significantly influenced investors' decision-making processes (Hasan et al., 2023; Zhang, 2024). This increased uncertainty has widespread effects on various markets, including stock,

commodity, and foreign exchange markets, and deeply impacts economic stability and growth (Antonakakis et al., 2018; Foglia and Dai, 2021; Malhotra et al., 2024). Since investors are naturally risk-averse, they typically look for assets that offer diversification, reduced risk, and greater potential returns (Hasan et al., 2023; Naeem et al., 2022). Gold (Beckmann et al., 2019; Ciner et al., 2013; Hassan et al., 2021; Mensi et al., 2022c), foreign currency (Ranaldo and Oderlind, 2010), and commodities (Rubbiani et al., 2022; Bouri et al., 2020) have established themselves as safe havens during times of financial instability. Additionally, due to their conservative nature, Islamic stocks and bonds have also emerged as potential safe havens, particularly during the 2008 financial crisis (Asl et al., 2024; Hasan et al., 2022b; Hkiri et al., 2017).

Cryptocurrency markets are characterized by high volatility and unpredictability. A predictive model capable of effectively navigating these price fluctuations is essential for accurate cryptocurrency price forecasting and portfolio development. However, there is a lack of comparative studies on statistical and econometric models and their respective strengths and weaknesses (Lobell and Burke, 2010). Beyond these traditional models, machine learning algorithms (MLA) are dynamic and well-suited to handle complexities within timeseries (and other) data, offering the potential for high forecasting accuracy. Researchers have applied MLA models such as Decision Trees (DT), Gradient Boosting (GB), Support Vector Regression (SVR), and Multi-Layer Perceptrons (MLP). Furthermore, feature engineering and extraction using ML models can significantly improve prediction performance. In early studies, Cohn et al. (1996) found that statistics-based learning architectures, combined with mixtures of Gaussians and locally weighted regression, could enhance forecasting accuracy. Many more advanced statistics-based and machine learning algorithms have now been developed for forecasting prices (Fildes et al., 2008; Hu et al., 2021).

Recent research on forecasting has increasingly incorporated deep learning (DL) and hybrid models, combining traditional approaches such as the ARIMA model with artificial neural networks (Suhartono et al., 2017). Li et al. (2022) used a hybrid model to enhance the forecasting accuracy of foreign currency, showing that the hybrid data decomposition model outperforms econometric, machine learning, and deep learning models. Chen (2023) predicted the next day's Bitcoin price and found that the random forest (RF) model provided better accuracy than long short-term memory (LSTM). Yet there is still a gap in studies using dynamic methods to predict the prices of multiple cryptocurrencies and fine-tune parameters for improved forecasting accuracy (Derbentseva et al., 2021).

Material and Methods

Daily cryptocurrency market returns were gathered from Gemini and CEX.io exchange platforms, with closing prices and trading volumes collected between September 14, 2017, and August 25, 2024 (where available). Stablecoins were excluded from the dataset, leaving 134 cryptocurrencies available for inclusion into portfolios. Data analysis was

conducted on market prices. Data from September 2017 until November 2020 were used to train machine-learning algorithms. Data from December 2020 were used to set up initial weights for investment strategies. These initial weights were then used to build portfolios from January 2021 until August 2024. Portfolios performance was evaluated monthly. Rebalancing was also performed monthly. Strategies are compared based on average gains (losses) achieved compared to a benchmark (equal-weighting strategy).

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