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Portfolio Optimization Based on MPT-LSTM Neural Networks: A case study of Cryptocurrency Markets

Habib Zouaoui[1]*, Meryem-Nadjat Naas[2]

Department of Finance and Accounting, University of Relizane, Relizane, Algeria[1]
Department of Management, University of Relizane, Relizane, Algeria[2]
* Corresponding author

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Abstract

Purpose: This study aims to examines advanced portfolio management techniques using Long Short-Term Memory (LSTM) networks, the study was applied to investing in cryptocurrencies whose markets are characterized by high-frequency trading, and using behavioral finance models based on the concept of return-risk and deep learning based on the work of artificial neural networks (ANN) and long-term memory (LSTM) algorithms
Design/Methodology/Approach: This study adopts quantitative approach. Moreover, A random portfolio consisting of 25 cryptocurrencies was selected based on the database of the website: https://finance.yahoo.com/crypto/ during the period 2021-2024 AD and programming the Python language. And an attempt to evaluate the performance of the models used in accurately predicting the optimal relative weights of the investment portfolio, which proved the relative effectiveness of deep learning models by estimating the values of the mean square error (MSE) at a level of 0.0218% to predict the optimal portfolio weights for 5 days based on training 80% and testing 20% of the study data.
Findings: The second hypothesis of this study was accepted, which states the effectiveness of deep learning algorithms to predict the weights of optimal portfolios with a return estimated at 1.7239% and a risk of 1.1219% and a Sharpe index value estimated at 1.5365%, while the Markowitz return-risk model portfolio came with a return rate estimated at 31.15% and a risk of 39.05%. With no diversification of investment on all portfolio assets and a Sharpe index value of 0.7978%.
Practical Implications: This study provides important insights that machine learning offers significant advantages in portfolio optimization, from improved forecasting of asset returns to dynamic rebalancing, better risk management, and automation. The ability to handle high-dimensional, non-linear, and non-stationary data makes ML an ideal tool for optimizing portfolios in complex and fast-moving markets; especially in cryptocurrency markets. However, challenges like data quality, overfitting, and interpretability must be addressed to ensure effective deployment of ML in real-world portfolio.
Originality/Value: This study provides an original and timely contribution to understanding the use of deep learning for portfolio optimization represents a significant advancement over traditional financial models by offering several original and valuable benefits. These include the ability to capture complex non-linear relationships, dynamic rebalancing in response to real-time data, processing of unstructured data (like sentiment analysis), advanced risk management, and the integration of high-dimensional data. The combination of these capabilities enables more accurate, adaptive, and robust portfolio optimization, ultimately enhancing portfolio performance and reducing risk.
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* Address Correspondence:
E-mail: habib.zouaoui@univ-relizane.dz[1]
meryemnadjat.naas@univ-relizane.dz[2]

INTRODUCTION

Portfolio optimization is a cornerstone of modern finance, focusing on the strategic allocation of capital across various assets to achieve specific investment objectives, such as maximizing returns or minimizing risk. Traditional methods, such as the Markowitz mean-variance model, rely on statistical assumptions and linear relationships, which may not adequately capture the complexities of financial markets. Given that these markets often exhibit non-linear dynamics and intricate interdependencies, Deep Learning (DL) emerges as a compelling alternative for portfolio optimization. This literature review explores the application of DL techniques in optimizing portfolios, highlighting their capacity to model non-linear relationships and enhance predictive accuracy. We examine various DL architectures, including neural networks and reinforcement learning, and their efficacy in addressing the limitations of traditional models. The review also discusses practical implications, such as feature selection and data preprocessing, and identifies future research directions to further integrate DL methods into portfolio optimization frameworks. Ultimately, this review underscores the potential of deep learning to revolutionize portfolio management in an increasingly complex financial landscape (Zhang et al. 2025).

However, Artificial intelligence is one of the sciences that the world has begun to rely on in various areas of life due to the ability of this science to collect and analyze big data (Big Data) and make decisions and reach accurate results that exceed the ability of the human element. As for the field of financial markets, with the increasing complexities of financial globalization that have increased the conditions of future uncertainty and high risks, asymmetry of circulating information and problems of fear and panic among investors, and in light of the emergence of the Fourth Industrial Revolution, automation of financial services and high-frequency trading, more than 80% of daily global stock market trading has become trading done through artificial intelligence (AI) and algorithmic trading, as they are trading done without any human intervention. Artificial intelligence enables investors to trade by creating, examining and testing data and making investment decisions automatically through machine learning. Machine learning is programmed through algorithms and placing orders according to specific criteria such as average daily trading and comparing them with trading averages in past periods, price changes, offered quantities, market fluctuations as a whole, price changes in the derivatives market and the future outlook of the economy, taking into account, for example, news related to stimulus packages or any news affecting the market by decision makers, in order to study and analyze them and reach a final result by machine learning, which leads to the implementation of a specific investment order. Trading in this innovative method results in objectivity in the investment decision. Behavioral Finance is predominant in humans during trading, meaning that they are more likely to be affected behaviorally by the environment and economic changes, which leads to a change in the investment decision that was previously taken, and this change in behavior and investment decision may result in unexpected losses. One of the benefits of this innovative trading method is the speed of executing trading orders, as an investment opportunity is searched for, information about it is collected, and a huge amount of data is analyzed accurately, and the appropriate investment decision is made through machine learning. This entire process is completed in a matter of seconds. As the human being's ability to search for a similar opportunity and implement the appropriate investment decision regarding it takes longer, which may lead to wasting the investment opportunity.

Generally, our study will try to test the following hypotheses:

H1: The DL models provides the forecasting of cryptocurrencies portfolio optimization with higher accuracy than MPT model.

H2: The MPT model provides the forecasting of cryptocurrencies portfolio optimization with higher accuracy than DL models.

LITERATURE REVIEW

Table below is a summarized comparison of results from recent studies (2020–2025) on portfolio optimization using deep learning models versus Harry Markowitz's Modern Portfolio Theory (MPT) model. These results highlight the key findings and performance metrics from the studies.

However, MPT remains a cornerstone of portfolio optimization due to its simplicity and effectiveness in diversification. However, its limitations in handling dynamic and complex markets have led to the rise of alternative approaches like Deep Learning (DL) models (e.g., LSTM, GRU), which offer superior adaptability and predictive power. Hybrid models combining MPT and DL are emerging as a promising direction for robust portfolio optimization

Table 1. Reviewed Previous Studies

Authors/Year	StudyTitle	Methodology	Key Findings
Heydarpour et al. (2024)	Robust Portfolio Optimization using LSTM-based Stock And Cryptocurrency Price Prediction: An Application of Algorithmic Trading Strategies	VLMA, FLMA, EMA, and SMA algorithms based on the LSTM's predicted price	LSTM and RNN capture temporal dependencies, outperforming MPT markets. in dynamic better to time- LSTM/RNN adapt series data; MPT assumes static correlations.
Yu (2023)	Mean-variance Portfolio Optimization by LSTM-based Predictions	LSTM Model and based calculated the predicted returns on a rolling basis	Hybrid model which combine the stock price forecasting with asset allocation can indeed bring excess returns
Xu et al.(2022)	LSTM-MPT Based Quantitative Portfolio Decision Model,	Combining Markowitz mean-variance model, Monte Carlo algorithm, and LSTM prediction price curve	a comparative analysis with the four commonly used portfolio model strategies shows that the LSTM-MPT decision model is valid and reliable for long-term investments
Cui et al. (2023)	Portfolio constructions in cryptocurrency market: A CVaR-based deep reinforcement learning	the CVaR risk measure and a deep reinforcement learning optimization	unfolding that CVaR measure with deep learning outperforms the traditional portfolio construction technique
Xu et al. (2025)	Cryptocurrency Portfolio Optimisation Based on LSTM Time Series Forecasting	combining Long Short-Term Memory (LSTM) time series forecasting with traditional portfolio optimization methods	The results indicate that the LSTM-enhanced portfolio optimization method yields higher returns and better risk management compared to traditional methods
Zhang et al. (2025)	Portfolio Optimization with Lstm-Based Return and Risk Information	deep learning-based portfolio strategy with prediction-based return as well as prediction-based risk information	LSTM and RNN capture temporal dependencies, outperforming MPT in dynamic markets
Durall (2022)	Asset Allocation: From Markowitz to Deep Reinforcement Learning	MPT, and on ML approaches based on deep reinforcement learning	DRL method has the potential to construct a promising investment strategy
Sebastian et al. (2024)	Deep Learning for Stock Price Prediction and Portfolio Optimization	LSTM- MPT. Mean-Variance Optimization	The study hence concludes that combining forecasting theory with portfolio selection could improve portfolio returns

Source: Authors' analysis from literature review (2025).

Broadly, the integration of deep learning techniques into cryptocurrency portfolio optimization has garnered increasing attention due to the unique challenges posed by the highly volatile and non-linear nature of cryptocurrency markets. This literature review systematically examines recent advancements in applying deep learning methods for optimizing cryptocurrency portfolios. We analyze various architectures, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and reinforcement learning, assessing their effectiveness in predicting price movements and enhancing portfolio performance. The review highlights key findings on the ability of deep learning models to capture complex relationships and patterns within cryptocurrency price data, leading to improved risk-adjusted returns. Additionally, we discuss the implications of feature selection, data preprocessing, and model evaluation metrics critical for successful implementation. The review concludes by identifying gaps in the current literature and proposing directions for future research, particularly in the areas of model interpretability and the incorporation of macroeconomic factors into deep learning frameworks for cryptocurrency portfolio optimization. (Ashy et al. 2024).

MATERIALS AND METHODS

Modern Portfolio Theory (MPT) model

Modern Portfolio Theory (MPT) provides a rigorous, quantitative framework for portfolio construction that emphasizes diversification and the tradeoff between risk and return. While it has become a cornerstone of modern investment theory, its assumptions of normal returns and constant correlations can limit its practical application in volatile or non-normal market conditions. However, MPT continues to serve as a benchmark, and modern variations (e.g., Black-Litterman model, Dynamic MPT) have been developed to address some of its shortcomings (Zouaoui and Naas 2021).

Furthermore, We should present the MPT mathematical model, moreover, we consider a more general case with n risky securities Notations: for i = 1,..., n,

$\mathbf{W} = (w_1, \dots, w_n)$: is the vector of portfolio weights.
$\mathbf{R} = (R_1, \dots, R_n)$: is the vector of asset returns.
$\overline{\mathbf{R}} = (\overline{R}_1, \dots, \overline{R}_n)$: is the vector ofasset returns expectations.
$\mathbf{e} = (1, \dots, 1)$: is the vector with all components equal to 1.
$\mathbf{V} = [\sigma_{ij}]_{1 \le i,j \le n}$: is the $(n \times n)$ variance-covariance matrix of returns. The matrix **V** is supposed to be invertible.

Denote by **W**' the vector deduced from transposition of the vector **W**. For each given expected return, we have to determine the minimal variance portfolio.

Therefore, following the Markowitz approach to determine optimal weights of portfolio, we have to determine the set of portfolios which minimize the variance for given expected returns $\mathbb{E}[R_P]$. This leads to the following quadratic optimization problem (Prigent 2007):

$$\begin{gathered} \min_{\mathrm{w}} \mathrm{w}'\mathrm{V}\mathrm{w}, \\ with\ \mathrm{w}'.\overline{\mathrm{R}}' \ = \mathbb{E}[R_P] \\ \mathrm{w}'.\mathrm{e} \ = 1 \end{gathered} \tag{1}$$

The first constraint corresponds to the fixed expectation level. The second constraint is simply that w is a vector of weights. However, short selling is allowed and no other specific constraints are introduced. The expected return of any portfolio **P** with weights w is given by:

$$\mathbb{E}[R_P] = \sum_{i=1}^{n} w_i \mathbb{E}[R_i] = \mathrm{w}.\overline{\mathrm{R}}' \tag{2}$$

The variance of the return of **P** is equal to:

$$\sigma^2(R_P) = \mathrm{w}'\mathrm{V}\,\mathrm{w} = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n}\sum_{j=i+1}^{n} w_i w_j \sigma_{ij} + \sum_{i=1}^{n} w_i^2 \sigma_i^2 \tag{3}$$

The previous relation shows the decomposition of the variance of the portfolio return into two components. This relation proves that the marginal contribution of a given asset to the risk of the whole portfolio is not reduced to its own risk (its variance), but also takes account of its potential correlations to other securities. This latter property induces the diversification effect.

From relation below, the partial derivative with respect to any weight w_i is deduced:

$$\frac{\partial\sigma^2(R_P)}{\partial w_i} = 2\sum_{j=1}^{n} w_i\sigma_{ij} \quad (4)$$

Denote by σ_{iP} the correlation coefficient between asset i and portfolio P. Then:

$$\sum_{j=1}^{n} w_j\sigma_{ij} = \sum_{j=1}^{n} w_j \, Cov(R_i, R_j) = Cov\left(R_i, \sum_{j=1}^{n} w_j \, . R_j\right) = Cov(R_i, R_j) = \sigma_i P \quad (5)$$

and finally:

$$\frac{\partial\sigma^2(R_P)}{\partial w_i} = 2\sigma_i P. \quad (6)$$

Deep learning (DL) models

This section is devoted to briefly describe the basic principle of four *Non-linear* machine learning models or deep learning models that will be used later for cryptocurrency forecasting namely RNN, LSTM (Zouaoui and Naas 2023).

Recurrent neural networks (RNN)

Forecasting with recurrent neural networks (RNNs) is a common application in time series analysis, where the goal is to predict future values based on past observations. RNNs are particularly well-suited for sequential data due to their ability to capture temporal dependencies. Here's a general guide on how to use RNNs for forecasting (Ibri and Slimane 2022):

a. **Data Preparation**:
   - Collect and preprocess the time series data (e.g., normalize or standardize the data).
   - Create input-output pairs by sliding a window over the sequence. For example:
     - Input: $(x_t, x_{t+1}, \dots, x_{t+n-1})$
     - Output: x_{t+n} (the value to predict).

b. **Model Design**:
   - Choose the RNN architecture (e.g., LSTM, GRU).
   - Define the number of layers, hidden units, and activation functions.
   - Add a dense layer at the end to produce the final output (e.g., a single value for univariate forecasting or a vector for multivariate forecasting).

c. **Training**:
   - Use a loss function like Mean Squared Error (MSE) or Mean Absolute Error (MAE) to measure the difference between predicted and actual values.
   - Optimize the model using backpropagation through time (BPTT) and an optimizer like Adam or SGD.

d. **Evaluation**:
   - Evaluate the model on a test set using metrics like RMSE, MAE, or MAPE.
   - Visualize the predictions against the actual values to assess performance.

e. **Forecasting**:
   - Use the trained model to predict future values by feeding it the most recent sequence of data.

Longshort-term memory (LSTM) model

LSTM (Long Short-Term Memory) is a specialized type of Recurrent Neural Network (RNN) that is capable of learning long-term dependencies. It was introduced **by** Hochreiter & Schmidhuber in 1997 to address the vanishing gradient problem encountered by traditional RNNs. LSTM achieves this by using **gates** that regulate the flow of information in the network (Brown et al. 2023).

Moreover, the LSTMs are highly effective for tasks involving sequential data, such as time series forecasting, natural language processing (NLP), speech recognition, and more (Zeroual et al. 2020). Furthermore, Figure 1 shows a complete diagram of LSTM, similar to Figure1 with RNN. The LSTM has four components: input gates, forget gate, cell state, and output gate.

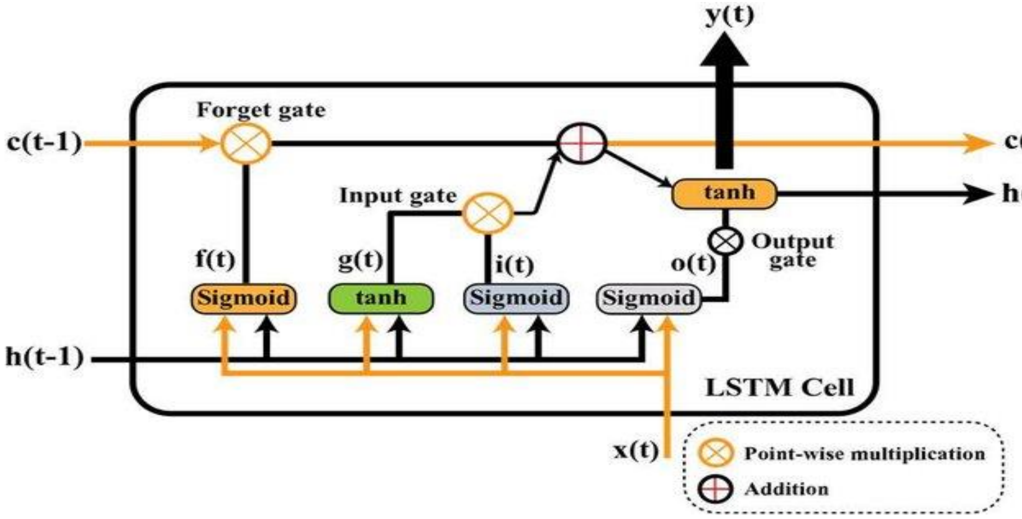


Figure 1. Schematic diagram of LSTM model

○ ***Input Gate (r_t)*** & ***Candidate Cell State(d_t):*** The input gate decides which new information to store in the cell state:

$$r_t = \sigma\big(W_f.[h_{t-1}, x_t]\big) + b_f \tag{7}$$

The candidate cell state represents the new information that could be added to the cell state.

$$\mathrm{d_t} = \tanh(W_d.[h_{t-1}, x_t]) + b_d \tag{8}$$

○ ***Forget Gate:*** The forget gate decides how much of the previous memory should be discarded from the cell state:

$$\mathrm{f_t} = \sigma(W_i.[h_{t-1}, x_t]) + b_i \tag{9}$$

When: σ = Sigmoid function that outputs values between 0 and 1 (0 means "forget" and 1 means "retain").

○ ***Cell State Update:*** The new cell state is updated based on the forget gate and input gate decisions:

$$C_\mathrm{t} = \mathrm{f_t}.C_{t-1} + r_t.d_t \tag{10}$$

The **forget gate** C_t scales the previous cell state C_{t-1}, and the **input gate** r_t scales the candidate cell state d_t.

○ ***Output gate:*** The output gate controls what part of the cell state to output as the next hidden state h_t:

$$o_\mathrm{t} = \sigma(W_0.[h_{t-1}, x_t]) + b_0 \tag{11}$$

$$h_\mathrm{t} = o_\mathrm{t}\tanh C_\mathrm{t} \tag{12}$$

The output gate decides how much of the cell state should be passed to the next time step.

Performance Metrics

Table below summarizing the key risk-adjusted performance metrics in portfolio optimization**:** Sharpe Ratio**,** Sortino Ratio**,** Variance (Var)**,** and Conditional Value at Risk (CVaR)**.** Moreover, this table highlights how these metrics are used in portfolio optimization to balance risk and return, such as purpose in optimization and interpretation of results.

Table 2. Key risk-adjusted performance metrics in portfolio optimization

Metric	Formula	Purpose in Optimization	Interpretation
Sharpe Ratio	$\text{Sharpe Ratio} = \dfrac{\mathbb{E}[R_P] - R_f}{\sigma_P}$	Maximize risk-adjusted return relative to a risk-free rate	Higher values indicate better risk-adjusted performance.
Sortino Ratio	$\text{Sortino Ratio} = \dfrac{\mathbb{E}[R_P] - R_f}{\sigma_{down}}$	Maximize risk-adjusted return, focusing only on downside risk.	Higher values indicate better performance with less downside risk.
Variance (Var)	$Var(R_P) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \, Cov(R_i, R_j)$	Minimize the dispersion of returns around the mean (reduce volatility).	Lower variance indicates less risk and more stable returns.
Conditional Value at Risk (CVaR)	$\text{CVaR} = \dfrac{1}{1-\text{c}} \int_{-\infty}^{\text{VaR}} x p(x) dx$	Minimize the average loss in the worst α% of cases (reduce tail risk).	Lower CVaR indicates less exposure to extreme losses.

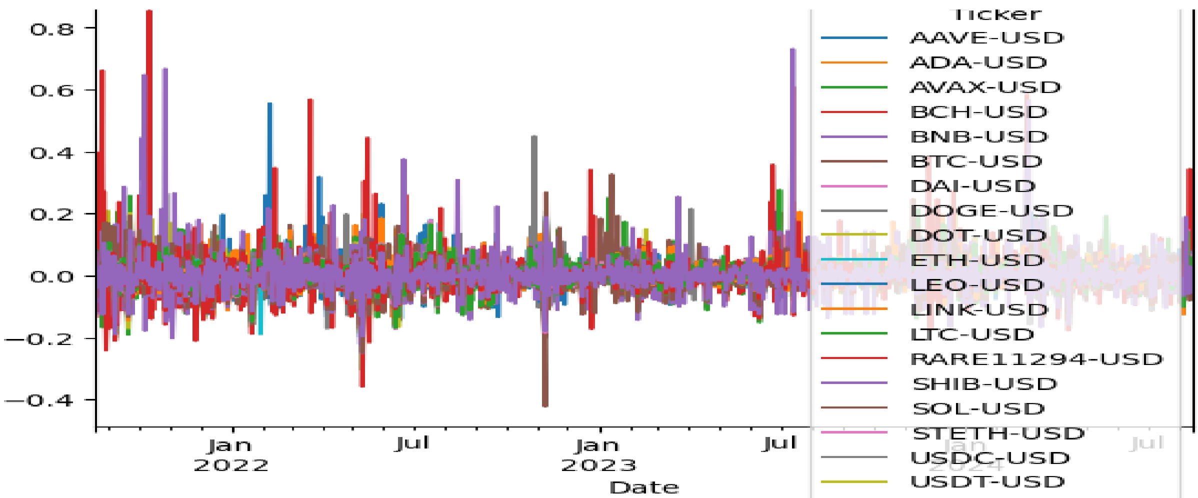
Source: Prigent (2007).

RESULTS AND ANALYSIS

Data description

This study constructs an optimal investment portfolio for high-frequency, high-risk cryptocurrency markets by conducting a comparative analysis between traditional Markowitz mean-variance optimization and advanced deep learning models. By evaluating their performance across key metrics—such as risk-adjusted returns, volatility resilience, and scalability—we aim to identify the most effective strategy for algorithmic cryptocurrency trading. Our findings will provide actionable insights for quantitative investors, hedge funds, and automated trading systems operating in ultra-volatile digital asset environments.

Therefore, The study was applied to real data of time series of daily prices of a financial portfolio consisting of twenty-five (25) cryptocurrencies with high market values and the most traded in the market, during the period between (08/15/2021-08/16/2024) at 1093 observations based on the database of the website: https://finance.yahoo.com/crypto/ and Python programming. However, the following figure shows the development of the returns of the portfolio assets during the study period.



Source: based on python code github/https://github.com/dimasthoriq/DL-portfolio optimization/blob/main/experiment.ipynb/ Yahoo, https://finance.yahoo.com/markets/crypto/all

Figure 2. The returns of cryptocurrency portfolio assets

The cryptocurrency market witnessed many fluctuations during the study period, especially with the beginning of the Covid-19 crisis, which was a difficult and harsh year, until 2022, when cryptocurrencies faced more than one dilemma that caused them to face the largest wave of losses since the Corona crisis. The losses are not only due to the return of central banks around the world to warn against this market, which has no controls yet. But with central banks moving to tighten monetary policy and raise US interest rates to high levels, 2022 witnessed a mass wave of investors fleeing risky asset markets, including "crypto" and stocks, to hold the US dollar. Due to the waves of mass exodus of investors, some platforms failed to return customers' dues, which is what happened with the "FTX" platform, which declared bankruptcy and is currently being investigated, and its CEO is scheduled to appear before an investigation committee in the US Congress. In terms of trading during 2022, the combined market value of cryptocurrencies fell by 614 percent, losing about $1,340 billion after their total value fell from $2,182.5 billion at the beginning of the year's trading to about $842.5 billion at the end. During 2023, the market value of cryptocurrencies witnessed mixed developments, as the total market value of cryptocurrencies increased from about $800 billion at the beginning of the year to nearly $1.1 trillion by the end of 2023, an increase of 37.5%. Bitcoin (BTC) maintained its position as the largest cryptocurrency in terms of market value, reaching $450 billion by the end of the year, followed by Ethereum (ETH), which came in second place with a market value of $300 billion. Thus, the gap between Bitcoin and Ethereum narrowed during the year, as it was about $250 billion at the beginning of 2023 and decreased to $150 billion by the end of the year. Other cryptocurrencies such as Ripple (XRP) and Coin Lite (LTC) recorded growth in their market value, but at lower rates than Bitcoin and Ethereum. In general, the cryptocurrency market witnessed a remarkable growth in total market value during 2023, with Bitcoin and Ethereum dominating the sector. The analysis of these fluctuations is linked to several reasons, including the occurrence of many fraud operations through cryptocurrencies, which led to tarnishing their reputation.

Moreover, the occurrence of more than one hacking operation on cryptocurrency platforms. The declaration of bankruptcy by some platforms, the most famous of which was the largest platform, FTX, which was declared bankrupt.

Furthermore, the exit of cryptocurrency platforms and their cessation in some major countries due to tightening restrictions and their move to other less powerful markets. The rules and laws began to be tightened more in some countries, perhaps the most prominent of which is the United States of America, which was the opposite of the year 2022. Some political unrest and geopolitical factors around the world also boosted the rise in the price of Bitcoin in particular, which recorded record increases exceeding 100 percent (but it has not reached peak levels yet), which analysts attributed to technical and economic effects, in addition to the impact of recent geopolitical tensions (the Russian-Ukrainian war - and the war on Gaza), so that its price exceeded forty thousand dollars. In 2024, cryptocurrency markets are witnessing a noticeable decline during today's trading, with the prices of many major digital currencies declining. Bitcoin, the largest cryptocurrency by market value, recorded a 0.83% decline to reach $64.8 thousand, after approaching the $70,000 barrier in the past weeks. Ethereum was not immune to these declines, as it fell by 0.80% to reach $3,514, and other currencies such as Tether, BNB, and Solana also declined by varying percentages, as these currencies fell by 0.04%, 0.49%, and 0.68% respectively, reflecting a general downward trend in the market until August.

Broadly, the period from 2021 to 2024 has been marked by extreme volatility and varying returns in the cryptocurrency market. Understanding these dynamics is crucial for effective portfolio management and optimization strategies. Investors should continuously monitor market conditions and adjust their strategies accordingly.

Application of the MPT model

Before applying the Mean-variance model and finding the optimal portfolio weights as well as the return and risk of the investment portfolio, we calculated the model inputs for the cryptocurrency prices to be invested in, including calculating the returns and standard deviation and extracting the variance-covariance matrix that gives us an idea of the effectiveness of diversification in maximizing the objective function as shown in the tables below:

- **Download study data using Jupyter Notebook:**

Using yfinance in Jupyter Notebook, you can easily download financial data from Yahoo Finance for analysis. This approach is particularly useful for portfolio optimization studies, where you need historical price data, returns, and other financial metrics. By automating the data download process and organizing your data efficiently, you can streamline your analysis workflow:

```
#Import Libraries
import math
importnumpy as np
import pandas as pd
importtensorflow as tf
fromtensorflow import keras
fromkeras.models import Sequential
fromkeras.layers import Dense
fromkeras.layers import LSTM
importmatplotlib as mpl
importmatplotlib.pyplot as plt
importseaborn as sns
importplotly.express as px
importplotly.graph_objects as go
import plotly.io as pio
importrandom
importos
importyfinance as yf
importdatetime
data = yf.download(dji_stocks, start=start_date, end=end_date)
stocks_df = data['Close']
[*********************100%%**********************]  25 of 25 completed
```

Source: based on python code github/https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb

○ **Heatmap Correlation Matrix**

A heatmap of the correlation matrix (appendix 1) is a valuable tool for portfolio optimization. It helps investors identify diversification opportunities, manage risk, and make informed decisions about asset allocation. By combining this visualization with tools like Modern Portfolio Theory (MPT) or Deep Learning (DL), you can build robust and efficient portfolios (Figure 6).

```
fig = px.imshow(returns_df.iloc[:,0:25].corr(), text_auto=True, aspect="auto",title='Correlation Heatmap')
fig.write_image("correlation_Heatmap.png")
fig.write_html("correlation_Heatmap.html")
fig.show()
```

The table below summarizes the statistical characteristics of the MPT framework allows for effective risk-return trade-offs, enabling investors to construct optimized portfolios tailored to their investment goals. Understanding these metrics is crucial for effective portfolio management and decision-making.

Table 3. Characteristics of Statistics for MPT optimization

STOCKS	P-Weights (Cvar)	P-Weights (Sortino)	P-Weights (Variance)	P-Weights (Sharpe)
ADA-USD	0	0	0	0
BNB-USD	0	0	0	0
BTC-USD	0	0	0	0
DAI-USD	0	0	0	0
DOGE-USD	0	0	0	0
ETH-USD	0	0	0	0
LINK-USD	0	0	24.09	4.21
LTC-USD	0	0	0	0
USDT-USD	0	0	0	0
XRP-USD	0	0	0	0
XLM-USD	0	0.67	0.08	40.03
BCH-USD	0	0	0	0

STOCKS	P-Weights (Cvar)	P-Weights (Sortino)	P-Weights (Variance)	P-Weights (Sharpe)
WETH-USD	0	0	0	0
WBTC-USD	0	0	0	0
AVAX-USD	0	0.2	0	16.39
SHIB-USD	0	0	0	22.9
DOT-USD	0	0	0	0
LEO-USD	15.38	0.86	25	4.78
SOL-USD	43.79	0	25.4	4.69
USDC-USD	0.24	0.2	0	0
STETH-USD	40.58	98.07	25.42	7.01
AAVE-USD	0	0	0	0
VUSDT-USD	0	0	0	0
RARE11294-USD	0	0	0	0
VBTC-USD	0	0	0	0
Annualized Return	**0.39**	**1.26**	**0.27**	**31.15**
Annualized Volatility	**0.47**	**0.63**	**0.96**	**39.05**
Skewness	**-16.88**	**-29.22**	**-245.2**	**65.63**
Kurtosis	**2905.05**	**3066.74**	**20780.99**	**678.6**
Max Drawdown	**-0.34**	**-0.55**	**-1.19**	**-59.42**
Count Data	**1093.00**	**1093.00**	**1093**	**1093**
Sharpe Ratio	**0,8331**	**2.0032**	**0.2781**	**0.7978**
CVaR	**1.16**	**2.29**	**1.84**	**95.38**
Sortino Ratio	**100.42**	**257.00**	**29.22**	**122.77**
Variance	**0.00**	**0**	**0.01**	**15.25**

Source: based on python code github/ https://github.com/dimasthoriq/DL-portfolio optimization/blob/main/experiment.ipynb

This study investigates the optimal relative weights derived from the Markowitz Mean-Variance model, focusing on a comprehensive summary of statistical characteristics for each optimal portfolio. We implemented various strategies to enhance the objective function, utilizing performance evaluation indicators such as the Sharpe Ratio, Sortino Ratio, variance, and Conditional Value at Risk (CVaR). The analysis highlights the benefits of Markowitz diversification in managing risk through an examination of the correlation matrix between the returns of the portfolio's assets (Zaki 2021). Furthermore, we compare the performance of these traditional optimization approaches with those derived from deep learning algorithms (DL). By assessing the strengths and weaknesses of both methodologies, this research aims to provide insights into the effectiveness of deep learning in enhancing portfolio optimization, ultimately contributing to more robust investment strategies in an increasingly complex financial environment (Yifu et al. 2024).

Application of the deep learning (DL) models

In order to create this type of portfolio, which consists of assets with different risk levels, a comprehensive analysis was conducted. Unlike previous portfolios that were created based on historical data only, this portfolio will leverage the predictions of the LSTM model to predict the optimal combination of assets that will generate the highest returns over 5, 10, 15, and 30 days. The process followed to build this diversified portfolio involves a series of sequential steps. The figure below illustrates and summarizes the general approach taken to create the model (Li and Liu 2023).

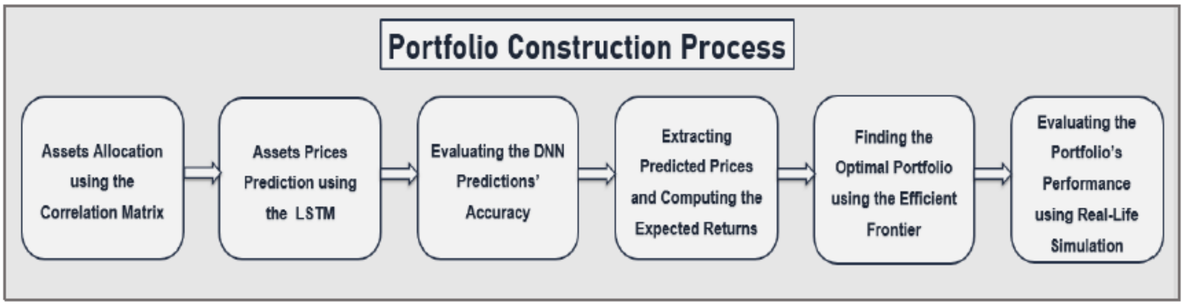


Figure 3. Portfolio Construction Process

Therefore, splitting the data into training and testing or splitting it into training, validation, and testing is common in supervised machine learning projects (Espiga-Fernández et al. 2025) The training set is used to fit and train the model while the test set is used to evaluate the trained model to get a better idea of how well the model will perform on new data and how it will behave in a production environment. Therefore, the test data should be similar to what is expected to be seen in a production environment. Another common splitting technique is splitting the data into three datasets: training, validation, and testing. The validation dataset will be used to choose the best hyperparameters for each model (Ketkar et al. 2021):

```
n = len(returns_df)
# Split the data
train_data = returns_df[:int(0.8*len(returns_df))]
val_data = returns_df[int(0.8*len(returns_df)):int(0.2*len(returns_df))]
test_data = returns_df[int(0.2*len(returns_df)):]
train_data.shape, val_data.shape, test_data.shape
((874, 25), (0, 25), (875, 25))
```

We proceeded to build an LSTM model algorithm. To build the RNN to accurately predict the returns of cryptocurrencies and from there build an optimal portfolio based on return and risk and evaluate its performance using the Sharpe ratio, some modules had to be imported from Keras. After that, an LSTM layer and other dropout layers were added. Regarding the LSTM layer, the dimensions of the output space were set to 50 units. 20% of the layer was selected to be dropped and a dense layer with a single unit output was added. Adam was chosen as the optimizer for the model clustering and the loss was set to be the mean square error (MSE). After that, the model was fit to 100 epochs, a batch size of 32, a learning rate of 0.001, and a neural network of 200 cells (Nafia et al.2023):

```
#Model 1 (5-day window)
model1 = tf.keras.models.Sequential([
LSTM(64, return_sequences=True, input_shape=(5, stocks_df.shape[1])),
LSTM(32, return_sequences=True),
Dense(units=stocks_df.shape[1])])
history1 = compile_and_fit(model1, window1.train_ds, window1.val_ds)
perf_v={}
perf={}
perf_v['5 days'] = model1.evaluate(window1.val_ds)
perf['5 days'] = model1.evaluate(window1.test_ds, verbose=0)
```

Table 4. The effectiveness of LSTM models for predicting optimal portfolio returns

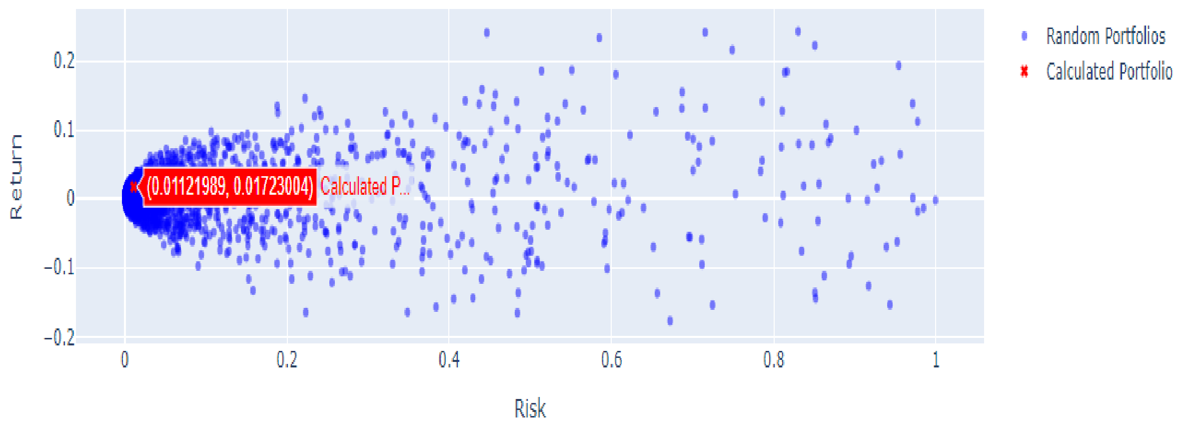
	Validation Performance		Test Performance		Time
Date	**Loss**	**MAE**	**Loss**	**MAE**	**Epochs/Time**
5 days	0,0016	0,0230	0,0012	0,0218	14/14--1s 29ms/step
10 days	0,0016	0,0233	0,0011	0,0219	13/13--1s 42ms/step
15 days	0,0017	0,0246	0,0012	0,0222	12/12--2s 110ms/step
30 days	0,0018	0,0255	0,0012	0,0228	10/10--0s 4ms/step

Source: based on python code github/ https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb

We noted from the outputs of the application of the LSTM model to predict the returns of the cryptocurrencies that make up the portfolio assets, (Junhuan et al. 2024) where we note the superiority of the LSTM model in predicting for 5 days to the last day in the series of subsequent returns with the lowest mean square error rate estimated at 0.0218 for the test (Test_loss) and 0.0230 for the verification (Val_loss). Thus, the algorithm of this model can be adopted to estimate the optimal portfolio and extract the ratios for financial investments in the cryptocurrency assets that make up the investment portfolio, and then compare them to the space of previous solutions for the Markowitz model and trying to compare them based on the Sharpe index to evaluate the quality of the performance of the extracted portfolio (Das et al. 2024).

○ **The Efficient Frontier of cryptocurrency optimal portfolio**

```
# Plot efficient forntier and our portfolio
fig = go.Figure()
fig.add_trace(go.Scatter(x=portfolio_volatilities,y=portfolio_returns,mode='markers',marker=dict(size=5,color='blue',opacity=0.5),name='Random Portfolios'))
fig.add_trace(go.Scatter(x=[sigma],y=[portfolio_return],mode='markers',marker=dict(size=6,color='red',symbol='x'),name='Calculated Portfolio'))
fig.update_layout(title='EfficientFrontier',xaxis_title='Risk',yaxis_title='Return',showlegend=True,hovermode='closest')
fig.write_image("efficient_forntier.png")
fig.write_html("efficient_forntier.html")
fig.show()
```



Source: based on python code github/ https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb

Figure 4. Efficient frontier

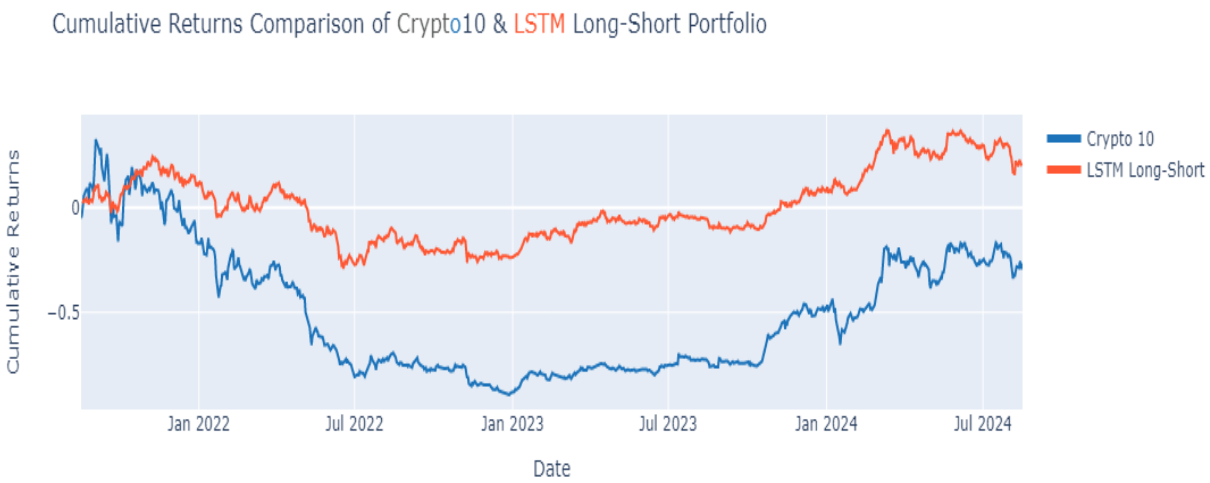
RESULTS AND DISCUSSION

Through the previous simulation of time series of cryptocurrency returns using one of the traditional behavioral finance models (Markowitz model) and deep learning models using the LSTM algorithm based on the Sharpe index in evaluating the quality of the solution (optimal portfolio performance), (Tamuly et al. 2024).the outputs of the comparative study were summarized in the following table:

Table 5. The performance comparison of MPT-LSTM Models

STOCKS	P-Weights(Sharpe)	P-Weights(LSTM)
ADA-USD	0	0.014606
BNB-USD	0	-0.05918
BTC-USD	0	-1.44428
DAI-USD	0	-4.74505
DOGE-USD	0	4.70012e-05
ETH-USD	0	2.26891
LINK-USD	4.21	0.0689542
LTC-USD	0	0.0518116
USDT-USD	0	0.57744
XRP-USD	0	0.0210249
XLM-USD	40.03	-0.0330404
BCH-USD	0	-0.035509
WETH-USD	0	-2.70253
WBTC-USD	0	1.41132
AVAX-USD	16.39	0.00331112
SHIB-USD	22.9	0.00729518
DOT-USD	0	-0.0759262
LEO-USD	4.78	0.0481682
SOL-USD	4.69	0.033132
USDC-USD	0	-0.315186
STETH-USD	7.01	0.443353
AAVE-USD	0	0.0234812
VUSDT-USD	0	5.36088
RARE11294-USD	0	0.00904898
VBTC-USD	0	0.0679007
Annualized Return	**31.15**	**0.017239**
Annualized Volatility	**39.05**	**0.011219**
Count Data	**1093**	**1093**
Sharpe Ratio	**0.7978**	**1.5365**

Source: based on python code github/ https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb



Source: based on python code github/ https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb

Figure 5. Cumulative returns comparison of crypto10 vs LSTM

Through the results shown above and according to the distribution of optimal weights for the investor's expected investments during the year 2024 AD for the next 5 days, we note the effectiveness of the deep learning model using the LSTM algorithm (Alzaman 2024) with an expected rate of return for the optimal portfolio estimated at: 1.7239%, the highest and lowest risk level estimated at 1.1219% compared to the outputs of the Markowitz model, which estimated the rate of return for the optimal portfolio at 31.15%, and a relatively higher risk rate estimated at 39.05%. The results confirm the validity of the second hypothesis, which states that deep learning algorithms can benefit better from the investment diversification method. As for the Markowitz portfolio weights, investment in most cryptocurrencies was not employed and only seven (7) were used, namely LINK-USD, XLM-USD, AVAX-USD, LEO-USD, SOL-USD, STETH-USD, due to the limited operation of the model-based on the correlation coefficient and generating a limited number of possible portfolios, which achieved an average Sharpe index that is not motivating for investment according to the selected portfolio, estimated at 0.7978%. In contrast, the deep learning model that trains a large number of predicted portfolios gave an excellent Sharpe index estimated at 1.5365% for the performance of the selected optimal portfolio. This means that this may be an ideal investment decision. While adding a new asset class to the portfolio increases risk, the sharply higher ratio indicates that it is a risk worth taking. The high risk of cryptocurrency price fluctuations can also be explained by the global conditions that the world has gone through, especially since the study period coincided with the repercussions of the Corona pandemic (Covid-19) and political factors (the US elections) and geopolitical factors (the Ukraine war, the war on Gaza), where cryptocurrency trading platforms experienced several collapses due to investors' fears for their assets. However, the results of the study remain relative, especially in the field of deep learning, which raises the issue of the transparency of big data that depends on its training in the field of making investment decisions in financial markets, with the possibility of changing the basic parameters in building the LSTM model to reduce errors and even the possibility of adding GRU and Bilstm algorithms in future studies to increase the power of deep learning in the investment process in high-risk markets (the cryptocurrency market) while increasing the number of observations to become big data that helps in training and testing (Xu et al. 2025).

CONCLUSION

This study has highlighted the transformative potential of deep learning techniques in the realm of cryptocurrency portfolio optimization. Traditional methods often fall short in capturing the inherent complexities and non-linear dynamics of cryptocurrency markets. Deep learning approaches, including neural networks and reinforcement learning, demonstrate a superior ability to model intricate relationships among assets, leading to enhanced predictive accuracy and improved risk-adjusted returns.

The review also underscored the importance of data preprocessing, feature selection, and the evaluation of model performance metrics, which are critical for effective implementation. Despite the promising results, several gaps remain in the literature, particularly concerning the interpretability of deep learning models and their adaptability to changing market conditions.

Therefore, future research should focus on integrating macroeconomic factors and exploring hybrid models (Das et al. 2024) that combine traditional financial theories with advanced machine learning techniques. Additionally, empirical studies assessing the long-term performance of deep learning-based portfolios could provide valuable insights. Ultimately, leveraging deep learning in cryptocurrency portfolio optimization represents a significant advancement in investment strategies, offering a more nuanced approach to navigating the complexities of modern financial markets

However, the integration of Long Short-Term Memory (LSTM) neural networks with MPT for cryptocurrency portfolio optimization presents a compelling solution to these challenges. LSTM, a deep learning model designed for sequential data, can effectively capture the time-series dependencies inherent in cryptocurrency prices, which fluctuate based on factors like market sentiment, regulatory news, and macroeconomic trends. When combined with MPT, LSTM can address many of the limitations of traditional portfolio optimization methods by incorporating dynamic forecasting, non-linear relationships, and the ability to adapt to changing market conditions.

Furthermore, based on current results, future research can anticipate substantial performance enhancements by further optimizing the parameters of deep learning models. Fine-tuning these parameters is expected to increase the accuracy of predictions and overall portfolio performance. Additionally, exploring hybrid approaches that combine deep learning with traditional financial models could yield new insights and strategies for effective portfolio management.

Finally, as the cryptocurrency landscape continues to evolve, continued investment in developing robust, data-driven optimization techniques will be essential for navigating its inherent volatility and complexity. This ongoing exploration promises to advance both theoretical frameworks and practical applications in the field of finance.

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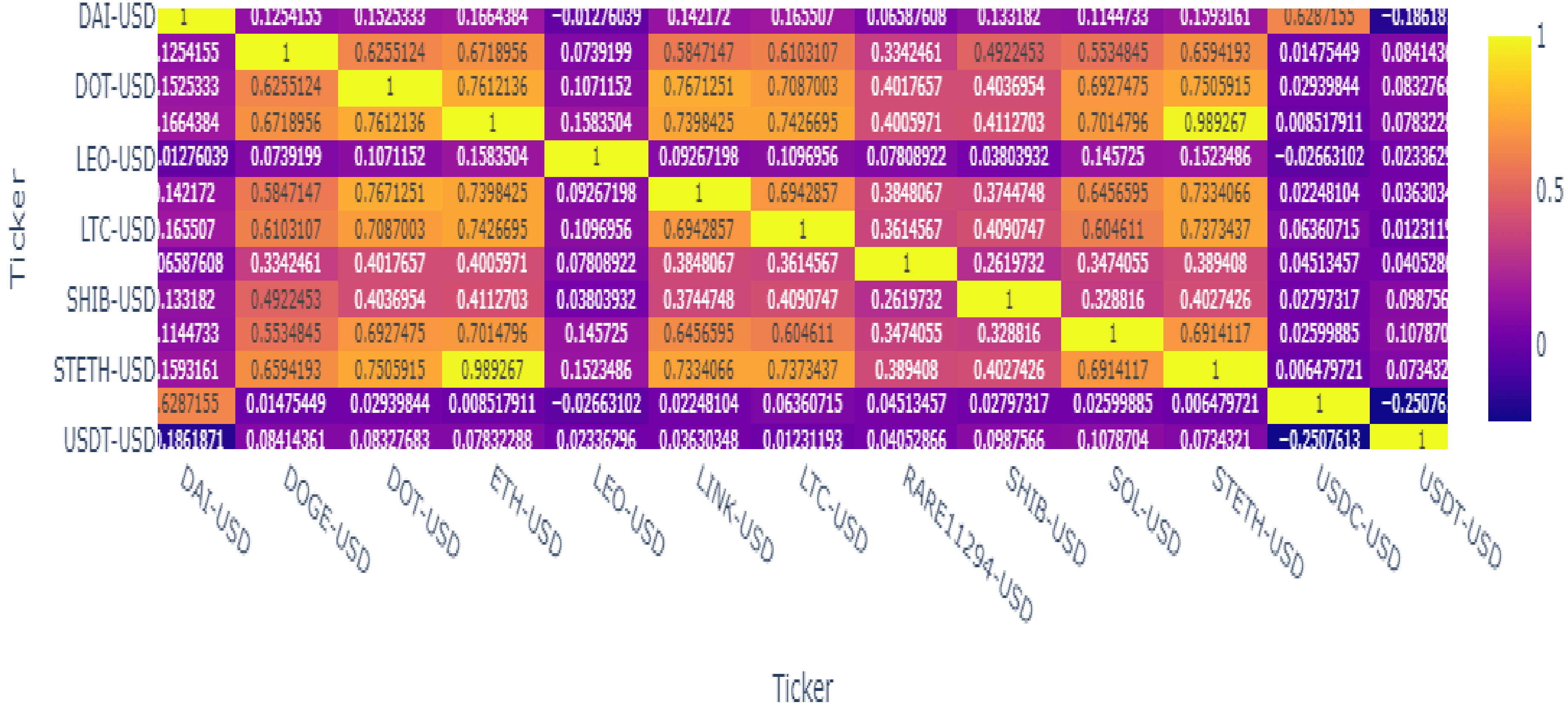
APPENDIX 1



Source: based on python code github/https://github.com/dimasthoriq/DL-portfolio-optimization/blob/main/experiment.ipynb

Figure 6. Heatmap of the correlations matrix