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# Cryptocurrency Financial Risk Analysis using Machine Learning

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**Abstract:** ***Cryptocurrency is a form of digital currency that relies on cryptography to maintain and verify transactions, instead of a centralized authority. However, this decentralized nature can lead to several risks that can impact the assessments carried out by risk auditors. Money laundering is a significant financial risk associated with the growing popularity of cryptocurrency. This paper proposes a machine learning - based approach that uses Hierarchical Risk Parity and unsupervised machine learning to analyse the financial risk associated with cryptocurrency markets. The study finds that machine learning algorithms can effectively capture the complex relationships between variables and provide accurate risk management. The study underscores the potential of machine learningbased analysis to improve financial risk management in the constantly evolving world of cryptocurrencies.***

**Keywords:** Cryptocurrency, Risk Management, Financial Risk, Money Laundering.

## 1. Introduction

The financial market is a complex system that has not been widely accepted by universities in terms of its definition of complexity, leading to disagreements on how to define and understand the interactions between its elements. Modelling complex systems is a daunting task, as they are structured hierarchically with their own subsystems, and these hierarchical models are used to extract resources. Portfolio construction can be challenging due to the lack of a correlation matrix within a hierarchical structure, and the highly volatile nature of cryptocurrency. The value of cryptocurrency can fluctuate rapidly and unpredictably, impacting both regulated and unregulated environments [7] - [10]. News outlets also closely monitor price changes and significant market movements. Rules and regulations have been implemented to safeguard investors and prevent money laundering [11]. To manage tail risk and achieve positive outcomes, [11] proposes the use of the Hierarchical Risk Parity (HRP) strategy for multi - asset, multi - factor allocation. Similarly, Jain et al. [12] utilized the HRP strategy to analyse fifty indexes of NIFTY stocks. According to the 2020 report by Chartered Professional Accountants Canada (CPA Canada), investing in cryptocurrencies poses several unique risks, including:

- Cryptocurrencies are not subject to the same regulations as traditional investments, which can make them more susceptible to fraud, market manipulation, and other illegal activities.
- Investors should be aware that cryptocurrencies are known for their extreme volatility, making them susceptible to sudden and unpredictable price changes that could result in substantial financial losses.
- Cryptocurrencies are stored electronically, and therefore, are vulnerable to hacking, theft, and other cyber - attacks. Investors must take appropriate measures to protect their cryptocurrency holdings.
- Despite the growing popularity of cryptocurrencies, they are not widely accepted as a form of payment, which can limit their usefulness and adoption.

Unlike traditional investments, such as stocks and bonds, cryptocurrencies do not have an intrinsic value, which makes it difficult to determine their true worth.

Cryptocurrencies have made a significant impact in both regulated and unregulated environments, with news outlets closely monitoring price fluctuations and market movements. Regulatory frameworks have been established to protect investors and prevent money laundering. To manage risk and produce favourable outcomes, the Hierarchical Risk Parity (HRP) strategy is recommended for allocating multiple assets and factors. In summary, the main contribution of this study is:

1. Implementation of the Hierarchical Risk Parity approach for cryptocurrency portfolio management using machine learning techniques.

The proposed system analyses the professional accounting perspective by assessing the associated risks of cryptocurrency and the anticipated impact on financial statements. Identifying the cryptocurrency's highest probability risk.

| AUTHOR | PROPOSED APPROACH | PROBLEM | SOLUTION |
|---|---|---|---|
| Kim et al. (2020) | A deep learning-based volatility prediction model | Volatility | Taking care of both historical prices and market news to forecast future volatility |
| Rainer et al. (2020) | A hybrid blockchain that combines the benefits of public and private blockchains, | Regulation | Greater transparency and accountability while still complying with regulatory requirements. |
| Bariviera et al. (2019) | Liquidity measure based on the trading volume and spread of a cryptocurrency. | Liquidity | Help investors identify which currencies are more liquid and therefore easier to buy and sell. |

**Figure 1:** Comparison of the recent cut - edge in Cryptography risk analysis.

The paper is structured as follows: Section 2 offers a brief overview of the literature on cryptocurrency risk management. Section 3 outlines the systematic framework for the proposed risk management system. Section 4 explains the implementation process and provides information about the development environment. Lastly, the conclusion section wraps up the paper.

## 2. Money Laundering in Cryptocurrency

Money laundering using cryptocurrencies involves using the technology to conceal the origin of illegal funds. Cryptocurrencies have been attractive to money launderers because they can provide a level of anonymity and can be traded easily across borders. Financial institutions face challenges in combating cryptocurrency - related crimes due to the advanced technological features of cryptocurrencies, which can be difficult to understand for banks and regulatory agencies. This knowledge gap can create barriers in the fight against money laundering and other illicit activities carried out using cryptocurrencies. Figure 2 presents study of money laundering cases in India and Figure 3 presents a comparison of the market capitalization of six different cryptocurrencies as of March 2023 as per CoinMarketCap.

| CASE | YEAR | SCAM |
|---|---|---|
| The GainBitcoin scam | 2018 | The founder of GainBitcoin, Amit Bhardwaj, was arrested for allegedly running a Ponzi scheme that involved using cryptocurrency to launder funds. |
| The Unocoin case | 2018 | The founders of Unocoin, a popular Indian cryptocurrency exchange, were arrested for allegedly setting up an unlicensed Bitcoin ATM and using it to launder funds. |
| The Hawala case | 2020 | Indian authorities arrested four individuals for allegedly using cryptocurrency to launder money in a hawala scheme. |

**Figure 2:** Case Study of Money Laundering in India

### 2.1 The Effects of Money Laundering on Financial Institutions

It is true that financial institutions and banks are often primary targets for money laundering activities. When banks are involved in money laundering, it can damage their reputation and erode the trust of customers, who may become concerned about the safety of their funds. When a bank experiences a loss of confidence, it may result in a decrease in its overall value. This situation may arise due to various reasons such as financial instability, poor management, or fraudulent activities. Similarly, customers may become more hesitant to use the bank's services if they perceive that it is not taking adequate measures to prevent money laundering. Therefore, it is important for financial institutions and banks to have robust anti - money laundering policies and procedures in place to prevent and detect money laundering activities.

| Cryptocurrency | Market Capability Value |
|---|---|
| Bitcoin (BTC) | $752 billion USD |
| Ethereum (ETH) | $421 billion USD |
| Binance Coin (BNB) | $115 billion USD |
| Cardano (ADA) | $87 billion USD |
| Solana (SOL) | $78 billion USD |
| XRP (XRP) | $68 billion USD |

**Figure 3:** Market Capability of Cryptocurrency as of March 2023

### 2.3 Legislation and Regulation governing Cryptocurrency

In India, there is currently no specific legislation or regulation governing cryptocurrencies. However, there have been some developments in this area. The PMLA is a financial regulation that requires financial institutions to identify and verify the identity of their customers and to maintain records of their transactions. This regulation applies to cryptocurrency exchanges in India as well. The Income Tax Act requires individuals and businesses to pay taxes on their income, including income generated from cryptocurrency transactions. The GST is a value - added tax that applies to goods and services sold in India. The GST also applies to cryptocurrency transactions in India.

It is worth noting that the regulatory landscape for cryptocurrencies in India is still evolving, and there may be new developments soon.

| Name of Bank | Year | Paid Penalty |
|---|---|---|
| State Bank of India (SBI) | 2020 | $1.5 million USD |
| Punjab National Bank (PNB) | 2018 | $90 million USD |
| Axis Bank | 2016 | $1.8 million USD |
| ICICI Bank | 2019 | $15 million USD |

**Figure 4:** Paid penalities by Indian Banks for Money Laundering

## 3. Methodology

This section provides details of the proposed approach for predicting exchange rates, which utilizes the graph - based theory of HRP and machine learning techniques. The approach involves three key steps: clustering, recursive bisection, and quasi - diagonalization. The first step includes clustering assets using the Hierarchical Tree Clustering algorithm. The correlation matrix between two assets x and y is converted to the correlation distance matrix A using Equation 1.:

$$A(x, y) = \sqrt{0.5 * (1 - \rho(x, y))} \;\ldots\ldots (1)$$

The subsequent stage involves evaluating the pairwise Euclidean distance between columns, which results in the generation of the augmentation matrix distance, as demonstrated by Equation 2.

$$\hat{A}(x, y) = \sqrt{\sum_{m=1}^{i}(A(m, x) - A(m, y))^2} \;\ldots (2)$$

Through the recursive approach, clusters are formed based on Equation 2. The initial cluster is designated as the first element in the set of clusters, denoted as C.

$$C[1] = argmin_{x,y}\hat{A}(x, y) \;\ldots (3)$$

Using this method, the distance matrix is updated for the (2) evaluation process, and all assets use the single clustering linkage C [1]. As a result, for any asset x that is not part of the cluster, the distance of the new cluster is calculated according to Equation 4:

$$\hat{A}(x, C[1]) = min(\hat{A}(x, x^*), \hat{A}(x, j^*)) \;\ldots\ldots. (4)$$

| # | Mean | Min | Max |
|---|---|---|---|
| Block | 0.0012 | -0.4715 | 1.7762 |
| Dash | 0.0027 | -0.2048 | 0.4381 |
| Burst | 0.0042 | -0.2705 | 1.4078 |
| GRS | 0.0120 | -0.3057 | 1.4043 |
| NAV | 0.0117 | -0.6686 | 5.6764 |
| PND | 0.0702 | -0.7811 | 6.0000 |
| RDD | 0.0114 | -0.6780 | 2.2124 |
| TRC | 0.0102 | -0.7880 | 13.0000 |
| VTC | 0.0056 | -0.3385 | 1.3042 |

**Figure 5:** Data

The data used consists of daily cryptocurrency prices from 2017 to 2020, obtained from the coinmarketcap. To ensure compatibility with the applied algorithm, missing data information was excluded and reliable forwarded observations were used to fill in any gaps. The total dataset contains ten thousand records, with 80% allocated for the training set and 20% for the testing set. Figures 3, 4, 5, and 6 provide evidence of significant growth during 2016 and 2017, followed by a sharp decline.

### 3.1. Risk Management Using Reinforcement Learning

Reinforcement learning (RL) referred to a type of machine learning algorithm that relies on feedback in order to improve system performance. The process of using RL for risk management is depicted in Figure 2. In this proposed system, risk management involves identifying, evaluating, and prioritizing system risks.

## 4. Result

Out of all traditional well - known approaches like risk - based asset allocation strategies: Inverse Volatility (IV), Minimum Variance (MV), and Maximum Diversification (MD), using HPR gave the optimal results. HPR portfolio used a 350 - day covariance estimation. The HPR annualized volatility and return were 0.7718 and 1.7802, respectively. Comparing the results with the other traditional approaches, the balance between risk and return of HPR had a significant impact, as it provided the best trade - off between risk and return.

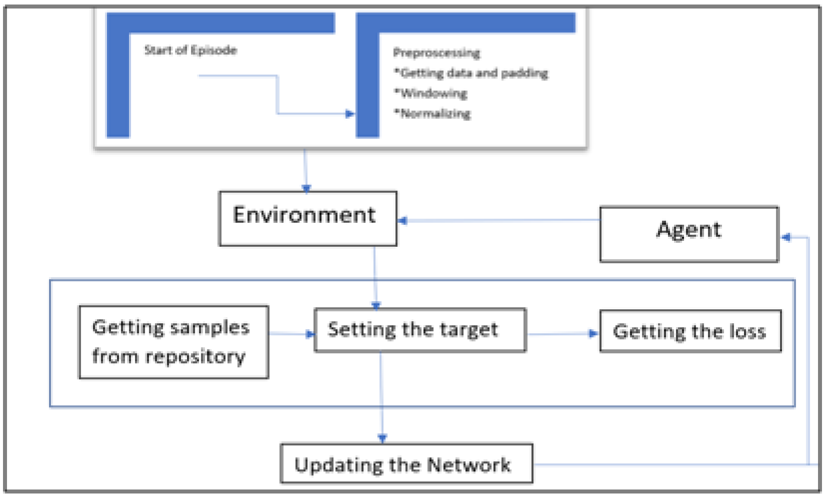


**Figure 6:** Reinforcement Learning based architecture for risk management

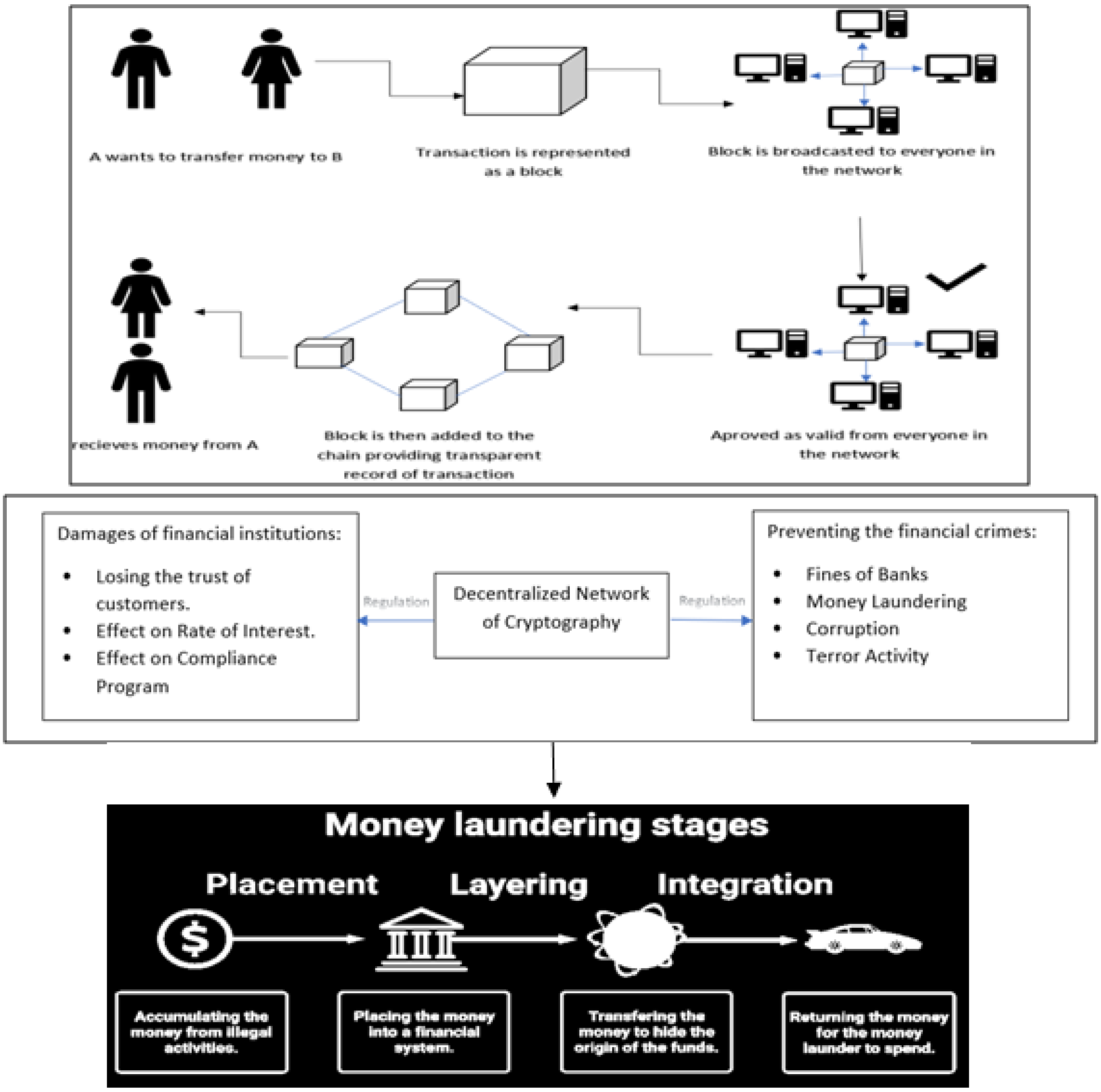


**Figure 7:** Cryptocurrency Working

## 5. Conclusion

This study aims to analyze the risk management of cryptocurrency networks by utilizing the Reinforcement Learning (RL) technique and the Hierarchical Risk Parity (HRP) asset allocation method in a cryptocurrency portfolio. RL produced high - performance evaluation results compared to other machine learning techniques used in this field. The learning - based approach of RL makes it suitable for providing accurate information in this process. HRP was chosen due to its desirable diversification and properties. The results were analyzed using various estimation windows and methodologies, and the selected period was rebalanced similarly. The study proposes future research to extend this technique by conducting out - of - sample testing performance on more assets and classes and using optimization techniques to identify risk evaluation and improve risk management performance. The keywords for this study are cryptocurrency, riskmanagement, Reinforcement Learning, Hierarchical Risk Parity, and asset allocation.

| Co-variance matrix sample | | | | | Co-variance matrix shrinkage | | | |
|---|---|---|---|---|---|---|---|---|
| # | HRP | IV | MV | MD | HRP | IV | MV | MD |
| Panel A : Window = 350 | | | | | | | | |
| Annualized return | 1.7802 | 1.5411 | 1.2417 | 3.4232 | 1.3167 | 1.5411 | 1.2414 | 2.3535 |
| Annualized volatility | 0.7718 | 0.7668 | 1.3345 | 1.7562 | 0.8704 | 0.7668 | 1.0501 | 1.4338 |
| Risk value (10%) | 0.0087 | 0.0004 | 0.0032 | 0.0120 | 0.0124 | 0.0004 | 0.0010 | 0.0035 |
| Conditional risk value (10%) | 0.0018 | 0.0011 | 0.0004 | 0.0018 | 0.0038 | 0.0011 | 0.0003 | 0.0018 |
| Draw down | 0.2161 | 0.2430 | 0.6058 | 0.7348 | 0.2716 | 0.2430 | 0.4711 | 0.6171 |
| Max draw down | 0.3324 | 0.3278 | 0.6644 | 0.7723 | 0.5041 | 0.3287 | 0.5811 | 0.6806 |
| Sharp ratio | 0.1605 | 0.1470 | 0.0741 | 0.0717 | 0.1714 | 0.0470 | 0.1050 | 0.1063 |
| Calmar ratio | 5.4074 | 5.0312 | 2.0215 | 4.1214 | 5.5226 | 5.0312 | 2.2872 | 3.2650 |
| Sortino ratio | 0.0061 | 0.0055 | 0.0057 | 0.0110 | 0.0080 | 0.0055 | 0.0052 | 0.0081 |

**Figure 8:** Risk Performance Portfolio Return

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