



Machine Learning-Based Analysis of Cryptocurrency Market Financial Risk Management

KOLAREYA KARTHIK¹, Dr. G Venkata Rami Reddy²,
Mr. K. Balakrishna Maruthiram³

¹Department of information technology, Jawaharlal Nehru Technological University,
Email Id: karthikkolariya97@gmail.com

²Professor, Department of Information Technology, Jawaharlal Nehru Technological University,
Email Id: gvreddi@jntuh.ac.in

³Assistant Professor, Department of Information Technology, Jawaharlal Nehru Technological University, Email Id: kbkram@jntuh.ac.in

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ABSTRACT:

Cryptocurrency has emerged as a significant player in the global financial landscape. Its evolving nature has led to various challenges that influence risk management practices. The rise of digital currencies has introduced a high level of risk in the financial sector, particularly concerning tax avoidance. Financial institutions, such as banks and regulatory bodies, are increasingly taking on the roles of risk assessors, bank managers, and guardians of compliance in the context of digital currency transactions, especially when it comes to identifying illicit funds. This study utilizes the Cryptocurrency System to examine the Hierarchical Risk Assessment and employ Machine Learning techniques. It aims to provide insights into the risks associated with digital currencies, including their likelihood and potential financial impact. Digital currency transactions are known for their elevated risk, primarily due to the possibility of unauthorized access to private keys. Professional cryptocurrency traders, possessing a higher level of expertise, tend to encounter fewer risks in comparison to those with limited knowledge in this field. When looking to maximize the effectiveness of risk management techniques, the Hierarchical Risk Assessment method has proven to be the most fruitful. The efficacy of the model is highlighted in the "Results" section in realigning the areas of strength across various segments and its utilization in assessing covariance windows.

KEYWORDS - Risk management, cryptocurrency, inherent risk, ineffective exchange control

1. INTRODUCTION:

The financial market stands out as a complex system for which a universally accepted definition of complexity remains elusive within academic circles. However, consensus has been reached concerning the interactions between elements within complex systems. Modeling complex systems is akin to tackling a formidable task, with its hierarchical structure organized to encapsulate various subsystems. These subsystems are accessed through the use of hierarchical models. Regrettably, the portfolio construction process encounters a significant challenge in the form of the absence of a correlation matrix within the hierarchical structure. This shortcoming presents a pronounced



difficulty, particularly in cases involving matrices with high covariance. There are now more than 2,500 different cryptocurrencies available, all of which have emerged in the last few decades, with a total trading volume amounting to \$252.5 trillion. Cryptocurrency market fluctuations occur in unpredictable environments. News outlets have taken a heightened interest and paid closer attention to price fluctuations, as well as the surge in trading activity. Rules have been put in place to protect investors and prevent money laundering.

Recently, the global financial landscape has witnessed the rapid rise and proliferation of cryptocurrencies, fundamentally altering traditional concepts of currency and financial transactions. Led by Bitcoin, digital currencies have introduced novel paradigms for conducting transactions, emphasizing decentralization, security, and confidentiality. However, alongside the numerous advantages, the world of digital currencies also presents a complex and evolving array of risks that carry significant implications for financial analysts and risk assessors.

Regulators & risk management experts must now account for a new and significant set of hazards brought about by the explosive expansion of digital currency. One of the most prominent challenges posed by digital currencies is their potential facilitation of illicit activities, such as money laundering. The decentralized nature of digital currencies has provided a platform for malicious actors to engage in financial transactions that obscure the origins and destinations of assets, raising concerns about anti-money laundering efforts, the role of banks, and the oversight of financial institutions.

As financial institutions strive to adapt to this evolving landscape, experts in risk management, compliance, and banking are confronted with the task of comprehending and mitigating the unique risks associated with cryptocurrency transactions. The convergence of technology, finance, and regulation demands a nuanced understanding of these risks, their likelihood of occurrence, and their potential financial impacts. This study delves into the realm of cryptocurrency risks by applying advanced analytical methods, specifically the Hierarchical Risk Parity and individual artificial intelligence techniques, to the world of digital currency. The goal is to do a thorough analysis of the potential dangers connected to cryptocurrency investments, taking into account such things as the likelihood of an event happening and its potential monetary impact. A critical aspect of this investigation revolves around distinguishing between experienced and less experienced cryptocurrency users, with the former presumed to possess a better grasp of value-based intricacies, consequently resulting in reduced risks and some of the financial risk managements are shown in fig.1.



Figure.1. learn financial risk management.

The following are some of the unique hazards associated with cryptocurrencies that were reported by the CPAC in 2018:

- Selecting a cryptocurrency exchange based on an entity that lacks transaction control can lead to an imbalance in the entity's account.
- The cryptocurrency wallet associated with the entity does not maintain an account.
- Losing the private key makes it impossible to access the cryptocurrency.
- If a third party obtains the private key, it could result in the theft of all the cryptocurrency.
- Manipulating the entity's private key is a significant concern.
- Sending funds to an incorrect address from the entity may result in irreversible loss within the cryptocurrency realm.
- Cryptocurrency transactions are recorded by the entity, but the transactions remain anonymous within the blockchain, making it impossible to identify the parties involved.
- Cryptocurrency transactions may experience delays towards the end of the transaction period.
- Maintaining accurate records of financial conditions and events becomes challenging.
- The private key is a unique, secret number that only one person knows, and it grants that person access to all of the funds stored on the blockchain. The most significant risk that slows down the cryptocurrency process is the loss of the key used to gain access to the coin. The following is a brief synopsis of this study's most important findings:
- Leveraging Using ML, we improve upon the Hierarchical Risk Parity strategy for managing cryptocurrency holdings.
- The provided system can analyze professional accounting practices concerning cryptocurrency risk and its anticipated impact on financial statements.
- Identifying inherent risks with negative correlations within the cryptocurrency domain.
- Control risks at the exchange level are assessed & ranked based on likelihood assessments.
- Determining the cryptocurrency with the highest likelihood of encountering specific risks.

2. LITERATURE REVIEW:

In 2008, a group of people came up with the idea of using cryptographic hashes as a means of exchanging value. It enables peer-to-peer transactions without the need for traditional banks. Numerous articles have highlighted the cryptocurrency's significant role in the proliferation of financial crimes. As per Cipher Trace's anti-money laundering report, approximately \$125 million has been lost or stolen due to various security breaches. The 2018 BIS Annual Economic Report underscores how cryptocurrency is reshaping trust in long-standing financial institutions through its decentralized architecture. Leveraging the global reach of the internet, most cryptocurrencies offer cost-effective alternatives to traditional banking systems, reducing associated financial fees [1].

To get a full picture of where things stand with crypto risk management right now, please refer to Table.1.



Table 1: literature survey summery.

Author	Proposed method	Problem	solution
Rui Ren et al (2020)	In order to have a full picture of where bitcoin risk management is at right now,	The bitcoin market's inherent duality	Individual risk factors are identified, and the network architecture is obtained through the use of spillover effects.
Xinwen et al (2021)	Risk index for cryptocurrency stability using automated learning systems	Variability risk in the market	Examining how the new regulation's risk origination could affect the market
Debi Eka et al (2021)	Possible Losses and Gains When Investing in Cryptocurrencies	Stick to the legal stipulation	Heteroscedastic model-based risk assessment

Cryptocurrency Market Risk Management: The improvement of advanced types of cash has introduced novel financial instruments that require convincing bet the board methods. Computerized monetary standards have been connected with various risks, including unlawful duty evasion, nonattendance of regulatory oversight, and market eccentrics. Ensuring the security of trades and protecting against potential money related infringement has transformed into a focal concern for both regulatory bodies and financial establishments [2].

Machine Learning Techniques for Risk Management: ML techniques have procured prominence in the field of money related bet the board in light of their ability to separate colossal datasets, perceive models, and make data driven conjectures. These techniques engage the improvement of models that can assist with recognizing misleading activities, assessing market risks, and smoothing out adventure philosophies [3].

Hierarchical Risk Parity (HRP) Algorithm: One amazing system analyzed in the composing is the Hierarchical Risk Parity (HRP) computation. This computation utilizes solo ML to smooth out asset assignment inside a portfolio. By stalling the relationship grid of assets, HRP constructs a different evened out tree structure that aides in expanding and chance diminishing. The HRP computation has shown ensure in further developing bet changed returns in advanced cash portfolios [4].

Research Contribution of Shahbazi and Byun: Applying the Dynamic Bet Correspondence and independent ML to examine the financial risks related with the computerized cash market. The audit inspects characteristic perils related with advanced monetary forms, similar to the likelihood of unapproved induction to private keys. The makers display that the proposed model is strong to different re-changing ranges and covariance window appraisals, underlining the practicality of the HRP estimation in risk the chiefs [5].

Cryptocurrency Market Dynamics and Money Laundering: The review includes the powerlessness of the computerized cash market to tax avoidance and money related wrong doings. Crimes including cryptographic types of cash address a test to regulatory bodies and money related associations. The obscure thought of advanced cash trades has worked with tax avoidance and raised stresses over the uprightness of the money related system [6].

Regulatory Efforts and Financial Institutions: Managerial undertakings have been made to address the risks related with cryptographic types of cash. Money related associations have changed techniques to prevent unlawful expense evasion and unlawful trades. Regardless, the decentralized and pseudonymous nature of advanced monetary standards presents challenges for convincing oversight and rule [7].

Performance Evaluation and Comparison: The outline presents a broad assessment of various bet the chiefs' frameworks, including Uniform Buy and Hold (UBAH), Three popular investment strategies are the BCRP, PAMR, and EG, which stands for the "Exponential Gradient" method. The introduction of these frameworks is wandered from the proposed help learning-based approach, showing the reasonable power of the last choice in risk abatement and portfolio headway [8].

For a task that requires a wide variety of abilities, propose a hierarchical risk parity approach. The large effects on tail risk are recognized. The fifty Clever files were agreed upon using a similar technique to the unique stocks, we analyse the performance of the ruling class and resolve multiple variants of HRP (HERC and HCCA). Brauneis, among others. Due to the Markowitz improvement that comes with the extreme dimension, uses the mean-vacillation arrangement to investigate the make-up of digital currency [9].

Projected the relation between cryptographic forms of services taking everything in mind preminent supporter repetition. The introduced foundation gives the result of valuable advertising shard of information and gives the fee to the consultant to further expand the foundation substance, shows the estimate blunder in term of cause appraisal back as opposite to naively changed $(1/N)$ whole. Essentially, they handled the model of Dark Litter man taking everything in mind the dissimilarity necessity to help the civilized portfolio process for amount control of the fundamental methods to handle the electronic transactions representing money used the wavelet-located inspection for electronic transactions representing money multi-scale vital connection between the fluid cryptographic forms of services to count the brokers and fiscal backers' various habit of propelling. In order to avoid the possibility of trading, suggest the different standard of trading term of common oscillator [10].



3. METHODOLOGY:

In this article, we'll go over the specifics of the method we've come up with for predicting future currency exchange rates. The HRP idea is a graph-based theory that uses machine learning technologies in a three-step process.

- Clustering
- Recursive bisection
- Quasi-diagonalization

Initially, we'll apply the Hierarchical Tree Clustering technique to the assets to classify them. Steps to transforming a pair of assets' (x, y) correlation matrix into a correlation distance matrix (A):

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

The next step is to use the Euclidean distance process to compare all the pair-wise way columns. As indicated in Equation 2, this provides us with the augmentation matrix distance A:

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

The recursive technique was used to generate the groups from Equation 2. By designating the collective of clusters as "C," and the initial cluster as "1," as (x*, y*), we can solve Equation 3:

$$C[1] = \operatorname{argmin}_{x,y} \hat{A}(x, y) \quad (3)$$

All the assets switch to using the C [1] single clustering linkage as a result of the A assessment procedure being modified by the given distance matrix. For each outlier object x, we then used Equation 4 to determine its distance to the next cluster, and Fig. 2 depicts the whole system design:

$$A(x, C[1]) = \min (A(x, x^*), A(x, j^*)) \quad (4)$$

Drawbacks:

- Picking the business of mathematical bills on account of the element holds no control on exchanges and it's over equalized for the maintained accompanying record of the part.
- Cryptographic services billfold that is bearing a place accompanying the stuff has no record.
- It's impossible to admittance to cryptographic services by falling the secret key.
- On the off chance that an not sanctioned body catch some admittance to the secret key, all the mathematical bills captured.
- Deception of private key important.
- The wrong element was sent from the sender to the district that is mind-boggling of recovery from cryptographic services.



- The exchanges of mathematical bills take written from entity that has no apparent evidence chance taking everything in mind the concealment of the exchanges in block chain.
- The cryptographic services hold the delay of exchanges toward the finish of ending.
- Financial disputes can be resolved more easily if the relevant events and circumstances are documented.
- Involving the Progressive Gamble Equality for the cryptographic services portfolio taking everything in mind the use of ML forms.
- The projected foundation can resolve the expert accounting on account of the accompanying gamble of digital money and the effect as most would deal with expected common from commercial charge.
- Finding the characteristic gamble that are agreed unfavorably in the digital money.
- Positioning the business level control risk on account of the contingency evaluation.
- Finding ultimate exalted contingency chance of the certain cryptographic services.

Benefits:

- The projected foundation completes activity a chart located theory and taking advantage of the following is a suggested structure for administering Machine Learning projects:
- Grouping datasets.
- Recursive disconnection on datasets.
- Semi diagonalization on datasets.

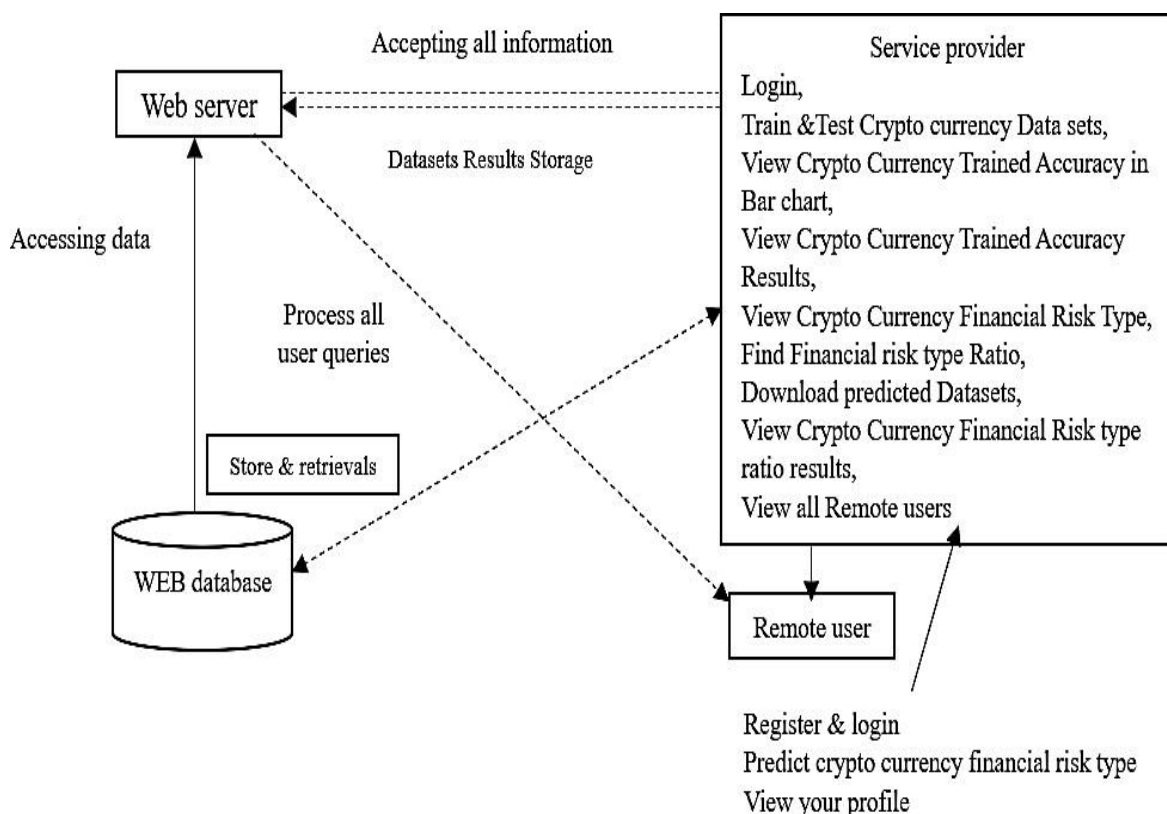


Figure.2. System Architecture

Modules:

To do the task referenced above, we've made the accompanying modules:

- Utilizing this module, we will place information into the framework for information investigation.
- Utilizing this module, we will peruse information for handling.
- Utilizing this module, we will divide the information into train and test data.
- Model age: DT, Gradient Boosting, KNN, LR, NB, RF, and SVM are utilized to assemble the model.
- User enlistment and login: Utilizing this module allows clients to join and sign in.
- Client input: Utilizing this module allows clients to give input for expectation.
- Forecast: the end expectation is shown.

Implementation:

DT: A decision tree is a drawing that utilizations arms to show each reasonable result for a likely information. You can draw a choice tree manually or employ an illustration program or intense compute to make one. Casually, conclusion seedlings can assist an assemblage accompanying selecting what to consider when they need to chase a conclusion.

GB: In machine learning, gradient boosting is a standard approach for categorization and reversion questions. Boosting is a type of ensemble education at which point each model is prepared happening slowly, and each new model tries to fix the mistakes fashioned for one former model. It converts a assemblage of breakable pupils into an accumulation of fantastic graduates.

KNN: K-Nearest Neighbors is individual of the plainest composition methods that utilizations supervised ML. It sorts all facts point in light of how allure neighbors are organized. It monitors everybody of the current cases and sorts new one into bunches in light of how corresponding they are.

LR: Logistic regression is a supervised ML action namely mainly used to predict the possibility that a case has a place accompanying a distinguishing class or not. A sort of judgments method takes a glance at how a bunch of free determinants and a bunch of district twofold determinants do business each one. It is an intensely beneficial implement for merely determining.

NB: Naive Bayes is a honest education method that applies Bayes' standard and a complete hypothesis that, likely the class, the statuses are severely free. By and by, this forwardness of independence is in many cases crushed, still Naive Bayes still repeatedly gives excellent arrangement accuracy.

RF: Random Forests is a method for ML that tackles individual of ultimate weighty issues definitely Trees, that is top-secret "dissimilarity." Decision Trees is a voracious prediction, even though that it is easy to resort to and maybe transformed. Instead of considering how the split will influence the whole seedling, it tries to decide ultimate persuasive procedure for dividing the indicated bud.



SVM: SVM, it demonstrates SVM is a simple model for problems with both describing and recovering from them. It does a great job for many certain-globe queries in resolving both undeviating and non-linear ones. An unequivocal idea underpins SVM. The pattern produces a hyperplane or line that divides the dossier into differing classes.

To improve the efficiency of government bureaucracy, researchers have developed a machine-learning technique called reinforcement learning (RL) shows how RL is secondhand for risk administration. In the submitted method, risk administration resources judgment, judging, and rating bureaucracy's warnings. The administration question of the portfolio defines the RL-located profession method accompanying analyses, allowing for possibility risks and gains. In agreements of how the portfolio administration question is articulated in the RL design, bureaucracy power gives the procedures for business property in the current capital advertise background.

All the information about purchasing merchandise is connected to the environment. The profession plan likely apiece power. The review concerning this business method reports the consumer the reward and gives bureaucracy facts about the next state and the below output screen of the fig 3 shows the registration view of the proposed method and then the Fig 4 displays the user login page for authentication and then the fig 5 displays the crypto currency datasets trained and tested results screen and then the fig 6 displays the graphical view of the predicted results and then the Fig 7 displays the crypto currency trained accuracy results and then the Fig 8 displays the crypto currency market financial risk type and then the Fig 9 displays the crypto currency financial risk type ratio details and the graphical view of the crypto currency ration details are shown in the Fig 10 and finally all remote users are shown in the list in Fig 11.

4. RESULTS:

Figure 3 Registration phase.



Figure 4 Login Screen



Figure 5 Dataset screen

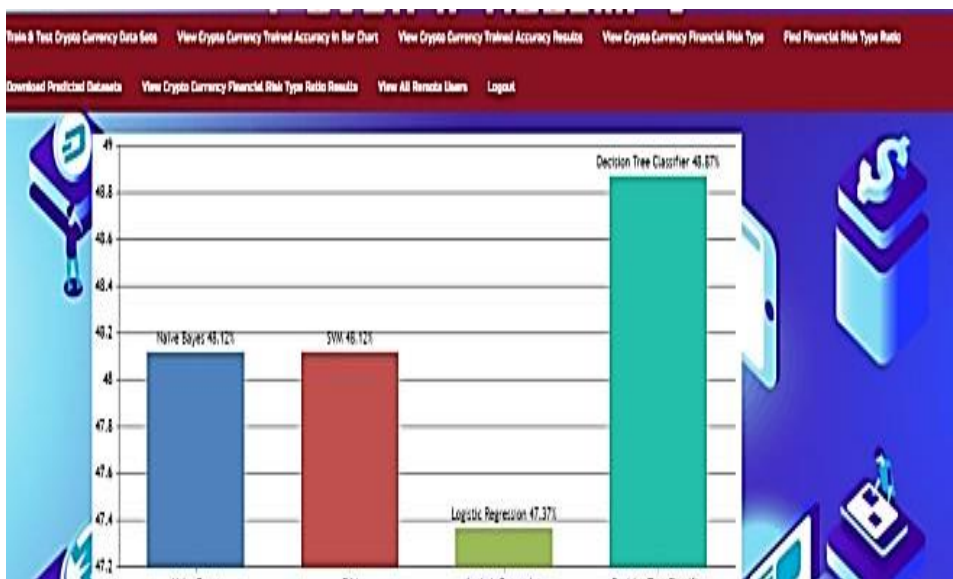


Figure 6 graphical representation Screen



Figure 7 Analysis of crypto currency trained result Screen

View Crypto Currency Market Financial Risk Type

Volume_Used_24H	available_supply	idn	last_updated	market_cap_usd	max_supply	name	percent_change_1h	percent_change_24h
1511330000	96165368	ethereum	1512549553	43529446198	0	Ethereum	-0.18	-3.93
61847500	259270538	cardano	1512549579	3231420437	45000000000	Cardano	-0.28	-5.8
409342000	54158908	Bitcoin	1512549542	5634497528	84000000	Bitcoin	-0.17	0.8
228943000	7736420	dash	1512549542	5794075589	18900000	Dash	1.22	-3.21
402067000	98125659	ethereum-classic	1512549556	2866554688	0	Ethereum Classic	-0.2	-3.47
60659900	115641028	lisk	1512549553	1046840406	0	Lisk	1.06	-2.52
2.94E+09	2.78E+09	3	1.51E+08	1.48E+10	2.78E+09	Iota	-3.24	-2.38

Figure 8 financial risk type Screen



Figure 9 Financial ratio details Screen

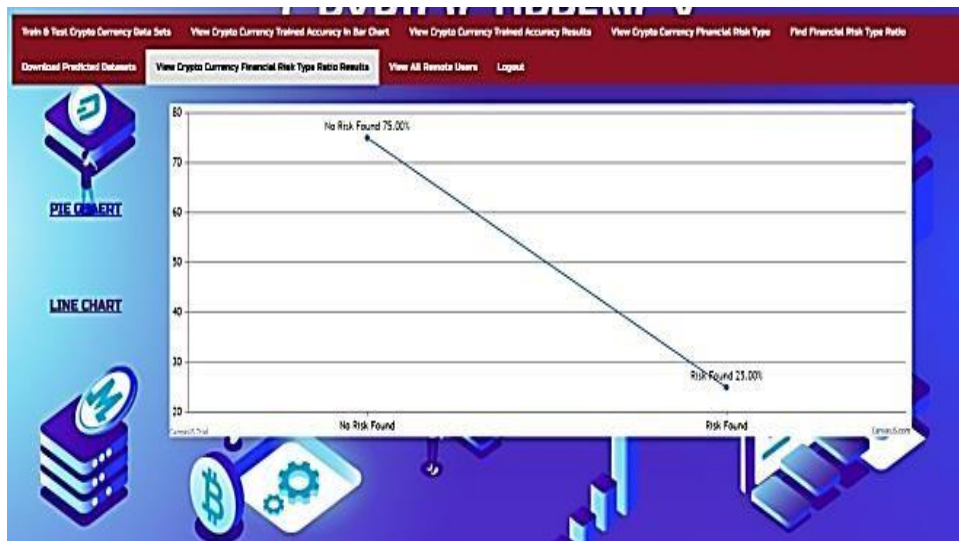


Figure 10 graphical view of ratio details Screen

USER NAME	EMAIL	Gender	Address	Mob No	Country	State	City
Rajesh	Rajesh123@gmail.com	Male	#7827,4th Cross,Vijayanagar	9535866270	India	Karnataka	Bangalore
Manjunath	tmksmanju13@gmail.com	Male	#782,4th Cross,Malleswaram	9535866270	India	Karnataka	Bangalore
karthik	karthikolarhya12@gmail.com	Male	flat no 405,hlg 11 block,chitrapuri colony,manikonda, hyderabad	8977244875	India	Telangana	Hyderabad

Figure 11 Remote users

5. CONCLUSION:

In this study, we employed Reinforcement Learning (RL) alongside a resource allocation strategy known as Hierarchical Risk Parity (HRP) to examine how risk is managed within a digital currency ecosystem. Reinforcement learning outperforms other machine learning techniques in this domain, primarily because it is rooted in the concept of learning, which yields high precision in acquiring accurate information. Furthermore, HRP exhibits the most desirable attributes and diversity that are sought after in such applications. The study evaluated the results across various prediction windows and methods, with periodic rebalancing of the chosen timeframe. The implementation of HRP offers valuable intermediate asset selection choices and enhances the risk management process. In future research, we intend to enhance the proposed strategy by conducting out-of-sample performance tests on additional assets and asset classes. Additionally, we will leverage optimization techniques to yield improved results in terms of risk management.

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