Smart Risk Management in Crypto Markets

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Abstract. Crypto money may be a well-known monetary state within the globe, posturing a assortment of perils that have an affect on the inborn hazard evaluation of hazard evaluators. Since its beginning, the rise of crypto monetary standards has displayed money related educate with a wide extend of dangers in terms of cash washing. Within the framework of the organization monetary bolsters such as opposed to currency laundering, bank enigma continue accordingly hazard master, bank supervisor, and compliance officer who includes a incitement for the associated exchange through crypto monetary forms and the clients who conceal the unlawful reserves. In this think about, the crypto money system was subjected to Progressive Chance Equality and unsupervised machine learning. The proficient bookkeeping method in terms of the inborn hazard related with bit-coin. The proficient crypto money involvement in the exchange mitigates risk compared to less experienced counter parts. In order to provide a better chance administration outcome, the Various levels Chance Equality provides a much higher yield in terms of returns or returns the balanced hazard tail. The resultant region shows up. Strong to various interims is the recommended show. the ones that undergo recalibration and the estimate of the covariance window.

Keywords : Machine Learning, Decision tree, Random Forest, MLP Classifier, Adaboost, Extra tree Classifier, ML techniques.

INTRODUCTION

Financial markets are intricate systems that involve the interaction of various elements. The structure of these systems is hierarchical, with subsystems that play their own role. However, when it comes to Portfolio assembly, there is a substantial challenge due to the absence of correlation matrix within the hierarchical framework, especially for large covariance. In recent years, the cryptocurrency market has seen a surge in popularity, with around 2500 types of cryptocurrencies trading a total value of 252.5 trillion dollars. The cryptocurrency market operates in a volatile environment, attracting attention from news publishers and investors alike.

Efforts have been made to regulate the cryptocurrency market, with rules in place to Combatting money laundering and protect investors. In spite of these endeavors, the market remains dynamic and prone to price fluctuations. Various models and techniques have been proposed to analyze and manage cryptocurrency portfolios. For example, Markowitz optimization and high-frequency relationships have been explored to provide insights and improve system stability. Estimation errors in return estimation and sophisticated portfolio techniques, such as the Black Litterman model, have been used to manage cryptocurrency investments more effectively.

Wavelet-based analysis has been applied to study the dynamic interdependence between liquid cryptocurrencies, revealing heterogeneous behavior among traders and investors. Different trading rules have been compared to develop effective trading strategies. It is recommended that investors and professionals in the industry be aware of the inherent risks associated with digital assets. Chartered Professional Accountants Canada (CPAC) has highlighted the importance of considering audit considerations specific to the cryptocurrency ecosystem.

Overall, the cryptocurrency market presents both opportunities and challenges, requiring a nuanced approach to portfolio management and risk assessment.

LITERATURE SURVEY

[1]. C. Y. Kim and K. Lee, ‘‘Risk management to cryptocurrency exchange and investors guidelines to prevent potential threats,'' in Proc. Int. Conf. Platform Technol. Service (PlatCon), Jan. 2018, pp. 1–6.

The allure and capital infusion into cryptocurrency are burgeoning, The value of Bitcoin surpassing $10000 as of November 2017. The future of this trend is uncertain. While blockchain technology offers enhanced security compared to traditional currency systems, falls short in terms of cryptocurrency distribution and management. Many people acquire cryptocurrency through exchanges and mining, often without adequate knowledge. This paper examines the vulnerabilities of cryptocurrency exchanges and user wallets and proposes risk management strategies following international standards like NIST and ISO. The focus is on analyzing blockchain weaknesses, implementing effective countermeasures, addressing investor vulnerabilities, and outlining server management and personal security tips.

[2]. I. U. Haq, A. Maneengam, S. Chupradit, W. Suksatan, and C. Huo, ‘‘Economic policy uncertainty and cryptocurrency market as a risk management avenue: A systematic review,'' Risks, vol. 9, no. 9, p. 163, Sep. 2021.

Cryptocurrency literature is growing quickly these days, with a focus on how the cryptocurrency market can help manage risks. This type of asset is still new and has gaps in existing research that need to be filled for future studies. A recent review looked at a lot of different studies on how cryptocurrencies can be used to manage risks related to economic policy ambiguity (EPU).The examination discovered that cryptocurrencies have different levels of connection to EPU in different countries, which affects how well they can help manage risks. These different connections are because EPU depends on the policies and decisions made by each country's regulatory authorities. Dealing with these varied connections requires different approaches to handle stock market ups and downs and economic policy ambiguity in various economies. The unique rules and regulations of the cryptocurrency market also affect how well it can protect against risks in each economy. Many different groups like investors, policymakers, fund custodians, or asset managers can benefit from this research. The authors suggest that future studies should look at different topics, data frequencies, and research methods to keep improving our understanding of how cryptocurrencies can help manage risks.

[3]. J. Gold and S. D. Palley, ‘‘Protecting cryptocurrency assets,'' Risk Manage., vol. 68, no. 3, pp. 12–13, 2021

Literature, as the advisory explains, suggests that companies facing exploit impacts should act swiftly by contacting law enforcement and implementing various technical measures to reduce risks. These measures involve creating new keys for cryptocurrency wallets or transferring assets to new wallets, employing physical wallets to secure private keys in a segregated location, setting up two-factor authentication for added security, removing affected hosts from the network, changing all associated passwords, and updating patches for software and hardware components. It is advised to scan systems thoroughly as a precaution for potential lateral movement by threat actors and the installation of additional malware. By taking these recommended actions promptly, companies can enhance their cybersecurity defenses and prevent unauthorized access to their systems.

[4]. I. Barkai, T. Shushi, and R. Yosef, ‘‘A cryptocurrency risk–return analysis for bull and bear regimes,'' J. Alternative Investments, vol. 24, no. 1, pp. 95–118, Jun. 2021.

The authors of this article introduce a fresh perspective for analyzing the risk-reward characteristics of prominent cryptocurrencies such as bitcoin, litecoin, ripple, and ethereum. They emphasize on examining how the price behavior of each individual cryptocurrency can impact the others. By dividing the returns of each cryptocurrency into different bull and bear market phases, they investigate how these phases overlap and change over time. Additionally, they explore the effect of distributed-denial-of-service attacks on these market phases to understand their influence on regime changes. Their research uncovers systemic risk indicators in the cryptocurrency market and reveals potential contagion patterns between different cryptocurrencies. These findings offer valuable insights for investors looking to manage risk in their portfolios and pave the way for future research in this rapidly evolving market. Overall, the study highlights the increasing systemic risk in the cryptocurrency market and the diminishing diversification benefits of holding a mixed portfolio of cryptocurrencies.

EXISTING SYSTEM

In the current system, deploying machine learning algorithms is somewhat challenging to construct due to insufficient data regarding the data visualization. The RL was compared to existing research endeavors and the prevalent benchmarks in this domain, the duo management evolve algorithms for portfolios and the fundamental Deep Q-Network(DQN) of the trading system. In terms of bit-coin risk management, the proposed RL algorithms are compared to other existing studies To surmount all these challenges, we leverage machine learning packages accessible in the scikit-learn library.

Disadvantages:

- High intricacy
- time-intensive

PROPOSED SYSTEM

We have put forward various machine learning models for categorizing the machine learning-based assessment of cryptocurrency market financial risk management. Correspondingly, analogous research endeavors have suggested models for appraising such performance. Hence, we advocate the utilization of Decision Trees, Random Forests, MLP Classifiers, AdaBoost, and Extra Tree Classifiers to forecast the risks.

Advantages:

- Maximum precision
- Simplifies time complexity
- Is simple to operate

BLOCK DIAGRAM

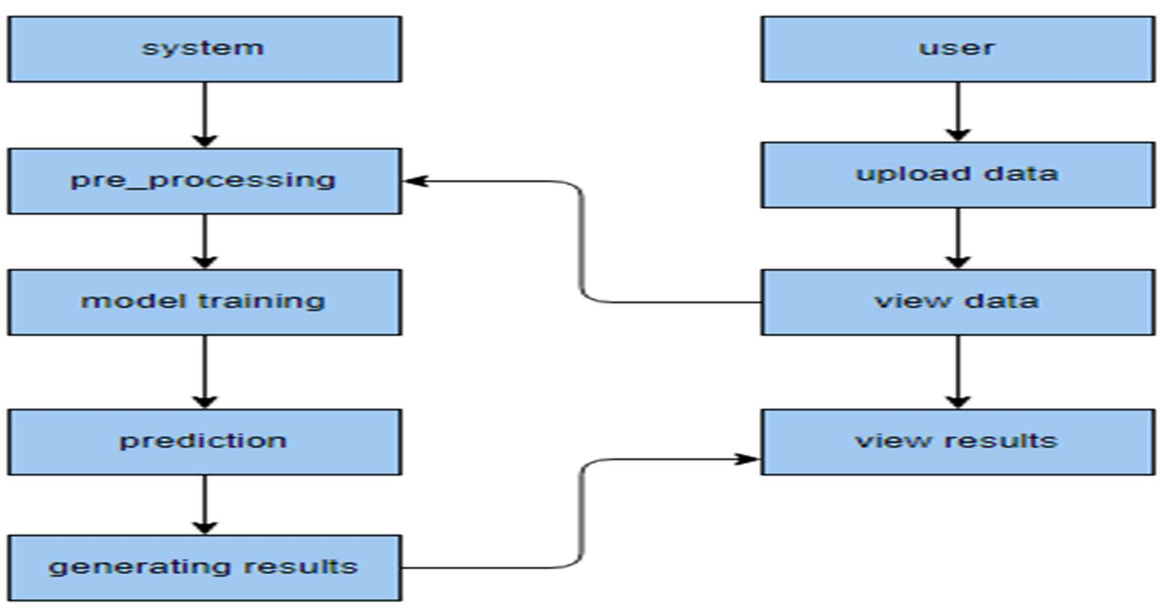

Figure 1 : Block Diagram

METHODOLOGIES

1. Decision Tree:

A decision tree is like a flowchart that makes a difference us make choices. It contains a tree structure where each inner hub speaks to a highlight, like a color or measure, and the branches appear the choice rules. At the conclusion of the branches, we have leaf hubs that appear the ultimate result. The beat hub is called the root hub, and the tree learns how to part based on distinctive highlights. This prepare of part is called recursive apportioning. Choice trees are incredible for decision-making since they see like flowcharts that people can effortlessly get it. To construct a choice tree, we to begin with choose the finest include to part the information. At that point, we keep part the information into littler bunches based on distinctive highlights until we reach a point where all the information focuses have a place to the same bunch, we run out of highlights, or there are no more information focuses cleared out. This way, choice trees offer assistance us make sense of complicated information in a straightforward way.

Formula : *Entropy(s)= -P(yes)log2 P(yes)- P(no) log2 P(no)*

2. Random Forest Classifier

A random forest is a cool way to use a bunch of decision trees to make smart choices. Instead of just relying on one tree, it combines the predictions of many trees to make better guesses about things. This helps avoid mistakes like overfitting and actually improves how accurately we can predict stuff. The random forest algorithm trains all these decision trees in a "forest" by using a special method called bagging. Bagging is like boosting the accuracy of machine learning by working together as a team. Some cool things about random forests are that they can handle missing data really well, they can make pretty good predictions without needing a lot of tuning, and they're great at stopping overfitting. Plus, they randomly pick different groups of features when making decisions. They also use clever ideas like entropy and information gain to make sure they're making the best choices possible. These ideas help reduce uncertainty and make the predictions more accurate. So basically, random forests are like a smart team of decision-makers that work together to get things right.

3. Multi Layer Perceptron:

Multilayer Perceptron (MLP) in Scikit-learn simplifies deep learning in Python but lacks an activation function in the output layer. It uses varied loss functions for regression and classification tasks and supports single and multiple target values regression without GPU support for accelerated computation. Unlike Keras, Scikit-learn's MLP restricts fine-tuning parameters per layer. MLPs, a subset of feedforward neural networks, comprise input, hidden, and output layers, trained using backpropagation. They consist of at least three layers: input, hidden, and output, with each node, except inputs, acting as a neuron with a nonlinear activation function. MLPs distinguish from linear perceptrons by handling non-linearly separable data. The term "multilayer perceptron" refers to multiple perceptrons organized into layers. MLP "perceptrons" diverge from true perceptrons by allowing arbitrary activation functions and handling both classification and regression tasks. MLPs offer stochastic problem-solving capabilities for complex problems like fitness approximation. Cybenko's theorem demonstrates MLPs' ability to approximate universal functions, facilitating mathematical model development. MLPs are effective classifiers, treating classification as a form of regression for categorical response variables.

Final Data Set

	last_updated	market_cap_usd	max_supply	name	percent_change_1h	percent_change_24h	percent_change_7d	price_btc	price_usd	rank	symbol	total_supply	Pred
128	69	1031	29	145	268	715	684	889	1214	0	181	406	1
455	68	1030	124	441	241	378	313	880	1205	1	423	656	1
130	93	1029	29	147	375	328	340	885	1210	2	107	408	1
664	86	1028	107	609	128	1076	1163	790	1115	3	714	923	0
1005	56	1027	122	976	309	389	227	466	789	4	1257	1005	0
331	57	1026	25	333	349	402	582	882	1207	5	300	270	1
723	57	1025	51	699	242	541	462	864	1189	6	671	576	0
132	97	1024	29	150	194	246	266	876	1201	7	191	407	1
789	59	1023	124	763	147	934	919	875	1200	8	1239	385	0
236	94	1022	119	239	232	322	304	361	678	9	24	988	1
457	71	1021	124	443	240	395	307	846	1171	10	421	658	1
816	74	1020	124	784	204	498	642	485	808	11	1225	952	0
442	85	1019	124	396	401	960	1027	783	1109	12	411	877	1
817	73	1018	124	785	350	278	399	854	1179	13	758	668	0
1108	64	1017	124	1078	121	1007	961	369	687	14	1235	1009	0
788	59	1016	124	760	557	1089	1161	837	1162	15	726	581	0
144	77	1015	35	134	302	621	652	877	1202	16	103	284	1
720	68	1014	124	693	338	427	656	813	1138	17	669	700	0
1306	74	1013	124	1275	188	757	370	878	1203	18	1282	151	0
854	87	1012	124	826	203	266	466	816	1141	19	799	719	0

Figure 2: Data Set

4. AdaBoost

AdaBoost, also known as Adaptive Boosting, is a method used in machine learning to make weak learners stronger. Unlike traditional boosting methods, AdaBoost pays more attention to wrongly classified data points, aiming to improve overall performance. The process involves creating decision trees one after the other, with each new model focusing more on fixing mistakes made by the previous one. This cycle continues until the desired number of base learners is reached. In AdaBoost, each tree is quite simple, with just a single node and two leaves, often called a "stump." This is different from random forests, which have a fixed number of trees. Imagine a dataset with three features and a Yes-No output; AdaBoost assigns a starting weight of 1/5 to each record to keep things fair. Over time, as the algorithm learns, these weights are adjusted to contribute to accurate predictions.

Formula : $W=1/N$

5. Extra Tree Classifier

The Extra Trees Classifier is an ensemble learning method that aggregates the outcomes of multiple uncorrelated decision trees to make classification predictions. It operates similarly to the Random Forest Classifier but varies in how it constructs decision trees within the forest. Within the Extra Trees Forest framework, each decision tree is created from the primary training sample. At every testing node, a randomized subset of features (termed 'k') is presented to each tree from the feature set. The decision tree then identifies the prime feature for data segmentation based on a mathematical criterion, commonly the Gini Index. This stochastic feature sampling leads to the formation of numerous uncorrelated decision trees. Regarding feature selection, while constructing the forest, the Gini Importance of each feature is computed, representing its contribution to the decision-making process. Features are ranked based on their Gini Importance, allowing users to select the top k features for further analysis.

$$Gain(S,A)=Entropy(S)-\Sigma_{vEValues(A)}\frac{|Sv|}{|S|}Entropy(S_v)$$

RESULT SECTION

The web application is intended to offer a user friendly platform for managing and analysing datasets. Upon initial use, new users are required to register using their email addresses and create a secure password to ensure data privacy and security. Subsequently, they can log in using their registered email and password to gain access to the application's features. Once logged in, users can navigate to the "load data" section, where they have the ability to upload disordered datasets in CSV format. The application then processes the uploaded data to create an ordered dataset, which users can subsequently view and manipulate. Furthermore, users can select from a range of machine learning algorithms to train their data and evaluate accuracy.

Home page

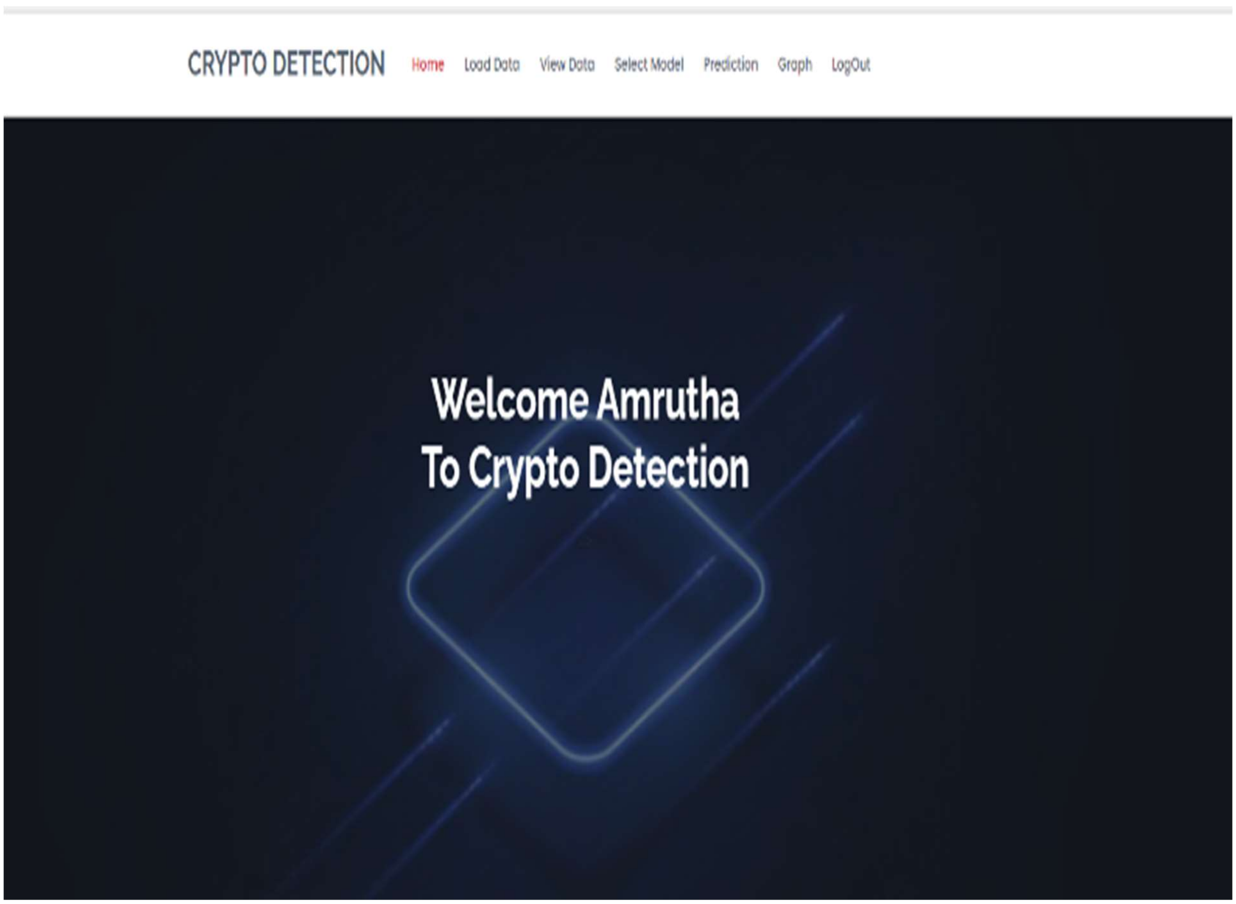

Figure 3: Home Page

Accuracy of different algorithms are given below.

	Models	Accuracy
0	DecisionTreeClassifier	96.733668
1	RandomForestClassifier	97.236181
2	AdaBoostClassifier	98.241206
3	MLPClassifier	93.969849
4	ExtraTreesClassifier	98.492462

Figure 4: Accuracy table

Graph

Among those algorithms Extra Tree Classifier has high accuracy.
Below graph describe the comparison among the algorithms

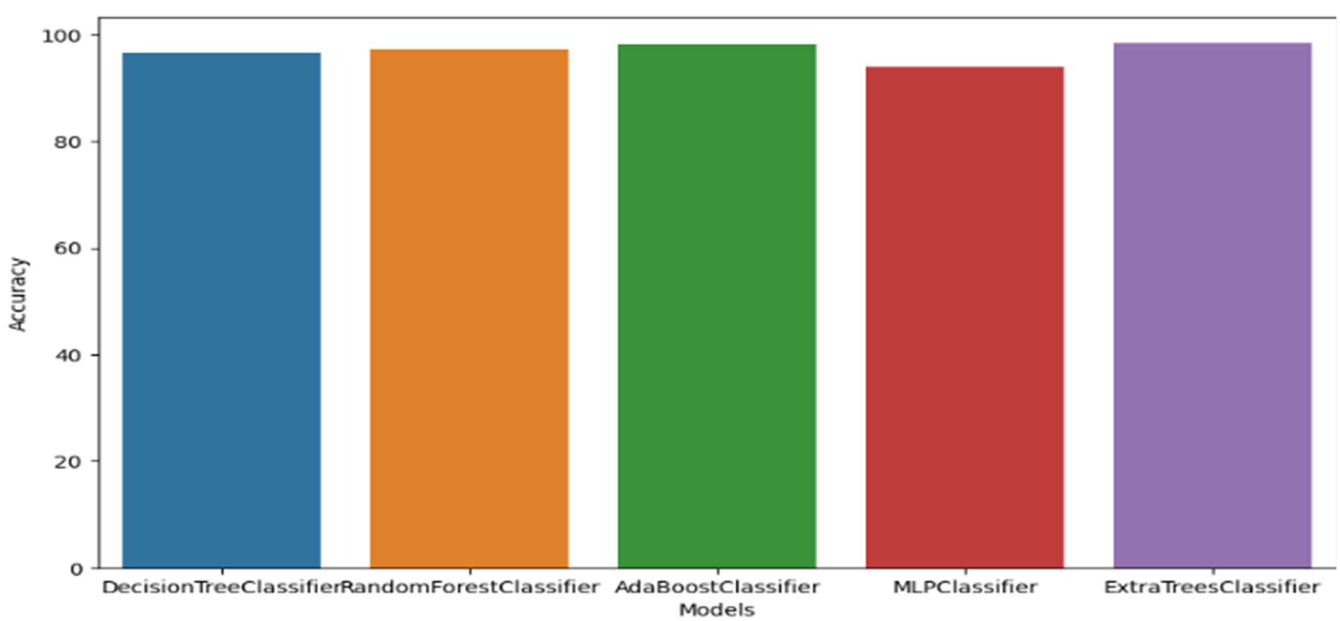

Figure 4: Graph

CONCLUSION

The risk management of a crypto currency network was examined in this study utilizing the Reinforcement Learning (RL) approach and an asset allocation strategy referred to as Hierarchical Risk Parity (HRP) were utilized for a cryptocurrency portfolio. When compared to other machine learning algorithms employed in this field, reinforcement learning produces superior performance evaluation discoveries. The primary justification for employing RL in this situation process is the learning-based characteristic of this technique enables system structures to attain high intricacy regarding providing the correct knowledge to the system's operations. Furthermore, the HRP framework possesses the best features and the most favourable diversification traits. The data were studied utilizing multiple estimating windows and approaches, as well as re-adjusting within the selected timeframe. The implemented HRP provides a viable alternative for transitional asset allocations.

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