Cryptohub and Sales Forecasting Using Machine Learning

Vidhya K[1],[2]Bhanu prakash rao hj,[3]anand k,[4]chethan g,[5]nandeep kr

Department of Information Science and Engineering, East West Institute of Technology, Bengaluru, Karnataka, India

1vidhyak@ewit.edu.in
2bbhanuprakashraohj@gmail.com 3anandkdghalli@gmail.com 4ewitchethan@gmail.com
5krnandeep@gmail.com

***Abstract*—**Cryptocurrency has recently attracted substantial interest from investors due to its underlying philosophy of decentralization and transparency. Considering cryptocurrency's volatility and unique characteristics, accurate price prediction is essential for developing successful investment strategies. To this end, the authors of this work propose a novel framework that predicts the price of Bitcoin (BTC), a dominant cryptocurrency. For stable prediction performance in unseen price range, the change point detection technique is employed. In particular, it is used to segment time-series data so that normalization can be separately conducted based on segmentation. In addition, on-chain data, the unique records listed on the blockchain that are inherent in cryptocurrencies, are collected and utilized as input variables to predict prices. Furthermore, this work proposes selfattention-based multiple long short-term memory (SAM-LSTM), which consists of multiple LSTM modules for on-chain variable groups and the attention mechanism, for the prediction model. Experiments with real-world BTC price data and various method setups have proven the proposed framework's effectiveness in BTC price prediction. The results are promising, with the highest MAE, RMSE, MSE, and MAPE values of 0.3462, 0.5035, 0.2536, and 1.3251, respectively.

***Keywords*—** Blockchain, cryptocurrency, Bitcoin, deep learning, prediction methods, change detection algorithms.

I. INTRODUCTION

With the advent of blockchain technology, there has been significant change in the form of currency as well as transactions. From its emergence to the present, currency's core role has been a means of payment as a medium of value delivery. This function relies on trust in the currency that is guaranteed and stabilized by a central agency (e.g., government, bank). However, central authorities have a critical shortcoming; there is the possibility of depravity that could risk transaction reliability. The blockchain, an open, anti-counterfeiting, and tamper-proof ledger, has created a currency called cryptocurrency. Based on blockchain technology, cryptocurrency can be trusted without the guarantee of a central authority, thus breaking away from the traditional relationship. Cryptocurrency that guarantees decentralization and transparency presents the possibility of a monetary system that relieves the isks of fraud and protects privacy [2]. The dominant cryp tocurrency, Bitcoin (BTC), is an exemplary cryptocurrency in terms of its difference from existing traditional currencies. BTCislimitedto21millionissuances,resultinginpractically no inflation that is caused by a central government's currency printing [3]. This strengthens the meaning of decentraliza tion, leading cryptocurrency to function not only as a method of payment but also as a means of value storage. In fact, in addition to traditional investment vehicles, investing in cryptocurrencies is currently deemed one of the most effec tive ways to increase asset value.

II. LITERATURE SURVEY

Crypto Hub is a machine learning-based framework that integrates multiple models, including LSTM, GRU, and ensemble methods, to forecast cryptocurrency prices and predict sales. The framework consists of three components: data preprocessing, model training, and prediction [1].

Machine Learning for Cryptocurrency Price Forecasting:
Studies have shown that machine learning models, particularly deep learning models like LSTM and GRU, can effectively capture complex patterns in cryptocurrency price data, making them well-suited for real-time applications [2]. Some notable findings include:

- A GRU model achieved the lowest MSE (5,954.89), RMSE (77.17), MAE (60.20), and MAPE (0.09%) in predicting Bitcoin prices.

- LSTM models have been widely used for cryptocurrency price forecasting, with some studies achieving accuracy rates of up to 56% [3].

Sales Forecasting using Machine Learning:

Machine learning models, such as XG Boost, Random Forest, and Gradient Boosting, have been shown to improve sales forecasting accuracy by 10-20% compared to traditional methods [4].

Some key techniques used in sales forecasting include:
- Time series models, such as ARIMA and Prophet, for capturing historical sales trends.
- Ensemble methods, such as Random Forest and XG Boost, for handling non-linear relationships and improving forecasting accuracy.
- Deep learning models, such as LSTM and GRU, for capturing complex patterns in sales data [5].

Comparison of Traditional and Machine Learning-based Forecasting:

III. RESEARCH AND METHEDOLOGY

A. Research

The first blockchain technology-based cryptocurrency that functions as an electronic peer-to-peer transaction system without a trusted third party was allegedly proposed by S. Nakamoto in 2009 [9]. The underlying philosophies cryptocurrency are threefold: safety, decentralization, and blockchain transparency. In the blockchain, each block con tains transaction information that is distributively stored using its own hash value to prevent fraud or infringe ment [10]. Nodes, which are participants in the blockchain network, act as financial institutions so that the existence of a central agency is no longer necessary. The information recorded in each block is transparently disclosed. These are called on-chain data and are applied as indicators. Due to these innovative characteristics, cryptocurrency has gained much attention from the public, and many cryptocurrencies have been created.

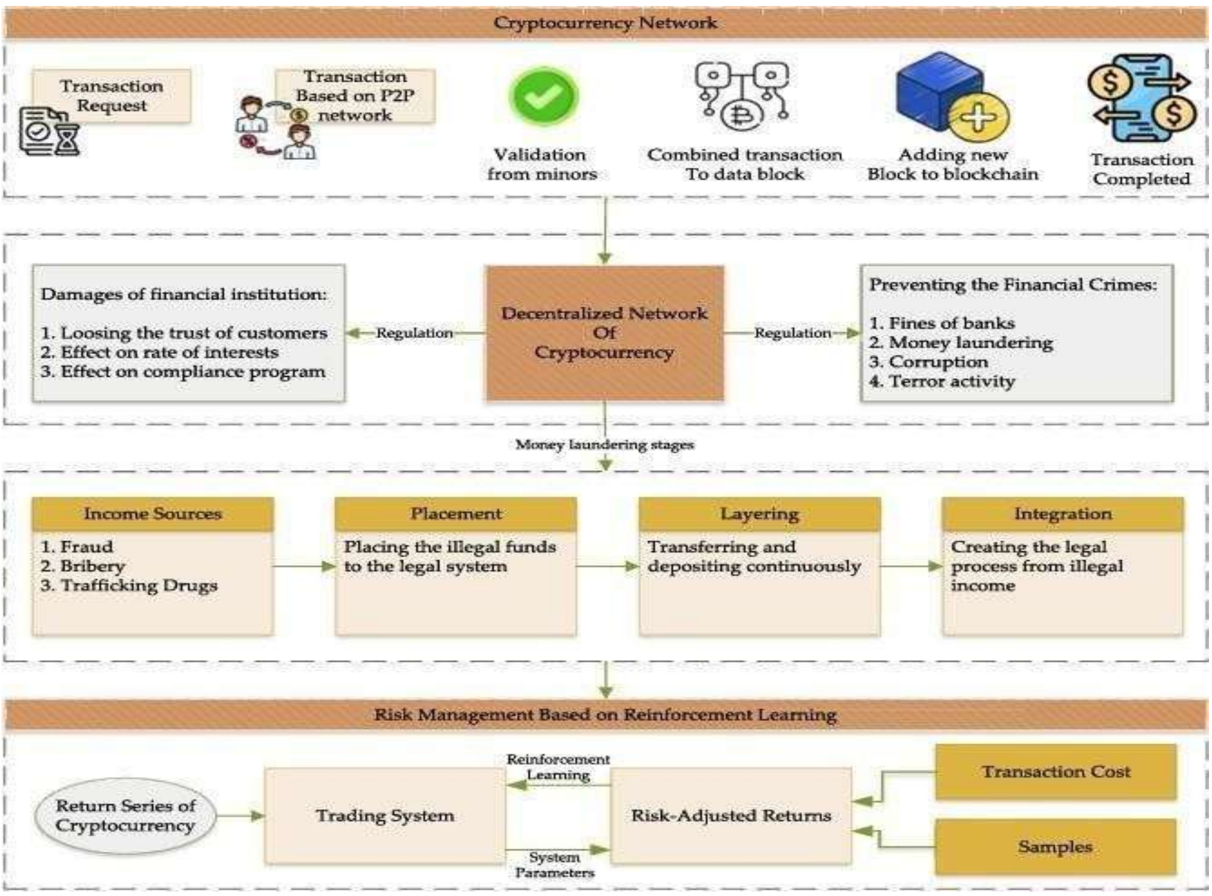

Figure 1:research figure of the model

B. Methodology

In this section we focus on details of proposed exchange rate prediction approach. HRP concept is graph-based theory and using the machine learning techniques in three main steps defined as: • Clustering • recursive bisection • quasi-diagonalization The first step initiate the assets into various clusters based on applying the Hierarchical Tree Clustering algorithm. The correlation matrix between two assets of x and y converted to the correlation distance matrix A in the following Equation 1: A(x ,y) = 0.5 ∗ (1 −ρ(x ,y)) (1)

Next step, shows the evaluation between all the pair-wise manner columns based on the Euclidean distance process which gives us the augmentation matrix distance ˆ A as following Equation 2: i ˆ A(x ,y) = (A(m ,x) − A(m ,y))2 m=1 (2)

By using the recursive approach, from Equation 2 the clusters created. By defining the set of clusters as C and the f irst cluster as (x∗ ,y∗) evaluated as Equation 3: C[1] = arg min x ,y ˆ A(x ,y) (3)

Based on this the defined distance matrix updates the ˆ A evaluation process and all the assets use the C[1] single clustering linkage. Therefore, for every asset x out of the cluster, the distance of new cluster evaluated as Equation 4: A(x ,C[1]) = min(ˆ A(x ,x∗), ˆ A(x, j∗)) (4)

gives the overview of the proposed risk man aggrement system. The first part shows the cryptocurrency network details which contains the request for transaction that process into the P2P network. After validation of the transaction request from minors the combined transaction goes into data block and add the news block to the blockchain and complete the transaction. There are two main parts in the cryptocurrency decentralized network which based on regulation prevent the financial crimes and damages of the financial institutions. In this process, there are four main things which mentioned to prevent as money laundering ,corruption, fines which banks suppose to pay and terror activities. The damages from this step cause the loosing trust of customer, it effects on the interest rates and compliance programs. There are four main process for the money laundering as the sources of income, placement, layering and integration which all of the are from the illegal incomes. To avoid this, we applied reinforcement learning technique for risk management of the digital coins transactions and money laundering.

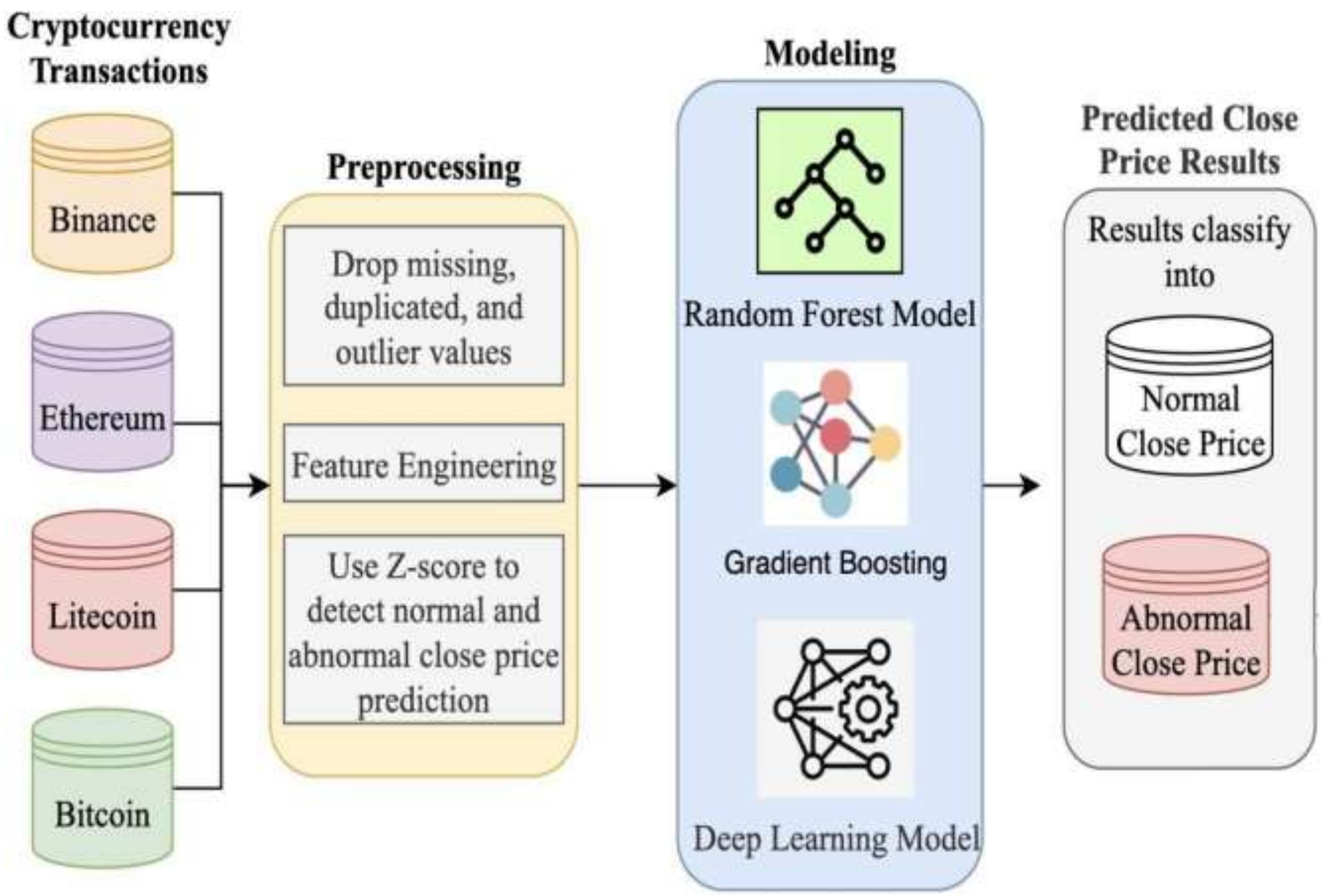

Figure 2:methodology of the model

IV. PROBLEM STATEMENT

Regarding to the generated results of the risk performance portfolio, the risk assessments implication analysed for further processing the system. There are three features as reference portfolio, Risk-min and determined portfolio that compares the five crypto currencies assets. In the first step, for each portfolio, the risk reduction assets compared with variance reduction against the portfolio of benchmark. In this process, four risk metrics downsides defined asset the portfolio of cryptocurrency by providing the risk protection down sides. More specifically, the Regret (RE), Semi-Variance (SV), Expected Shortfall (ES), Value-at-Risk (V R) evaluated for every portfolio. The details of results presented in The 30 days records also presented in Table 10. Both tables gives the report of cryptocurrency portfolios and risk-minimizing records which provide better result as compare with other portfolios. Similarly, adding the Ether in portfolio of risk- minimizing gives the high risk reduction as compare to another cryptocurrencies

V. OBJECTIVES

1. Cryptocurrency Price Forecasting:
- Develop a hybrid model that combines LSTM, GRU, and ensemble methods to forecast cryptocurrency prices.
- Evaluate the performance of the hybrid model using metrics such as MAE, MSE, and RMSE. - Compare the performance of the hybrid model with existing models.
2. Sales Forecasting:
- Develop a machine learning-based framework to forecast sales for e-commerce platforms.
- Evaluate the performance of the framework using metrics such as MAE, MSE, and RMSE. - Compare the performance of the framework with existing models.
3. Graph Neural Networks:
- Explore the use of graph neural networks to model the relationships between different cryptocurrencies and improve price forecasting accuracy.
- Evaluate the performance of the graph neural network using metrics such as MAE, MSE, and RMSE.
4. New Product Launches:
- Develop a machine learning-based framework to forecast sales for new product launches. - Evaluate the performance of the framework using metrics such as MAE, MSE, and RMSE.

VI. SYSTEM DESIGN

1. Microservices Architecture: Design Crypto Hub as a microservices-based system, with separate services for data ingestion, data processing, model training, and prediction serving.
2. Event-Driven Architecture: Use an event-driven architecture to handle real-time data streams and updates to the system.
3. Cloud-Native Architecture: Design Crypto Hub to be cloud-native, leveraging cloud services such as AWS, GCP, or Azure for scalability and reliability.

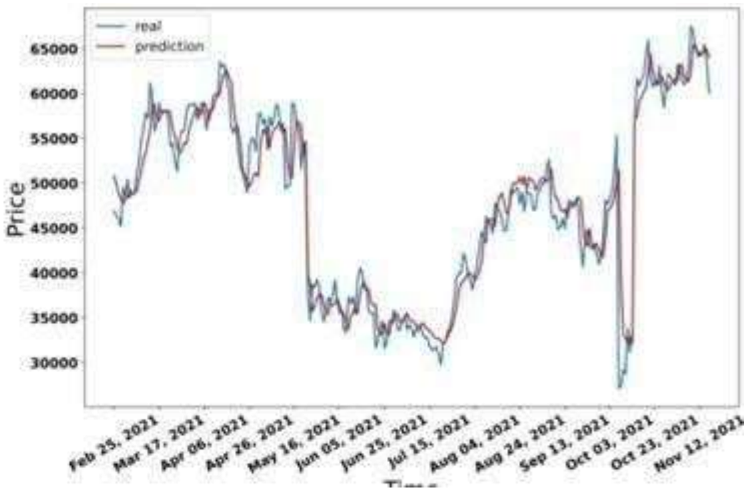

FIGURE 3: USER INTERFACE OVERVEIW

VII. RESULT AND DISCUSSION

In this process, we applied three famous risk-based assets traditional approach for allocation strategy to make the com parison with HPR that as mentioned in Table 6, 7 and 8, Inverse Volatility (IV), Minimum Variance (MV) and Maxi mum Diversification(MD). In this process we used the rolling window analysis and evaluate the average value of the defined range.

The rolling window set as 350, 600 and 850. The performance of the out-of-sample HPR portfolio in 350 days co-variance estimation summarized in Table 6. The HPR annualized volatility and return are in row 0.7718 and 1.7802. Moreover, MD gives the result of 3.42 more return result and IV decrease the volatility to 1.5 slightly. The balance of HPR in term of risk and return has the high effect which provides the trade-off best risk-return result comparing with sharp ratio. All the process follows for the 600 and 850 days in same way.

FIGURE 4: CRYPTOCURRENCY CLOSING PRICE OF BITCOIN.

FIGURE 5: CRYPTOCURRENCY CLOSING PRICE OF RIPPLE.

VIII. FUTURE SCOPE

- Graph Neural Networks: Use graph neural networks to model the relationships between different cryptocurrencies and improve forecasting accuracy.
- Natural Language Processing (NLP): Use NLP techniques to analyze social media and news articles to improve forecasting accuracy.
- Transfer Learning: Use transfer learning techniques to adapt pre-trained models to new cryptocurrencies and improve forecasting accuracy.
- Explainability Techniques: Develop techniques to explain and interpret the predictions made by CryptoHub, providing insights into the underlying factors driving price movements.
- Edge Computing: Use edge computing to enable real-time forecasting and reduce latency

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IX. CONCLUSION

In this study, the risk management of cryptocurrency net work analysed using the Reinforcement Learning (RL) technique and asset allocation method named as Hierarchical Risk Parity (HRP) that applied in cryptocurrencies portfolio. Reinforcement learning gives a high performance evaluation results as compare to other machine learning techniques have been used in this area. The main reason of applying RL in this process is the learning-based aspect of this approach which gives the opportunity to system structure to get the high accuracy in term of giving the right information to system. Moreover, the HRP has the highest properties and desirable diversification. The results analyzed using various estimation windows and methodologies and similarly rebalancing the selected period. The applied HRP gives the transitional asset allocations meaningful alternative and improve the risk man process. In future research, the proposed technique will extended by applying out-of-sample testing performance in more assets and classes and using techniques of optimization to get better performance in term of risk management.

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