Crypto-Currency Prediction and Comparing with Other Crypto-Coins Using Block-chain

E.Elakiya[1], K.Prince Suja[2], R.Divyabharathi[3], S.Shagarbhan[4]

[1]Assistant professor, Dept. of CSE, E.G.S.Pillay Engineering College, Tamil Nadu, India
[2]UG student, Dept. of CSE, E.G.S.Pillay Engineering College, Tamil Nadu, India
[3]UG student, Dept. of CSE, E.G.S.Pillay Engineering College, Tamil Nadu, India
[4]UG student, Dept. of CSE, E.G.S.Pillay Engineering College, Tamil Nadu, India

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Abstract – After the boom and bust of crypto currencies' prices in recent years, Bit-Coin has been increasingly regarded as an investment asset. Because of its highly volatile nature, there is a need for good predictions on which to base investment decision. To predict Bit-Coin price at different frequencies using machine learning techniques, we first classify Bit-Coin price by daily price and high-frequency price.Compared with benchmark results for daily price prediction, achieve a better performance, with the highest accuracies of the statistical methods and machine learning algorithms of 91% and 90.3%, respectively. Machine learning models including Random Forest, XGBoost, Quadratic Discriminant Analysis, Support Vector Machine and Long Short-term Memory for Bit-Coin 5-minute interval price prediction are superior to statistical methods, with accuracy reaching 94.2%. Our investigation of Bit-Coin price prediction can be considered a pilot study of the importance of the sample dimension in machine learning techniques. At the same time Ethereum values cam also be predicted efficiently with the above mentioned algorithms and with the datasets that has been collected. Also in the proposed technology the values of Lite-Coins are also processed which is four times faster that bit-coins and transactions time on lite-coins are much faster than bitcoin. As a result in the proposed methodology both bit coin, Ethereum and Lite-Coin's values can be predicted quiet accurately.

***Key Words*: Cryptocurrency, Bit-Coin, Ethereum, Lite-Coins.**

1. INTRODUCTION

Bitcoin is the first successful decentralized cryptocurrency system with a number of unique capabilities. First, it allows users to create accounts and transact with one another on the Bitcoin peer-topeernetwork in a decentralized fashion. There is no central authority that oversees the cash flow within the system. Second, it uses the Blockchain technology for secure computing without centralized authority in an open networked system.

The Blockchain is created and maintained using a peer-to-peer overlay network and secured through intelligent and decentralized utilization of cryptography with crowd computing.

Third, it employs a proof-of-work consensus protocol to verify and authenticate the transactions that are carried out in the network. Bitcoin is becoming increasingly popular and is widely recognized as the first successful example of the crypto currency economy.

Bitcoin transactions have made publicly available since its inception. Most existing research efforts have centered primarily on mining the statistical characteristics of the Bitcoin transactions.

That it is also important, though more challenging, Analyze the Bitcoin transactions collected to date to extract the distinctive characteristics of Bitcoin transactions and build Bitcoin transaction inference models for transaction forecasting, transaction tracking, and user identification, to name a few.

One way to learn the interesting transaction patterns is to model the Bitcoin network as a big graph with accounts (or nodes) in a Bitcoin network as vertices and transactions conducted between two accounts as the edge between two Bitcoin accounts (nodes).

2. LITERATURE REVIEW

2.1 Title: Cascading Machine Learning to Attack Bitcoin Anonymity

Authors: Francesco Zola, Maria Eguimendia, Jan Lukas Bruse, Raul Orduna Urrutia

Bitcoin is a decentralized, pseudonymous cryptocurrency that is one of the most used digital assets to date. Its unregulated nature and inherent anonymity of users have led to a dramatic increase in its use for illicit activities. This calls for the development of novel methods capable of characterizing different entities in the Bitcoin network. In this paper, a method to attack Bitcoin anonymity is presented, leveraging a novel cascading machine learning approach that requires only a few features directly extracted from Bitcoin blockchain data. Cascading, used to enrich entities information with data from previous classifications, led to considerably improved multi-class classification performance with excellent values of Precision close to 1.0 for each considered class. Final models were implemented and compared using different machine learning models and showed significantly higher accuracy compared to their baseline implementation. Our approach can contribute to the development of effective tools for Bitcoin entity characterization, which may assist in uncovering illegal activities.

2.2 Title: BotcoinTrap: Detection of Bitcoin Miner Botnet Using Host Based Approach

Authors: Atefeh Zareh, Hamid Reza Shahriari.

Bitcoin is one of the most successful cryptocurrencies. Many people invest money on creating new Bitcoins because of Bitcoin's market increase. They actually buy hardware and power to participate in Bitcoin mining. The market value of Bitcoin has also absorbed cybercriminals. They steal the process cycles from victims' machines and use them in mining activities by malware programs. There have been several security reports about these types of malicious activities. Although there are methods to detect botnets, to the best of our knowledge, none of non-commercial and published papers present detection method for these types. In this paper, we present Botcointrap, a novel approach to identify Bitcoin miner botnets (called Botcoin) based on dynamic analysis of executable binary files. This method benefits from a parameter value that all Botcoins must use across their computations and detect them in the lowest level of execution; therefore, our method can be used to overcome weaknesses of many other approaches. Our evaluation shows that the proposed approach efficiently identifies all simulated Botcoins.

2.3 Title: Crypto-Currency price prediction using Decision Tree and Regression techniques

Authors: Karunya Rathan; Somarouthu Venkat Sai; Tubati Sai Manikanta

Crypto-currency such as Bitcoin is more popular these days among investors. In the proposed work, it is studied to forecast the Bitcoin price precisely considering different parameters that influence the Bitcoin price. This study first handles, it is identified the price trend on day by day changes in the Bitcoin price while it gives knowledge about Bitcoin price trends. The dataset till current date is taken with open, high, low and close price details of Bitcoin value. Exploiting the dataset machine learning module is introduced for prediction of price values. The aim of this work is to derive the accuracy of Bitcoin prediction using different machine learning algorithm and compare their accuracy. Experiment results are compared for decision tree and regression model.

2.4 Title: User Reputation Analysis for effective Trading on Bitcoin Network

Authors: : Divya Singh; Lakshay Kumar; Somya Jain.

Signed network is a refined form of social network where connections or relationships between people are defined with strength. An edge in this network can contain a positive, negative or neutral sign to define friendly, foe or neutral relationship respectively. This paper aims to utilize the properties of signed network and hence builds a Bitcoin alpha (whom-trust-whom) network. This trading network is further scrutinized to estimate user's reputation i.e. predicting ranks of participating actors. Thus, are able to provide score to individual user to recommend whether he is safe to make transactions with. In addition, novel method for link prediction by calculating strength of path between two unconnected nodes is proposed. This strength value considers all the features of the nodes, edges and neighbors giving results that have higher accuracy over previously defined methods.

2.5 Title: Bitcoin Blockchain Transactions Visualization

Authors: Ajay Kumar Shrestha; JulitaVassileva.

Blockchains were originally used to support the Bitcoin cryptocurrency and now entire software ecosystems are being supported by blockchains. Despite their widespread use, not much is known about how peers in the bitcoin blockchain network use the system. The present visualizations to help in identifying some patterns in the usage of bitcoin blockchain supported technologies. Observe the bitcoin transaction continent-wise via a visualization of the locations from where peers in the bitcoin blockchain network were making their transactions, using WebGL technology. Analyzed regional bitcoin blockchain usage patterns by observing their clusters formation over time. Also presenting a pattern of how the value of the bitcoin changes over time.

3. Module Description

Data acquisition

In this module crypto currency data has been acquired which consists of crypto coin rate data and its variations. Large number of data is present in the acquired datasets, which is efficiently used to monitor and predict crypto coin rates in past and as well as in future.

Preprocessing

Acquired datasets are preprocessed and results are attained with better efficiency using ANN algorithm. ANN deeply analyses the entire data and datasets that are acquired and preprocessing has been done as a step by step process. As a result an initial level conclusion can be attained.

Classification

Preprocessed data are classified based on its structure or based on the rate prediction. For classification SVM has been proposed which compares and classifies large number of values in datasets and data present in the entire process. Classification is a process that has been carried out throughout the process which ensures next step to segment data.

Segmentation

Classified data results are segmented ad gathered as a group of data and information that has been present in the large number of datasets. As a result of segmentation of data classified results that are similar are grouped and predictions has been done with quiet better efficiency.

Feature Extraction

After segmentation an unique data from datasets are attained which are extracted from a series of data that are segmented. Whereas feature extracts process competes and provides accurate extraction of crypto-coin data that are involved in the system. Due to extraction of large amount of data using ANN and SVM accuracy has been attained up to 91%.

Performance Evaluation

By performing entire operation and its special features the performance evaluation of crypto currency predictions are attained with better results which enhances the complete system with higher order efficiency and attained results based on past and present are accurate which enormously enhances the procedures and attained results are maintained with better efficiency.

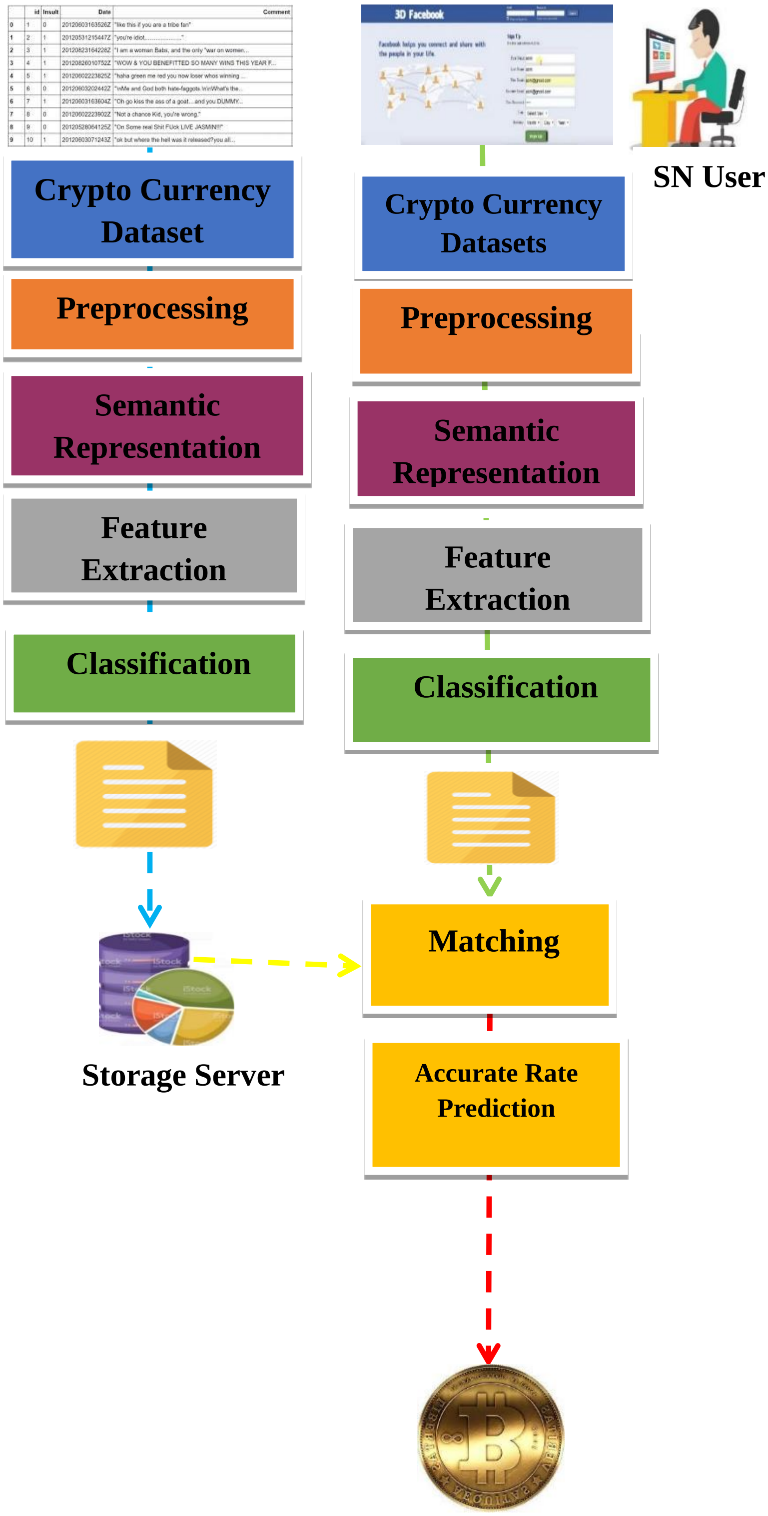

Fig 1 Module Diagram

4. PROPOSED SYSTEM

DLForecast, a Bitcoin transaction forecasting system, by leveraging deep network representation learning. Our goal is to predict transaction relationships among accounts on the Bitcoin network. One approach to achieving our goal is to utilize a artificial neural network (ANN) to learn important hidden features among transactions on the Bitcoin transaction graph, related accounts, transaction amounts, and temporal and spatial transaction properties. The development of our transaction forecasting ANN model consists of three main tasks. To extract observable features from a Bitcoin transaction dataset.

A transaction happened 8 years ago often has a negligible influence on the transaction patterns today. Motivated by these challenges, extract observable features of Bitcoin transactions by exploring spatiotemporal information in the data. The goal is to link the current transaction pattern between two or three crypto coins to the probability of the transaction. The dynamics of bitcoin transactions make it challenging to build a once-for-all transaction predictor due to the changing transaction pattern and the short life span of bitcoin transaction accounts. The set up a time slot for the transaction prediction model update. At the beginning of each time slot fine-tune the trained forecasting system with transactions and accounts in the previous time slot. By promoting such an on-the-fly evolution of the forecasting model, the provide a reasonably high forecasting accuracy. The third and final stage of the DLForecast development is to combine multiple transaction pattern graphs constructed using different types of extracted features.

Due to the changing dynamics of Bitcoin transactions, neither the time-decayed reachability graph nor the time-decayed transaction amount graph is capable of capturing different transaction patterns alone. Namely, no single feature graph can outperform all others. This motivates us to develop mechanisms that can combine different graphs constructed from different sets of the extracted features. To the best of our knowledge, this is the first paper applying ANN models on forecasting Bitcoin transactions using the real-world Bitcoin transaction data.

Accuracy predictions are done by using ANN which accurately predicts and provides detailed information of crypto coins. Due to implementation of ANN and SVM accurate crypto-coins rates and its specifications are attained. Comparison and compared results are maintained in a datasets which provides detailed structure of crypto coins rates and its future values are predicted with better efficiency.

5. SNEAKPEEKS OF IMPLEMENTATION

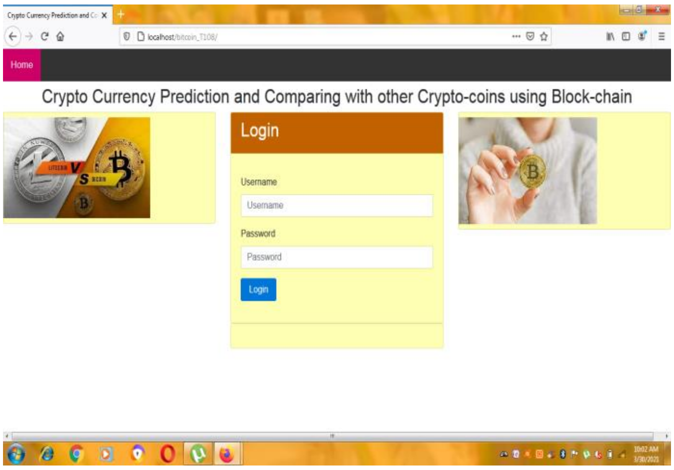

Fig 2 Login page

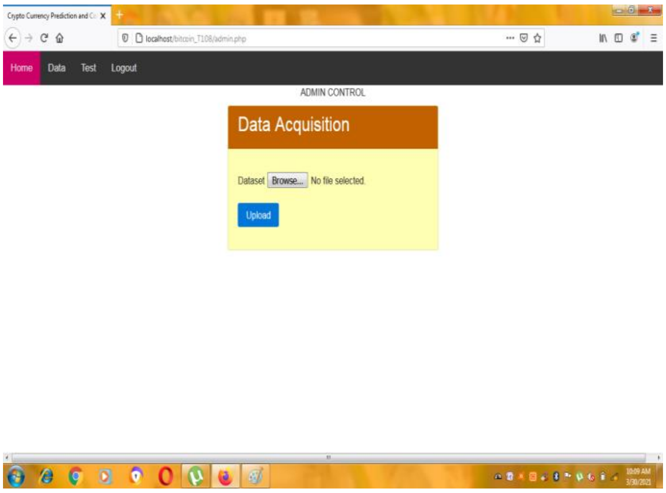

Fig 3 Data Acquisition

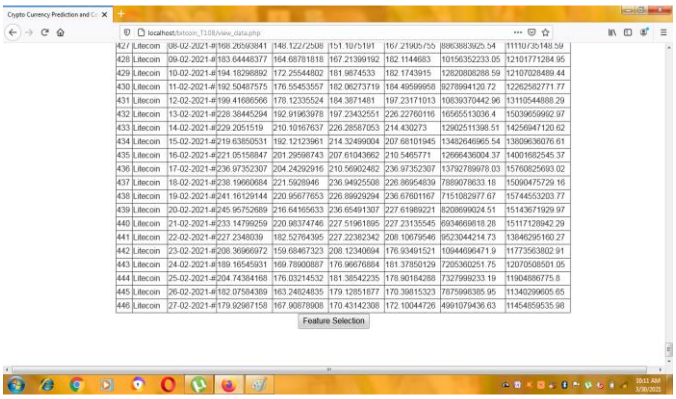

Fig 4 Feature Selection

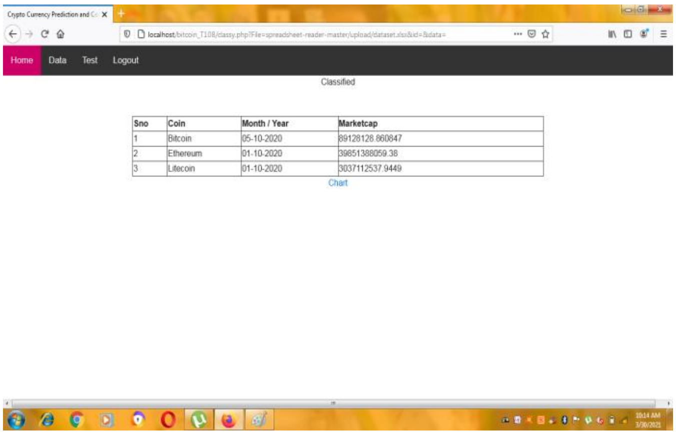

Fig 5 Classification

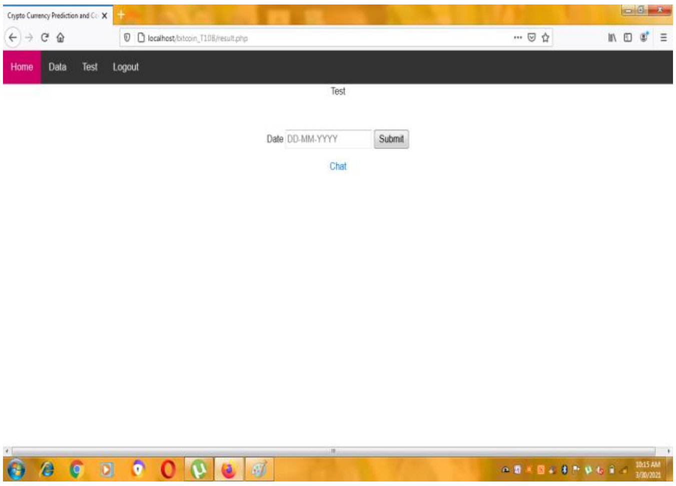

Fig 6 Testing

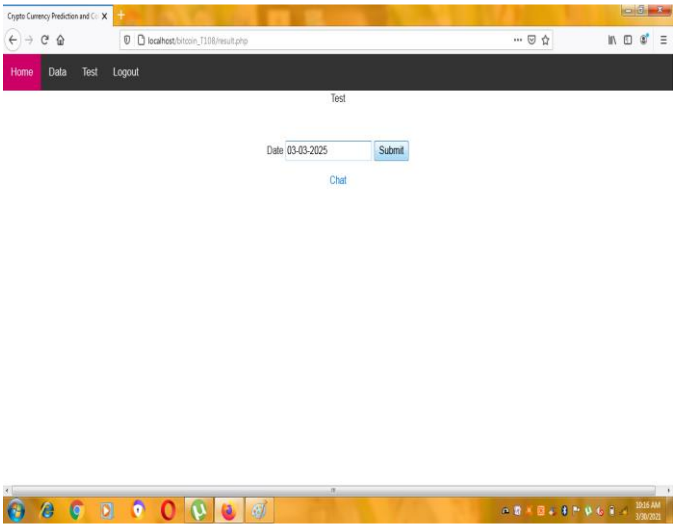

Fig 7 Date submit chat

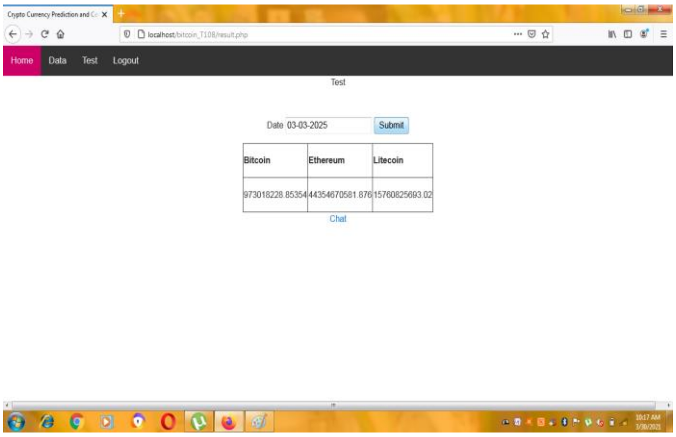

Fig 8 Result page

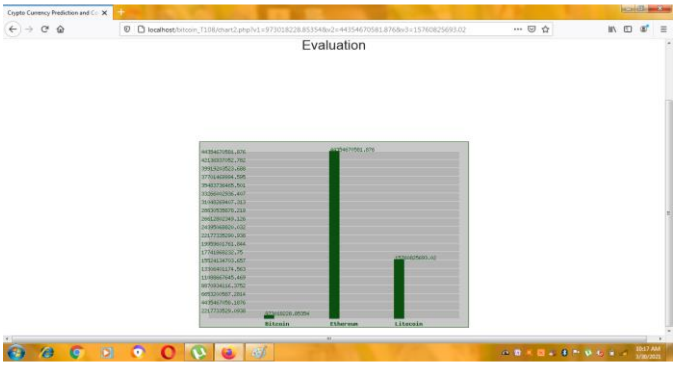

Fig 9 Evaluation

6. CONCLUSIONS

A Bitcoin transaction forecast system, which leverages deep neural networks to learn Bitcoin transaction network representations. This paper makes three unique contributions. First, we analyzed the Bitcoin transaction data by exploring their transaction-based connectivity patterns and their transaction amount patterns. Second, constructed a time-decayed reachability graph and a time-decayed transaction pattern graph to extract spatial and temporal features of Bitcoin transaction dynamics. Third but not the least, we learn Bitcoin transaction patterns through node embedding by mapping each of the constructed graphs into a low-dimension representation vector space. Through iterative network embedding training, we build a deep neural network-based Bitcoin transaction forecasting model, which is capable of making predictions on the transaction patterns between user accounts based on historical transactions and the built-in time-decaying factor. Evaluated on real-world Bitcoin transactions, we showed that our spatial-temporal forecasting model is efficient with fast runtime, effective with forecasting accuracy over 60%, and it improves the prediction performance by 50% when compared to the forecasting model built on the static graph. In addition to deploying DLForecast for Bitcoin transaction forecasting, the proposed system can also be used to detect and identify certain interesting transaction behaviors, e.g., some accounts may exhibit short term absence or presence in their history of transactions. DLForecast can additionally be used to monitor legitimate transactions and identify illicit actors in the crypto space. Even though Bitcoin transactions include no personally identifiable information about users, such as names, addresses, or social security numbers, the dynamic graphs constructed by the DLForecast system can be used to connect multiple transactions to the same account. Thus, such dynamic graphs can be utilized for identifying certain behavior patterns of a single address, such as long term transaction of a small amount of Bitcoins and a sudden large amount transaction, and for associating such transaction behavior with some real-world events or timeline, which may assist the law enforcement to track those transactions made by illicit actors (dark marketplaces, ransomware operators, fraudsters) and to identify those transactions made by legitimate actors (e.g., regulated exchanges, merchants, wallet services). Another interesting utility of DLForecast is to look into those cases where a transaction happens when the forecasting model predicts such a transaction as unlikely to happen for a given period. Although DLForecast is developed for analyzing and predicting Bitcoin transactions, the proposed system and algorithms developed can be applied to a range of cryptocurrencies and blockchain-based assets, such as those for storing financial records or any other data where an audit trail is required because every change is tracked and permanently recorded on a distributed and public ledger. The proposed system can help reducing compliance costs and monitoring and detecting criminal or illegal activities. Future Enhancement is based on the present implementation the extracted results are processed with crypto coins. Where as in future the same procedure can be implemented in various fields such as share market, money market, mutual funds, financial sectors, commodity markets etc. As a result predictions can be done in an accurate manner which provides best results in future. Same process can be accessed and attained in banking sectors, disaster funding procedures and so on.

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