*Original Article*

# Blockchain in Trust with Reputation Management for Financial Stock Market Using Distributed Ledger Technology and Bayesian Theory Based on Fault Tolerance Model

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## Abstract

Blockchain, which is at the heart of bitcoin and other digital currencies, is a game-changing technology, particularly in the stock market and financial technology. These characteristics make blockchain adoption appealing for enhancing information security, privacy and reliability in a variety of scenarios. This article develops the trust with reputation-based management for the financial stock market. Here distributed ledger technology (DLT) has been integrated for implementing the ledger in which data is stored across a network of decentralized nodes. By this, proof-based ledger has been maintained with transparency, traceability and security. DLT here used is based on trust design in mitigating the malicious activities of the financial stock marketing technology. Then using Bayesian theory based on the fault tolerance (BDLT_FT) model has been used in improving the efficiency of DLT and financial technology. This acts as the protocol which reduces energy consumption and enhance network scalability and security in digital transactions like cryptocurrency The financial data related to blockchain cryptocurrency were collected between the time period 2000 and 2020. The dataset of the stock market is evaluated under the fault tolerance model with statistical analysis. The statistical evaluation of financial data with developed BDLT_FT expressed that there is no association between the fault tolerance and the classification error.

## Keywords

Blockchain, stock exchange market, financial technology, trust, DLT, BDLTFT

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## Introduction

Modern finance aims at identifying efficient ways to understand, transform and visualize stock market data into useful information that will aid better in investment decisions. Financial tasks are highly complicated and multifaceted; they are often stochastic, dynamic, nonlinear, time-varying, flexible structured, and are affected by many economic and political factors. One of the most important problems in modern finance is finding efficient ways of summarizing and visualizing the stock market data that would allow one to obtain useful information about the behaviour of the market. The term 'blockchain' has lately gained popularity and is increasingly being used in marketing to draw attention to a company's products and services (Andoni et al., 2019). The ability to exchange data in areas where participants have established low levels of trust is claimed to be the main benefit (Chen et al., 2018). When an attacker breaches a shared protected resource and causes significant damage to the entire system, it is centralization that triggers various attack scenarios (Saberi et al., 2019). Because information is copied across hundreds of nodes, hacking one of them will not suffice (Min, 2019), the blockchain is said to be able to put an end to such crimes (Agbo et al., 2019). The term 'Attack 51% ' is used to describe this aspect of a distributed ledger, which is often positioned as a proactive way to prevent detrimental repercussions. However, because the effectiveness of a distributed system is dependent on the implementation approach, the immutability of a ledger does not necessarily show to be an obvious advantage in practise. The latter also creates various problems, given the distributed network's accessibility nature and the features incorporated in the technology's core principles (Mohanta et al., 2018).

Russian government officials are very interested in technology (Pan et al., 2020). Dmitry Medvedev, speaking at the Sochi Economic Forum in February 2017, emphasized the need of embracing blockchain technology, and directed the Ministry of Communications and Mass Media to identify areas that would gain the most from it. Furthermore, the blockchain is included in Russian Federation's digital economy program (Janssen et al., 2020). As a result, the topic's importance stems from fact that distributed ledger system, has just arisen, has undeniably significant potential for data security area and so deserves further investigation. Even now, businesses and governments all around the world are attempting to actively integrate distributed ledgers into their data transfer networks and number of new actors attempting to popularize blockchain technology is expanding (Akgiray, 2019). Transparency, security and safety are all advantages of employing this technology in new projects. As a result, it is excellent reinforcement for any services that exhibit a well-known low level of trust between parties involved in the data exchange process (Anwar, 2021). In comparison to well-established approaches to the construction of data systems, technology is currently being thoroughly investigated in terms of integration possibilities, approval and an evaluation of potential benefits and drawbacks (Casey et al., 2018).

The conventional technique focused on the exchange of information for data processing in the stock market. With the advancement of cryptocurrency, it is necessary to effectively process the data. However, the conventional scheme concentrated only on processing and gathering cryptocurrency data . With distributed ledger technology (DLT), the cryptocurrency can be processed effectively to improve the performance in the stock market. Additionally, the data can have threats that affects the overall cryptocurrency process in the market. This article aimed to develop reputation management through integrated DLT in the stored network with decentralized nodes. The developed scheme uses the Bayesian network model to increase the efficiency of the network and to minimize the malicious activity in the network. The analysis is based on the computation of the cryptocurrency data between 2000 and 2020. The statistical evaluation of financial data with developed Bayesian theory based on the fault tolerance (BDLT_FT) expressed that there is no association between the fault tolerance and the classification error.

## Blockchain and Cryptocurrencies

In general, transactions are the exchange of commodities or services between two persons. Because payments, goods and services may be irreversible, a successful transaction requires mutual trust between two parties (Evans, 2018). Involving a third-party intermediary in transactions is one option to overcome the trust issue. However, due of the time lag of third-party verification, use of intermediaries cannot totally eradicate these fundamental difficulties (Mselmi, 2020). In 2008, an anonymous person using pseudonym Satoshi Nakamoto developed a decentralized system called bitcoin, which is a blockchain application, for doing P2P electronic monetary transactions without use of trusted intermediaries (Bhandarkar et al., 2019). Each user on network is a node in the proposed system, and each new transaction is broadcast to all nodes. Users then check to see if the transaction is legitimate. The verified transaction is subsequently packed into a block with hash data from preceding and following blocks and added to a chain of blocks (Pashkevych et al., 2020). Because each block contains hash data from previous and subsequent blocks, changing the content of block is exceedingly costly, ensuring transaction integrity as well as irreversibility (Collomb et al., 2019). Cryptocurrencies are the most prominent application of blockchain technology among these (Collomb et al., 2019). Cryptocurrencies like bitcoin are in digital (Zhang et al., 2020) form without having any physical structure and every one can receive, transfer and or exchange digital currency (Michael et al., 2018). Instead of a central bank, a decentralized network controls supply of cryptocurrency. Various cryptocurrencies have different coin limitations and algorithms. Firms typically get involved with cryptocurrencies for a variety of reasons and at various levels. For instance, bitcoin mining was one of BTCS Inc.'s key companies in 2015 and Overstock.com, an online shop, takes bitcoins as a form of payment (Zhang et al., 2020). Some companies only trade cryptocurrencies or invest in blockchain startups as a side business and do not use blockchain method in their core business.

### *Fundamentals on Blockchain and Distributed Ledger Technology*

Initial bitcoin protocol (Akgiray, 2019) was introduced by Satoshi Nakamoto in 2008, and this was the first appearance of a blockchain. Dispersed nature of users network, permissionless access, consensus scheme and cryptographic methods that constitute system's security layer are four main pillars that make up a blockchain system. The theory of distributed ledgers (Ali et al., 2020) is the foundation of the blockchain. In this sense, integrity refers to the three major components of a software system: data integrity, behavioural integrity and security (Ali et al., 2020). To put it another way, the system must verify that the data it uses and maintains is comprehensive, true and free of inconsistencies, that it acts logically, and that data access as well as permissions are only granted to authorized users. Major innovation of blockchain was the introduction of a mechanism for ensuring precise recording as well as tracking of transactions in a public system with zero trust (Ross, 2016). Define a blockchain in terms of four pillars listed above.

**Definition 1:** Each block contains a set of valid transactions that are linked together using cryptographic methods to secure system's integrity over time. A blockchain is a permissionless defined P2P ledger that validates and permanently stores every transaction in a time-ordered chain of blocks using a software mechanism known as distributed consensus protocol.

In Appendix A, we present an altered version of the schematic as found in Zachariadis et al. (2019). This discussion underlines the fact that one of the primary distinguishing features of blockchain is that control of distributed ledger is shared by a subset, if not all, of the network's nodes. This is a key distinction between a blockchain as well as other technological frameworks employed in existing shared ledgers, like cloud computing or data replication (Knezevic, 2018). Because nodes' trust is unknown, the system's integrity is maintained by a set of rules that each peer must follow in order to identify, verify, and then permit the appending of a particular data record. Because of this lack of centrality, a single entity cannot approve insertion of a particular transaction to system. As a result, with a blockchain, adding new data and validating it is a collaborative endeavour governed by a consensus mechanism outlined by design.

Through a set of present cryptographic validation methods, a consensus process is required to determine whether a specific transaction is authentic or not. There are several mechanisms for reaching an agreement. The bitcoin protocol, for example, employs the Proof-of-Work (PoW) algorithm and data validation method is known as mining (Jaag & Bach, 2017). When people do not trust a government or a corporation to centrally record all aspects of a transaction with complete accuracy, decentralized nature of blockchain governance is a desired feature. That is, the blockchain was created in response to a lack of trust between parties and their ability to record transactions. Immutability is established using cryptography. In summary, a hash function can calculate a digital fingerprint from any input data that cannot be changed until input data is modified. Advantages and cons of new pattern offered by blockchain technology are undeniable. Furthermore, a hash function's result cannot be restored to its original input. Disintermediation, for example, is one of the benefits, as is a high level of integrity, immutability and openness, speedier transactions with fewer related costs and significantly enhanced traceability. Because a blockchain is a distributed system, it does not require the use of middlemen (Wu & Duan, 2019). A blockchain provides highest level of integrity of any network system, guaranteeing that all data saved in chain is always consistent and resistant to alteration. Furthermore, immutability characteristic is crucial since it retains history of every transaction record in system, adding to system's high integrity. Additionally, a blockchain is totally transparent in its original design. If someone in system tries to change a record, it will be noticed by all other users. In comparison to traditional centralized systems like banks, the technology also allows for speedier transactions. When we consider transactions involving international money transfers, this becomes even clearer. Because there are no additional intermediary processes with associated costs along way, a blockchain performs transactions at a cheaper cost, in addition to greater speed. Of course, transactions are not free, but because there are no intermediaries in the system, the final cost is substantially lower than with traditional methods. Last but not least, blockchain improves traceability. Every previous and present transaction may be traced in a transparent manner, allowing every node participating to be instantly and easily found.

**Definition 2.** A DLT is a P2P method of ledgers that requires decisions about user rights, consensus methods and cryptographic security in order to preserve immutability and integrity. Characterize a DLT by a tuple $\left(\zeta\left(.\right),\rho\left(.\right),\xi\left(.\right),\gamma\left(.\right),\alpha\left(.\right)\right)$ with a range of feasible choices over five variables, similar to how we did for a traditional blockchain system. We'll look at some of the design choices to see why certain businesses might wish to make exact DLT choices about components determined by tuple.

## Constructed Bayesian Fault Tolerance for Distributed Ledger Technology

Stock market prediction is regarded as the challenging task of financial time series prediction. Investors trade with stock index-related instruments to hedge risk and enjoy the benefit of arbitrage. Therefore, being able to accurately forecast the stock market index has profound implications and significance to researchers and practitioners alike There are umpteen research works carried out suggesting the predictability of stock markets. Initially, tests of predictability of stock market returns were motivated by market efficiency, where it is assumed that predictability was inconsistent with constant stock market returns and efficient markets paradigm. For a long time, the changes in the stock market are not able to predict accurately. To improve the standard of the stock market it is effective to design of appropriate economical manner. This article developed a Bayesian fault tolerance model for DLT termed as BDLT_FT. Figure 1 presents the overall architecture for the constructed BDLT_FT in the financial data of the firm. The constructed BDLT_TM model comprises the fault tolerance model integrated with multilayer perceptron (MLP). The fault tolerance network comprises of memory unit stored with neural network (NN) parameters with three layers such as input, activation layer and output layer. The constructed model uses the architectural vulnerability factor (AVF) for estimation of faults in the network. In AVF each layer is considered as the Bernoulli random variable based on the consideration of probability value $p$. Additionally, error bits also not assumed determined by the probability of $p$. The constructed BDLT_FT model encodes the data into a 32-bit floating-point number for the network input and output parameters.

With the constructed BDLT_FT model with Bayesian network with integrated NN with each neurons. In the bias environment weights are assigned at each layer of the network as shown in Figure 2. The network weights and biases are referred as $W$ and $b$ for the injected bitwise-XOR operation.

Within the constructed environment weights and biases are transformed as $W$ and $b$ for the injected error to perform bitwise-XOR operation. Based on the injected error each layer neuron distribution probability is examined at the output space for the assigned weights and probability $p$. The designed fault tolerance model for DLT comprises of the propagation scheme over NN with selection of each neuron in the activation function with estimation of fault behaviour. The E2E fault propagation mechanism in NN through automated statistical analysis model. In Figure 3 developed a NN model for fault tolerance scheme integrated with Markov chain model.

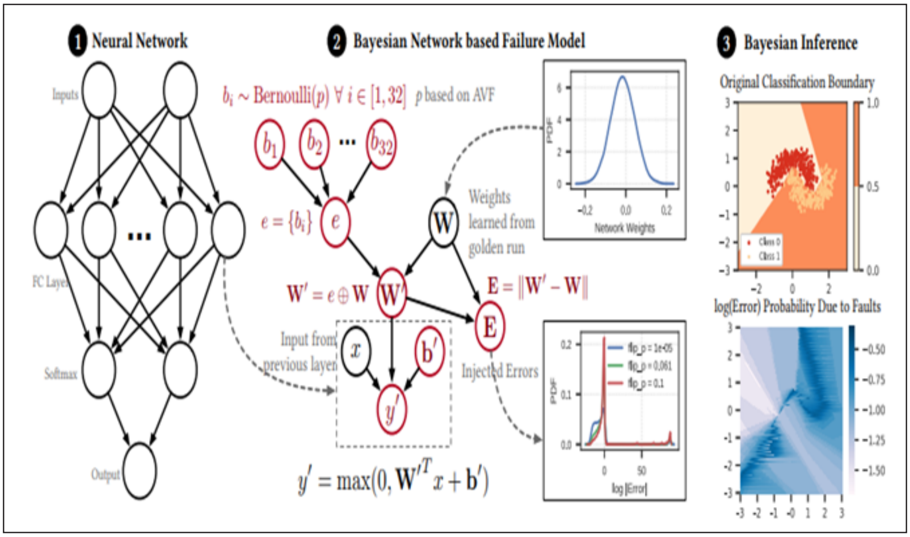


**Figure 1.** Overall Architecture of BDLT_FT.

**Source:** The authors.

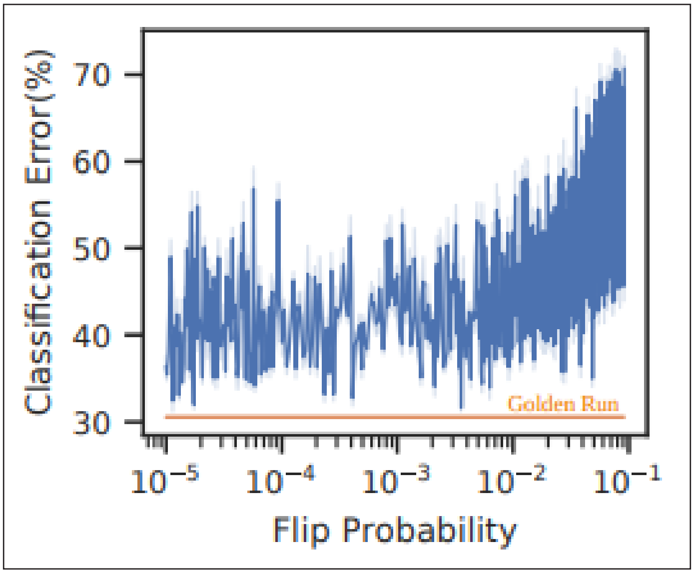


**Figure 2.** Error Distribution in BDLT_FT.

**Source:** The authors.

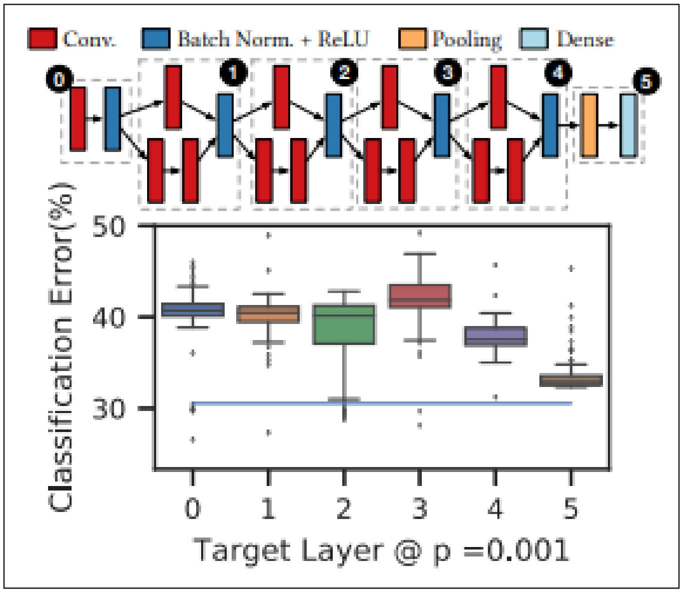


**Figure 3.** Layered Architecture for NN.

**Source:** The authors.

The faults are injected within the DLT for comparative examination of the classification accuracy with run distribution in the BDLT_FT. The distributed network performs Markov Chain Monte Carlo fault injected model those are adopted in following steps as follows:

1. Initially, network is trained to obtain or evaluate stock price weights to achieve good accuracy of classification.
2. The fault model and weights obtained through training in the network are evaluated for computation of error distribution in the assigned weighted network.
3. The constructed model with Bayesian architecture is evaluated at each neuron with error distribution in the network
4. To perform classification about uncertainty in the network for different probabilities flip for multiple Bayesian architecture environment.

## *Econometric Analysis*

As stated, the constructed BDLT_FT model uses VAR model for computation and processing of DLT. The developed framework comprises of the likelihood estimation, prior distribution, posterior distribution derivations, estimation of simulation parameters, posterior predictive density estimation and impulse response simulation.

Estimation of DLT of the financial data evaluated based on the capital investment for each year with stock analysis data. In the beginning of the year normal return is multiplied with the present value as represented in Equation (1)

$$\mathrm{MVE}_t = \mathrm{BVE}_t + \sum_{\tau=1}^{\infty} \frac{E_t\left[\mathrm{NIA}_{t+\tau}\right]}{(1+rf)^t} \tag{1}$$

As a result, the market value of the company is broken based on concurrent value for book value and present value for prediction of future trend also defined as unrecognized. The firm abnormal earring in the present year is expressed in the following equation:

$$\mathrm{MVE}_t = (1-k)\mathrm{BVE}_t + k\left(\varphi \mathrm{NI}_t - d_t\right) + \alpha v_t \tag{2}$$

where $\mathrm{NI}_t$ is period $t$'s net income, $d_t$ is period $t$'s dividends distributed, $v_t$ is period $t$'s other information, $k$ is a discount rate function, and an is a coefficient. Financial and non-financial disclosures, and other factors. Similarly, the Ohlson model with financial data estimation in the network in linear regression is presented in the following equation:

$$\begin{aligned} \mathrm{PRICE}_{i,t} = {} & \alpha + \beta_1 \mathrm{BVES}_{it} + \beta_2 \mathrm{NIS}_{i,t} + \beta_3 \mathrm{Keywords}_{i,t} + \beta_4 \ln \mathrm{AT}_{it} + \sum \beta_j \mathrm{YEAR}_j \\ & + \sum \beta_k \mathrm{INDUSTRY}_K + \varepsilon_{it} \end{aligned} \tag{3}$$

where $\mathrm{PRICE}_{i,t}$ is firm $i$'s stock price 3 months after end of fiscal year $t$; $\mathrm{BVES}_{it}$ is firm $i$'s equity book value those can be minimized with number of allocated shares in the $i$th year $t$. To determine if blockchain or cryptocurrency disclosures are valuable. This ensures that 10-K data is publicly available to investors.

## Research Methodology

### *Sample*

The proposed BDLT_FT model is examined for the fault tolerance in the stock market with cryptocurrencies. The examination of the stock market is based on the evaluation of the rate of rupees, troy ounce, nominal exchange value, nominal discount rate. The evaluation period for analysis is considered between 2000 and 2020. The information collected related to the stock market between the period of 2000 and 2020 tested with the VAR framework for the actual data. The data collected from different sources are presented between 2000 and 2020 with four parameters those are exchange rate, stock price, interest rate and gold price. Figure 4 presents the trend in financial stock data represented for DLT.

To perform the fault tolerance scheme bag-of-words based approach is derived for extraction and quantification of blockchain and cryptocurrencies for the observation sample period. The blockchain keyword utilized for analysis are DLT and blockchain. In case of cryptocurrencies the selected words are bitcoin, cryptocurrency, digital currency, Litecoin, and Ethereum. The collected sample comprises of the 10-K filing with electronic gathering of data and analysis. The data sources are collected between the time period 2000 and 2020 with consideration of 22,466 observations, with the 10-K filing of 176 for the year and form 124. In Table 1 presented the overall summary of collected data for analysis.

Through the collected sample, the proposed BDLT_FT model comprises of the breakdown model with consideration of different industries. The selected sample uniformly distributed over the period for panel A. Based on the SIC (standard industrial classification) one-digit code those can be breakdown into different sample. In Table 2 presented the breakdown sample for constructed period industry between the time period 2000 and 2020.

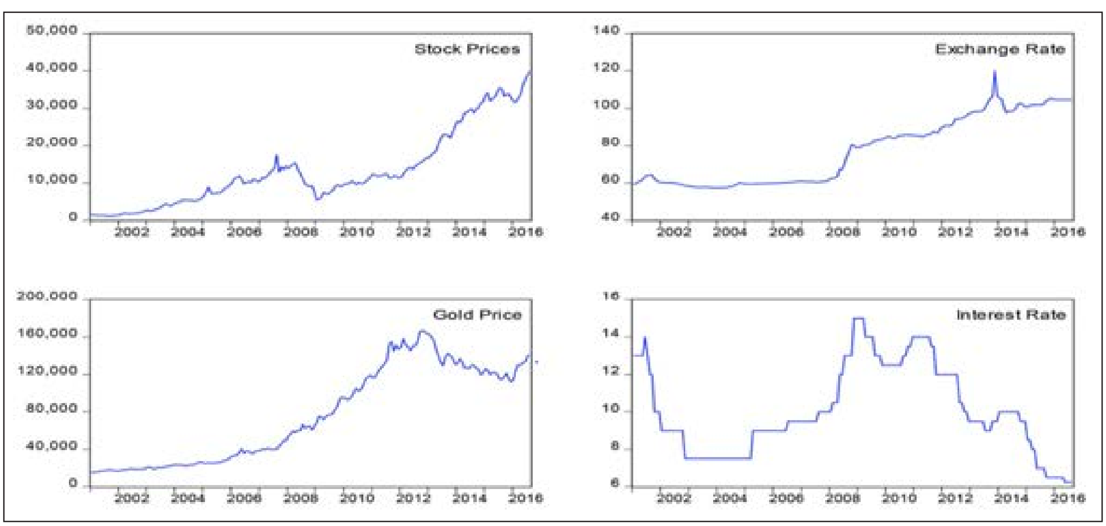


**Figure 4.** Estimation of DLT for Stock Determinants.

**Source:** The authors.

**Table 1.** Collected Sample.

| | # Firm-years | # Firms |
|---|---|---|
| Data period of 2000–2020 by CompStat | 55,432 | 15,257 |
| Missing variables | (26,699) | |
| Subtotal | 27,547 | 7,468 |
| Less: Merged data | 5,892 | |
| With blockchain or cryptocurrency keywords | 176 | 124 |
| Final sample | 22,564 | 5,946 |
| Without blockchain or cryptocurrency keywords | 22,466 | 5,820 |

**Source:** The authors.

**Table 2.** Breakdown of Sample and Industry.

| Panel A: Yearly Breakdown | | | | |
|---|---|---|---|---|
| Year | Total | | With Keywords | Without Keywords |
| 2014 | 4,703 | 20% | 4,695 | 8 |
| 2015 | 4,877 | 21% | 4,866 | 11 |
| 2016 | 4,832 | 20% | 4,814 | 18 |
| 2017 | 4,697 | 20% | 4,657 | 40 |
| 2018 | 4,630 | 20% | 4,526 | 104 |
| Total | 22,466 | 100% | 23,558 | 176 |

**Source:** The authors.

Furthermore, the table illustrates an upward trend in the number of companies that incorporate blockchain or cryptocurrency information availability size of 10-Ks from 2000 to 2020. Only eight companies disclosed blockchain or cryptocurrency information in 2014, but that number grew to 40 in 2017 and 104 in 2018, which is 13 times the number in 2014.

In addition, divided our sample based on frequency of blockchain and cryptocurrency terms; distribution is displayed in last two columns of panel B. Observe that more than half (56.91%) of the observations with blockchain or cryptocurrency keywords came from banking and insurance businesses, achieves 27.07% of service industries. As the constructed model uses the evaluation of the financial data is based on the encoded SIC code. The collected and processed with the sample are described as in Table 3.

All blockchain and cryptocurrency terms in our sample are distributed by firm–year in Table 3. Most common keyword is blockchain, which appears in 88 of the 181 10-K filings. Cryptocurrency/crypto-currency and digital currency are the second and third most commonly used keywords (at roughly 33.15% each). When we look at the data by year, we can see that the presence of cryptocurrency-related terms, such as bitcoin and digital currency, has been on the rise since 2014. Keywords like blockchain and DLT, on the other hand, do not exist until later in 2015–2016. Overall, according to the statistics in Table 2, the occurrence of all terms increased in 2018. The financial industry has more keywords, such as cryptocurrency, digital currency, blockchain, and DLT, but the service industry has more keywords like bitcoin. Similarly, in Tables 4 and 5 presented a breakdown year for the panel A and panel # for evaluation is presented.

**Table 3.** SIC Code for Collected Data.

| SIC 1 | | CompStat | | Sample | | Without Keywords | | Without Keywords | |
|---|---|---|---|---|---|---|---|---|---|
| | | Firm-years | Percentage | Firm-years | Percentage | Firm-years | Percentage | Firm-years | Percentage |
| 0 | Agriculture, fishing and forestry | 165 | 0.13 | 59 | 0.16 | 59 | 0.16 | 0 | 0 |
| 1 | Mining and construction | 7,014 | 11.59 | 1,752 | 7.38 | 1,752 | 7.44 | 0 | 0.00 |
| 2,3 | Manufacturing | 14,205 | 25.07 | 8,820 | 37.15 | 8,805 | 37.38 | 15 | 8.29 |
| 4 | Transportation, communications, etc. | 3,988 | 7.04 | 2,184 | 9.20 | 2,178 | 9.25 | 6 | 3.31 |
| 5 | Wholesale and retail trade | 2,694 | 4.75 | 1,732 | 7.30 | 1,724 | 7.32 | 8 | 4.42 |
| 6 | Finance, insurance and real estate | 21,679 | 38.26 | 5,467 | 23.03 | 5,364 | 22.77 | 103 | 56.91 |
| 7,8 | Services | 6,242 | 11.02 | 3,582 | 15.09 | 3,553 | 15.00 | 49 | 27.07 |
| 9 | Public administration | 693 | 1.22 | 142 | 0.60 | 142 | 0.60 | 0 | 0.00 |
| Total | | 55,767 | 100 | 22,466 | 100 | 23,558 | 100 | 176 | 100 |

**Source:** The authors.

**Table 4.** Keyword and Breakdown for Panel A.

| Firm-years | 2014 | 2015 | 2016 | 2017 | 2018 | Total | % |
|---|---|---|---|---|---|---|---|
| Keywords for blockchain | 0 | 2 | 7 | 17 | 67 | 93 | 47.65 |
| DLT | 0 | 0 | 2 | 7 | 18 | 26 | 13.46 |
| Number of firms with blockchain | | | | | | | 94 |
| Cryptocurrency keywords as bitcoin | 6 | 3 | 5 | 8 | 23 | 47 | 23.38 |
| Cryptocurrency | 0 | 3 | 6 | 4 | 48 | 64 | 32.14 |
| Digital current | 7 | 7 | 7 | 13 | 26 | 68 | 32.67 |
| Litecoin | 0 | 0 | 1 | 1 | 4 | 3 | 1.27 |
| Ethereum | 0 | 0 | 0 | 0 | 9 | 9 | 3.79 |
| Number of firms with minimal 1 cryptocurrency term | | | | | | | 124 |
| Number of firms with minimal crypto keywords | | | 176 | 99 | | | |

**Source:** The authors.

**Table 5.** Keyword and Industry Breakdown for Panel B.

| Firm Years | 0 | 1 | 2,3 | 4 | 5 | 6 | 7,8 | 9 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Keywords for blockchain | 0 | 0 | 9 | 6 | 5 | 39 | 29 | 0 | 86 |
| DLT | 0 | 0 | 2 | 0 | 1 | 11 | 8 | 0 | 24 |
| Number of firms with blockchain | 0 | 0 | 3 | 0 | 5 | 16 | 20 | 0 | 96 |
| Cryptocurrency keywords as bitcoin | 0 | 0 | 9 | 1 | 4 | 26 | 20 | 0 | 45 |
| Cryptocurrency | 0 | 0 | 3 | 0 | 4 | 47 | 6 | 0 | 64 |
| Digital current | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 66 |
| Litecoin | 0 | 0 | 2 | 0 | 0 | 1 | 4 | 0 | 4 |
| Ethereum | | | | | | | | | 9 |
| Number of firms with minimal 1 cryptocurrency term | | | | | | | | | 128 |
| Number of firms with minimal crypto keywords | | | | | | 176 | | | |

**Source:** The authors.

**Table 6.** Financial Keywords.

| Assigned Labels | Terms |
|---|---|
| Effective solution for blockchain technology | Blockchain technology, solute, product, development, applic, focus, market and economic platform |
| Risk factors | May, busi, cryptocurr, risk, oper, effect, technology product, chang |
| Descriptions of general business | End, share, fiscal, million, stock, year, agreement, fiscal, cudigit, company |
| Services involved in payment | Bank, service, card, mobile, finance, money, currency, transfer, payment |
| Transactions for bitcoin | Miner, mine, bitcoin, transact, block, network, user, user, exchange, cryptocurrency, power |

**Source:** The authors.

The evaluation is based on the consideration of different keyword in to processing of the financial data for evaluation with cryptocurrency. In Table 6 illustrated the number of topic assigned for estimation of financial keywords for processing.

Five areas were designated as payment services, risk factors, blockchain technology solutions, bitcoin transactions and basic business descriptions, according to the rules. Table 6 lists the exemplary phrases for each topic selected by LDA. Despite the fact that LDA allows for overlapping themes inside a text, simplified interpretation by conveying every disclosure to topic with highest likelihood.

## Empirical Analysis

Collected data is examined with the developed BDLT_FT model between the period of 2000–2020 is considered. The total data collected for the analysis is 22,466 with observation of firm data. The statistical data for examination is performed for the panels A B. The developed Bayesian model's performance was evaluated for statistical analysis using average firm value per share, while average NIS was around \$0.934. Additionally, disclosures blockchain or cryptocurrency is processed with consideration of 10-K files exhibits the 0.8%. Panel B also shows companies descriptive statistics presence of blockchain and cryptocurrency those with and without keywords based on 176 data points and 22,466 later. The disclosure value of cryptocurrency are evaluated with consideration of three quartile as first, median and third for blockchain cryptocurrency for different variables to zero. The differences in averages between these two groups are shown in the rightmost column in panel B. Firms with associated terms had higher stock prices, net income, book values and total assets with significance of 1% level. In Table 7 presented a assigned variables provided for the BDLT_FT scheme with consideration of different variables.

Similarly, in Table 8 definition of variable with the name are presented for statistical analysis. The estimation is based consideration of different name of variable considered for DLT.

Based on the collected data information about collected data were evaluated with statistical analysis of the data. In Table 9 descriptive statistics for panel A is presented.

In Table 10 descriptive analysis of the data with panel B results are presented for estimation of variables.

In Table 10 presented the Pearson correlations coefficient for computed blockchain variables. Second, for variable KW the disclosure for blockchain and cryptocurrency is estimated as (0.037), KW bc (0.037), and KW crypto (0.017) has been positively correlated with the stock price (PRICE). The estimation of cryptocurrency and blockchain are effective factor estimation of investors about decision making. At first, the terms stock price (PRICE) and book value (BVES) exhibits strong correlation value of 0.607.

**Table 7.** Variables for BDLT_FT.

| Variable Name | Description |
|---|---|
| Dependant variable | |
| Price | Three months stock prices over fiscal year |
| Main variable | |
| KW_bc | 1 if one or more blockchain keywords appear in 10-K filing and else |
| KW_all | If 10-K filing contains one or more blockchain and cryptocurrencies, it will be 1; otherwise, it will be 0. |
| KW_crypto | 1 if one or more cryptocurrency keywords appear in the 10-K filing, and otherwise |
| lnKW_bc | The total cryptocurrency keywords frequencies added with natural logarithm of one term |
| lnKW_all | Keyword with natural logarithm added with overall blockchain and cryptocurrency blockchain for keywords in 2-K filings |
| TP_1 | 1 if one or more paragraphs in the 1p-k filing are connected to first topic indicated by LDA |
| TP_2 | 1 if one or more paragraphs in the 1p-k filing are related to second topic indicated by LDA. |
| TP_3 | 1 if one or more paragraphs in the 1p-k filing are connected to third topic indicated by LDA. |

**Source:** The authors.

**Table 8.** Definition of Variable Name.

| Variable Name | Definition |
|---|---|
| InTP_1 | The paragraphs related to issues associated with LDA or 10-K filing evaluated through natural logarithm terms. |
| InTP_2 | Based on logarithm form pertaining paragraph associated with second issues of LDA of 10-K filing is presented. |
| InTP_3 | With natural logarithm pertaining issue with paragraphs of LDA third issues is presented for 10-K filling. |
| InTP_4 | The statement associated with pertaining the fourth issue related to LDA for 10-K filing based on natural logarithm. |
| InTP_5 | The statement associated with pertaining the fifth issue related to LDA for 10-K filing based on natural logarithm. |
| TP_4 | 1 if one or more paragraphs in the 10-K report are connected to fourth topic indicated by LDA. |
| TP_5 | 1 if one or more paragraphs in the 10-K filing are connected to fifth topic designated by LDA. |
| Independent variables | |
| BVES | The outstanding share count at the year end those can deflated for equity year. |
| NIS | Net income at fiscal year for the deflated outstanding share at end of the year. |
| InAT | Total assets as a natural logarithm at conclusion of year. |

**Source:** The authors.

**Table 9.** Descriptive Statistics Part A.

| Variable | Mean | SD | 1st Quartile | Median | 3rd Quartile |
|---|---|---|---|---|---|
| BVES | 14.447 | 15.766 | 3.123 | 9.235 | 18.736 |
| PRICE | 33.618 | 36.627 | 7.150 | 18.720 | 41.580 |
| LnAT | 6.924 | 2.251 | 5.363 | 6.977 | 8.418 |
| NIS | 0.934 | 2.627 | 0.306 | 0.576 | 1.894 |
| KW_bc | 0.004 | 0.062 | 0.0000 | 0.0000 | 0.0000 |
| InKW_all | 0.012 | 0.167 | 0.000 | 0.000 | 0.000 |
| KW_all | 0.008 | 0.087 | 0.000 | 0.000 | 0.000 |
| KW_crypto | 0.003 | 0.067 | 0.000 | 0.000 | 0.000 |
| InKW_bc | 0.006 | 0.118 | 0.000 | 0.000 | 0.000 |
| InTP_1 | 0.000 | 0.019 | 0.000 | 0.000 | 0.000 |
| InTP_2 | 0.002 | 0.043 | 0.000 | 0.000 | 0.000 |
| InTP_3 | 0.002 | 0.051 | 0.000 | 0.000 | 0.000 |
| InTP_4 | 0.001 | 0.048 | 0.000 | 0.000 | 0.000 |
| InTP_5 | 0.002 | 0.046 | 0.000 | 0.000 | 0.000 |
| TP_1 | 0.008 | 0.137 | 0.000 | 0.000 | 0.000 |
| TP_2 | 0.002 | 0.040 | 0.000 | 0.000 | 0.000 |
| TP_3 | 0.002 | 0.049 | 0.00 | 0.00 | 0.00 |
| TP_4 | 0.001 | 0.034 | 0.000 | 0.000 | 0.000 |
| TP_5 | 0.003 | 0.052 | 0.000 | 0.000 | 0.000 |

**Source:** The authors.

**Table 10.** Descriptive Statistics Part B.

| Variable | Mean | SD | 1st Quartile | Median | 3rd Quartile | Mean | SD | 1st Quartile | Median | 3rd Quartile | Diff. Means |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PRICE | 31.375 | 36.627 | 7.150 | 18.720 | 41.580 | 31.257 | 36.505 | 7.140 | 18.650 | 41.370 | 15.4036* |
| BVES | 13.755 | 15.766 | 3.123 | 9.235 | 18.736 | 13.719 | 15.705 | 3.122 | 9.214 | 18.699 | 4.7028* |
| NIS | 0.934 | 2.627 | 0.306 | 0.576 | 1.894 | 0.929 | 2.669 | –0.307 | 0.573 | 1.888 | 0.7276* |
| LnAT | 6.924 | 2.251 | 5.363 | 6.977 | 8.418 | 6.917 | 2.245 | 5.361 | 6.969 | 8.410 | 0.8340* |
| KW_all | 0.008 | 0.087 | 0.000 | 0.000 | 0.000 | | | | | | |
| KW_bc | 0.004 | 0.062 | 0.0000 | 0.0000 | 0.0000 | | | | | | |
| KW_crypto | 0.005 | 0.073 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnKW_all | 0.012 | 0.167 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnKW_bc | 0.006 | 0.118 | 0.000 | 0.000 | 0.000 | | | | | | |
| TP_1 | 0.008 | 0.137 | 0.000 | 0.000 | 0.000 | | | | | | |
| TP_2 | 0.002 | 0.040 | 0.000 | 0.000 | 0.000 | | | | | | |
| TP_3 | 0.002 | 0.049 | 0.00 | 0.00 | 0.00 | | | | | | |
| TP_4 | 0.001 | 0.034 | 0.000 | 0.000 | 0.000 | | | | | | |
| TP_5 | 0.003 | 0.052 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnTP_1 | 0.000 | 0.019 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnTP_2 | 0.002 | 0.043 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnTP_3 | 0.002 | 0.051 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnTP_4 | 0.001 | 0.048 | 0.000 | 0.000 | 0.000 | | | | | | |
| lnTP_5 | 0.002 | 0.046 | 0.000 | 0.000 | 0.000 | | | | | | |

**Source:** The authors.

**Note.** * refers to importance of the values obtained.

Blockchain-specific disclosures, according to preliminary studies, are more beneficial than bitcoin disclosures. Nonetheless, analyse VIF (variance inflation factors) following average regression value VIF value of 1.62, with maximal VIF value of 1.82. In Table 11 presented the BDLT_FT scheme for statistical analysis is presented.

The evaluation is based on the consideration of the F-statistic with estimation of critical values. With Bai–Perron multiple block point in the data analysis is performed and presented in Table 12.

The coefficient indicates that median-value companies with and without blockchain disclosures in 10-Ks have a 78.0% difference in stock price (14.606 over 18.720). However, we find no statistically significant differences in firm worth between firms that disclose cryptocurrencies and those that do not similar, as shown in column (5). The findings show that blockchain disclosures other than bitcoin disclosures are the primary source of value-relevant information. Bitcoin disclosures, on the other hand, may be more relevant to a company's investment plan or payment solutions. Our findings imply that former is more likely to be positively associated to firm value from perspective of investors. Based on the estimation of the breakpoints in the firm regression estimation in the blockchain for computation. In Table 13, regression analysis of blockchain with DLT with fault tolerance mechanism in bitcoin transactions.

The regression analysis of the proposed model stated that the estimation of the values for the *G, S, R* and *E* are computed based on the consideration of the different variables. The variable considered are

**Table 11.** Statistical Analysis of the BDLT_FT.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| PRICE | 1.00 | | | | | | | | | |
| BVES | 0.008 | 1.00 | | | | | | | | |
| NIS | 0.004 | 0.087 | 1.00 | | | | | | | |
| LnAT | 0.005 | 0.062 | 0.062 | 1.00 | | | | | | |
| KW_all | 0.012 | 0.073 | 0.073 | 0.062 | 1.00 | | | | | |
| KW_bc | 0.006 | 0.167 | 0.167 | 0.073 | 0.062 | 1.00 | | | | |
| KW_crypto | 0.008 | 0.118 | 0.118 | 0.167 | 0.073 | 0.062 | 1.00 | | | |
| lnKW_all | 0.002 | 0.137 | 0.137 | 0.118 | 0.167 | 0.073 | 0.062 | 1.00 | | |
| lnKW_bc | 0.002 | 0.040 | 0.040 | 0.137 | 0.118 | 0.167 | 0.073 | 0.062 | 1.00 | |
| TP_1 | 0.001 | 0.049 | 0.049 | 0.040 | 0.137 | 0.118 | 0.167 | 0.073 | 0.062 | 1.00 |
| TP_2 | 0.003 | 0.034 | 0.034 | 0.049 | 0.040 | 0.137 | 0.118 | 0.167 | 0.073 | 0.062 |
| TP_3 | 0.000 | 0.052 | 0.052 | 0.034 | 0.049 | 0.040 | 0.137 | 0.118 | 0.167 | 0.073 |
| TP_4 | 0.002 | 0.019 | 0.019 | 0.052 | 0.034 | 0.049 | 0.040 | 0.137 | 0.118 | 0.167 |
| TP_5 | 0.002 | 0.043 | 0.043 | 0.019 | 0.052 | 0.034 | 0.049 | 0.040 | 0.137 | 0.118 |
| lnTP_1 | 0.001 | 0.051 | 0.051 | 0.043 | 0.019 | 0.052 | 0.034 | 0.049 | 0.040 | 0.137 |
| lnTP_2 | 0.002 | 0.048 | 0.048 | 0.051 | 0.043 | 0.019 | 0.052 | 0.034 | 0.049 | 0.040 |
| lnTP_3 | 0.03 | 0.046 | 0.046 | 0.048 | 0.051 | 0.043 | 0.019 | 0.052 | 0.034 | 0.049 |
| lnTP_4 | 0.06 | 0.569 | 0.625 | 0.046 | 0.048 | 0.051 | 0.043 | 0.019 | 0.052 | 0.034 |
| lnTP_5 | 0.08 | 0.698 | 0.758 | 0.784 | 0.046 | 0.048 | 0.051 | 0.043 | 0.019 | 0.052 |

**Source:** The authors.

**Table 12.** Bai–Perron Sequential Multiple Break Point Test.

| Variables | *F*-statistic | Critical Value | Decision |
|---|---|---|---|
| $G$ | 49.064 | 8.58* | One breakpoint |
| $G$ at 1st difference | 7.8174 | 8.58 | No breakpoint |
| $S$ | 7.4724 | 8.58 | No breakpoint |
| $E$ at 1st difference | 4.0000 | 8.58 | No breakpoint |
| $E$ | 11.8756 | 8.58* | One breakpoint |
| $R$ | 3.2958 | 8.58 | One breakpoint |

**Source:** The authors.

**Note.** * refers to importance of the values obtained.

**Table 13.** Regression Estimation with Blockchain.

| Model/Variable | *G* | *S* | *R* | *E* |
|---|---|---|---|---|
| BVAR_1 | 7,581.062 | 1,909.914 | 2.724376 | 0.765622 |
| BVAR_2 | 7,414.453 | 1,909.165 | 1.606234 | 0.76589 |
| BVAR_3 | 7,921.226 | 2,029.670 | 2.452306 | 0.76485 |
| BVAR_4 | 8,055.165 | 2,051.136 | 2.437872 | 0.765135 |
| OLS_VAR | 8,106.243 | 2,054.469 | 2.457597 | 0.774183 |

**Source:** The authors.

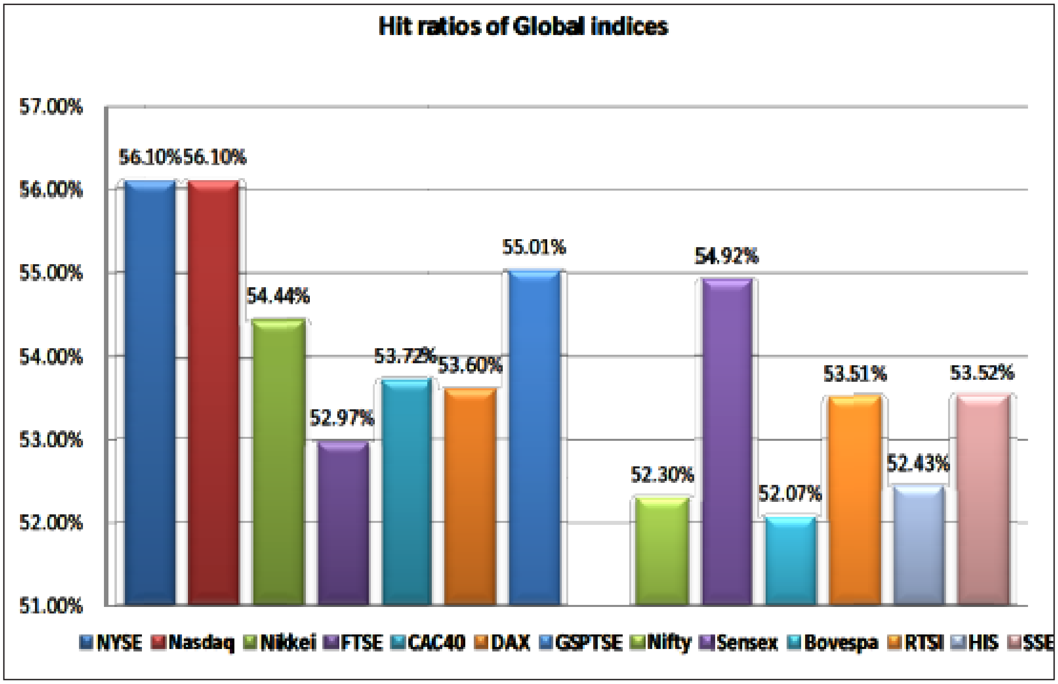


**Figure 5.** Hit Ratio Globally.

**Source:** The authors.

provides the regression estimation value above the 0.5. Topics of basic business descriptions and payment services, on the other hand, have no discernible impact. The findings utilizing the count variables are presented in column 2 and are similar. The number of disclosures labelled as blockchain technology solutions and risk factors are similarly positively associated with firm value, whereas the number of bitcoin transactions is negatively associated. Overall, topic analysis' findings mirrored those of bag-of-words, implying that investors place a higher value on blockchain disclosures that reference technology material. Cryptocurrency related information, on the other hand, has a poor value for investors. One reason we do not see firm value linked to basic business descriptions on blockchain/cryptocurrency is that cryptocurrency accounting regulations in terms of recognition, reporting and classification are currently being contested. The effect of fault tolerance mechanism is based on the consideration of decision boundary for estimation. In Figure 3 presented the constructed MLP network for the memory fault tolerance estimation mechanism. Based on the decision boundary the error classification is computed for reliable and safety system without interaction of much error values. The error probability estimation is performed for threshold and feature space with computation of the correctness and verification. In Figure 5 presented the graphical representation of hit ratio of Indian stock market. In Tables 14 and 15 hit ration of Indian stock market is presented.

In Table 16 based on the prediction term wise classification is performed.

The reliable DNN architecture is designed for flip probability and error classification in the network. The analysis expressed that the developed model exhibits the regimes with the classification accuracy.

**Table 14.** Index of Indian Market.

| Developed Markets | | Emerging Markets | |
|---|---|---|---|
| Index | Hit Ratio (%) | Index | Hit Ratio (%) |
| NYSE | 56.10 | NSE NIFTY | 52.30 |
| NASDAQ | 56.10 | BSE SENSEX | 54.92 |
| NIKKEI | 54.44 | IBOVESPA | 52.07 |
| FTSE | 52.97 | RTSI | 53.51 |
| CAC40 | 53.72 | HSI | 52.43 |
| DAX | 53.60 | SSE | 53.52 |
| GSPTSE | 55.01 | | |
| Average | 54.56 | | 53.12 |

**Source:** The authors.

**Table 15.** Hit Ratio with Global Index.

| Index | Hit Ratio (%) |
|---|---|
| NYSE | 56.10 |
| NASDAQ | 56.10 |
| GSPTSE | 55.01 |
| BSE SENSEX | 54.92 |
| NIKKEI | 54.44 |
| CAC40 | 53.72 |
| DAX | 53.60 |
| SSE | 53.52 |
| RTSI | 53.51 |
| FTSE | 52.97 |
| HSI | 52.43 |
| NSE NIFTY | 52.30 |
| IBOVESPA | 52.07 |

**Source:** The authors.

The analysis of the variable is based on the consideration of flip probability with statistical estimation analysis. The analysis expressed that the average classification error is significantly increased based on flip probability. The analysis expressed that no relationship exists between fault and error classification in the network.

**Table 16.** Term-wise Classification of NSE.

| | Long Term (364 days) | | Medium Term (170 days) | | Short Term (50 days) | | Very Short Term (25 days) | |
|---|---|---|---|---|---|---|---|---|
| Metrics | TI (%) | Cues (%) | TI (%) | Cues (%) | TI (%) | Cues (%) | TI (%) | Cues (%) |
| Hit ratio | 52.85 | 53.77 | 54.12 | 53.10 | 56.00 | 56.10 | 68.00 | 70.00 |
| Error rate | 47.15 | 46.23 | 45.88 | 46.90 | 44.00 | 43.90 | 32.00 | 30.00 |
| Kappa statistic | 0.0549 | 0.058 | 0.0743 | 0.0775 | 0.12 | 0.1708 | 0.359 | 0.3182 |

**Source:** The authors.

**Note:** TI—Technical indicators and Cues—global cues.

## Conclusion

This research involved in computation of effective model for cryptocurrency contribution of the stock market. The evaluation is based on the minimization of the error in the network. As the conventional technique the data processing model alone developed. This article constructed a BDLT_FT model for financial data associated with blockchain cryptocurrency. The estimation is based on construction of Bayesian network architecture for analysis of two panel data. The data related to stock market companies are considered and examined under panels A and B. The evaluation expressed that the developed BDLT_FT mechanism exhibits the significant performance for statistical analysis. The estimation of the variable expressed that the developed BDLT_FT exhibits significantly reduced the fault in the network. Also, the research findings stated that the probability error is not associated with the classification error. The analysis of the results demonstrated that the error classification with the proposed BDLT_FT model is minimal which can be applied directly over the stock market for prediction. As the developed model exhibits minimal classification error the prediction value of the stock market. In future, this research can be further extended with the time series analysis.

## Appendix A

Within the VAR model likelihood estimation is performed for $m = 4$ and presented in the following equation (Akbar et al., 2019; Banerjee et al., 2019; Yen & Wang, 2021):

$$Y_{T\times m} = Z_{T\times k}\Gamma_{\text{kom}} + U_{T\times m} \tag{A.1}$$

where '$T$' is number of observations and $k = mp + 1$ is number of parameters evaluated in each equation with $p$ lag terms. For analysis, the VAR coefficient estimation matrix is written as follows:

$$y_{mT\times 1} = \left(I_m \otimes Z\right)\gamma_{q\times 1} + u_{mT\times 1} \tag{A.2}$$

where $q = mk$. With $N\left(0,1\right)$ the likelihood function of network is presented in the following equation:

$$P\left(\frac{Y}{\gamma},\Sigma\right) \propto MN\left(\hat{\gamma},\Sigma\otimes(ZZ)^{-1}\right)\times IW\left(S,T-k-m-1\right) \tag{A.3}$$

The above function is resolved based on likelihood estimation as presented in the following equation:

$$P(y/\gamma,\Sigma)\propto\left|\Sigma\right|^{-\frac{k}{2}}\exp\left[-\frac{1}{2}\left\{(\gamma-\widehat{\gamma})\left(\Sigma^{-1}\otimes ZZ\right)(\gamma-\widehat{\gamma})\right\}\right]\times\left|\Sigma\right|^{-\frac{(T-k-m-1)+m+1}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\left(\Sigma^{-1}\,S\right)\right] \tag{A.4}$$

With multivariant analysis of normal distribution the posterior probability $MN(0,0)$ is evaluated under Minnesota prior estimation as presented in the following equation:

$$P\left(\frac{\gamma}{\Sigma},\mathrm{y},\mathrm{Z}\right)\propto\exp\left[-\frac{1}{2}(\gamma-\gamma)\bar{\Psi}^{-1}(\gamma-\gamma)\right]P\left(\frac{\gamma}{\Sigma},\mathrm{y},\mathrm{Z}\right)\sim MN(\bar{\gamma},\Psi) \tag{A.5}$$

The condition for estimation of variable in the DLT with computation of prior variance is presented in the following equation:

$$\mathrm{Var}(\gamma_j)=\begin{Bmatrix}\dfrac{\pi_1}{P} & i=j & \text{own lag}\\ \dfrac{\pi_{2\sigma^2}}{po^2} & i\neq j & \text{other lag}\\ \pi_3\sigma_i^2 & & \text{for constant}\end{Bmatrix} \tag{A.6}$$

The trials are carried out with various values for 1 2, 3, and 4 respectively, and the best values are chosen. The posterior distribution probability of the network is presented in the following equation:

$$P(\gamma,\Sigma/\mathrm{Z},\mathrm{y})\propto\exp\left[-\frac{1}{2}(\gamma-\widehat{\gamma})\left(\Sigma^{-1}\otimes ZZ\right)(\gamma-\widehat{\gamma})\right]\times\exp\left[-\frac{1}{2}(\gamma-\gamma_0)\Psi_0^{-1}(\gamma-\gamma_0)\right]$$
$$\times\left|\Sigma\right|^{-\frac{T}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\left(\Sigma^{-1}S\right)\right]\times\left|\Sigma\right|^{-\frac{(v0+m+1)}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\left(\Sigma^{-1}S_0\right)\right] \tag{A.7}$$

Equation (A.7) is simplified with posterior probability as per normal-inverse-Wishart in the following equation:

$$\mathrm{P}(\Gamma,\Sigma/\mathrm{y},\mathrm{Z})\propto\left|\Sigma\right|^{-\frac{k}{2}}\exp\left[-\frac{1}{2}\mathrm{tr}\left\{\Sigma^{-1}\left(\Gamma-\bar{\Gamma}\right)\bar{\Psi}^{-1}\left(\Gamma-\bar{\Gamma}\right)\right\}\right]\times\left|\Sigma\right|^{-\frac{T+v_0+m+1}{2}}$$
$$\exp\left[-\frac{1}{2}\mathrm{tr}\left(\Sigma^{-1}\bar{S}\right)\right]\mathrm{P}(\Gamma,\Sigma/\mathrm{y},\mathrm{Z})\sim\mathrm{MN}\left(\bar{\Gamma},\Sigma\otimes\bar{\Psi}\right)\times\mathrm{IW}\left(\bar{S},\mathrm{T}+\mathrm{v}_0\right) \tag{A.8}$$

$$\text{where, } \overline{\Gamma} = \overline{\Psi}\left(\Psi_0^{-1}\Gamma_0 + ZZ\overline{\Gamma}\right), \overline{\Psi} = \left(ZZ + \Psi_0^{-1}\right)^{-1}$$

$$S = S_0 + S + \widehat{\Gamma}ZZ\widehat{\Gamma} + \left(\Gamma_0\Psi_0^{-1}\Gamma_0 - \widehat{\Gamma}\ \overline{\Psi}^{-1}\overline{\Gamma}\right) \text{ and } S = \left(Y - \widehat{Y}\right)\left(Y - \widehat{Y}\right)$$

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