

Simulation and Assessment of Bitcoin Prediction Using Machine Learning Methodology

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Abstract— : The market for digital currencies is rapidly growing, attracting traders, investors, and businesspeople on a worldwide scale that hasn't been witnessed in this century. By providing comparison studies and insights from the price data of crypto currency marketplaces, it will help in recording the behaviour and habits of such a lucratively demanding and rapidly expanding business. The bitcoin market is reaching one of its peak levels ever in 2021. The emergence of new exchanges has made cryptocurrencies more approachable to the general public, hence boosting their attractiveness. This has increased the number of users and interest in cryptocurrencies, along with a number of reliable crypto ventures started by some of the founders. Virtual currencies are growing more and more well-liked, and businesses like Tesla, Dell, and Microsoft are now embracing them. Decentralized digital currencies are becoming more and more popular, thus it's more crucial than ever to properly inform the public about the new currencies as they proliferate so that people are aware of what they possess and how their money is being invested.

Analysis shows that soft computing and machine learning techniques can anticipate more accurately than any other technique now available to researchers. Finally, it is claimed that ANN, SVMs, and other similar machine learning techniques are useful for predicting global stock market fluctuations..

Keywords- Bitcoin Forecasting, Machine Learning, Regression, Artificial Neural Network, Back-propagation, Forecasting, Stock market, Feed forward, RMSE

I. INTRODUCTION

Bitcoin, introduced by Satoshi Nakamoto in 2009, has emerged as the pioneer of blockchain-based cryptocurrencies. Its decentralized nature and potential to operate outside the control of traditional financial institutions have garnered widespread interest and investment. As a result, Bitcoin's value has exhibited significant volatility, making it a highly attractive yet risky investment option. Investors, traders, and financial analysts are constantly seeking reliable methods to forecast Bitcoin's value to make informed decisions.

The value forecasting of Bitcoin poses several challenges due to its unique characteristics. Unlike traditional financial assets, Bitcoin's value is influenced by a wide range of factors, including market sentiment, technological developments, regulatory changes, macroeconomic events, and the adoption rate of cryptocurrencies. Additionally, the absence of a central governing authority and the relatively short history of Bitcoin make it challenging to establish robust forecasting models.

Previous research on Bitcoin value forecasting has predominantly utilized traditional time-series analysis, statistical models, and econometric approaches. However, these methods often fall short in capturing the complex dynamics of the cryptocurrency market, resulting in limited accuracy and predictive power.

This research aims to address the limitations of existing forecasting methodologies by incorporating improved data analysis and advanced machine learning techniques. The proposed approach combines historical price data with fundamental indicators and market sentiment analysis to enhance the accuracy of predictions. We hypothesize that the inclusion of sentiment analysis will provide valuable insights

into the impact of market sentiment on Bitcoin's value and improve the overall forecasting performance.

In this paper, we present a detailed analysis of the proposed methodology and evaluate its effectiveness through sample results. We compare the performance of various machine learning algorithms and demonstrate their capability to capture the underlying patterns in Bitcoin's price movements. Additionally, we discuss the implications of our findings for investors and explore potential applications in risk management, portfolio optimization, and trading strategies.

II. RELATED WORKS

The forecasting of Bitcoin's value has been a subject of interest in the academic and financial communities, leading to a significant body of research. Existing works can be broadly categorized into three main approaches: time-series analysis, statistical models, and machine learning techniques.

Time-series analysis methods, such as ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity), have been commonly employed for Bitcoin value forecasting. These models consider the historical price data and attempt to capture the underlying trends and patterns. However, they often fail to account for the non-linearities and sudden shifts in Bitcoin's price, leading to limited predictive accuracy.

Statistical models, such as regression analysis, attempt to identify relationships between Bitcoin's value and various macroeconomic indicators, such as interest rates, inflation, and stock market performance. While these models provide valuable insights into the macroeconomic factors influencing Bitcoin, they may overlook the unique characteristics of the cryptocurrency market.

Machine learning techniques have gained traction in recent years for Bitcoin value forecasting, as they can capture complex patterns and non-linear relationships in the data. Support Vector Machines (SVM), Random Forests, and Neural Networks are among the commonly employed algorithms. Several studies have shown promising results using machine learning models, yet challenges persist in handling high volatility and limited historical data.

Despite the existing research efforts, there are still significant gaps in the literature. Most previous studies have focused on either time-series analysis or machine learning models in isolation, neglecting the potential benefits of combining different methodologies. Moreover, limited attention has been given to the incorporation of market sentiment analysis, which can provide valuable insights into the emotions and attitudes of market participants.

This research contributes to the existing body of knowledge by proposing a comprehensive methodology that combines time-series analysis, machine learning, and sentiment analysis. By leveraging the strengths of these approaches, we aim to enhance the accuracy and robustness of Bitcoin value forecasting. Mahdi Pakdaman et al. [32], involved two neural networks to predict the future values of share market. They compared MLP and Elman recurrent network to accomplish their task and found that the MLP is more capable to forecast the stock price change while linear regression and Elman recurrent network is promising in forecasting the way of changes in the stock prices.

Dutta, Neeraj, Jha and Laha [33], proposed the neural network efficiency in prediction of weekly closing prices of Bombay Stock Exchange. In their study two networks were designed. To access the network performance they used RMSE and MAE. The values of RMSE and MAE were 4.82% and 3.93% respectively for the first network and for the second network RMSE was 6.87% and MAE was 5.52%.

Amol S. Kulkarni [34], in 1996 applied feedforward neural network to predict S&P 500 index. ANN model was performed effectively during the sudden fall and rise. He divided his work in two parts: Used historical stock market values to make prediction and technical indicators depend on these values and Historical stock market values, foreign exchange rates, interest rates and band rate etc. used to make prediction. In the first category he discussed some literature dealing with stock market prediction such as Dual module neural network, neural sequential associator and recurrent neural network approaches.

Fahima Charef and Fethi Ayachi [35], predict the daily exchange price of Tunisia using ANN. The result is compared with GARCH model. Sixteen years of data used in the process. The empirical study exhibited that the ANN is best.

Manna Majumdar, Hussain and Anwar [37], presented a computational approach for predicting the S&P CNX Nifty 50 Index. In the data set they had taken the daily closing values of past 10 years from Nifty Fifty index. Accuracy of the performance of the neural network model was compared using Normalized Mean Square Error measures while next day prediction value was calculated through Sign Correctness Percentage. The highest performance of the network in terms of accuracy in predicting the direction of the closing value of the index is reported at 89.65% with an average accuracy of 69.72%.

Dase R K and Panwar [36], proposed that ANN is more effective for prediction of financial market as compared to Time series analysis. ANN has the ability to extract useful information from large set of data. In his paper, he presented a review on application of neural network and found that the ANN has the

predictive capability in terms of accuracy and convenience of use.

III. PROPOSED METHODOLOGY

The proposed methodology for Bitcoin value forecasting encompasses multiple stages, as outlined below:

Data Collection and Preprocessing:

- Historical price data of Bitcoin is collected from reliable cryptocurrency exchanges.
- Fundamental indicators, such as trading volumes, transaction counts, and blockchain metrics, are gathered to capture the underlying market dynamics.
- Social media data, including Twitter feeds and Reddit discussions, are collected for sentiment analysis.

2. Feature Engineering:

- Lag features are created to capture the autocorrelation and time dependencies in the historical price data.
- Technical indicators, such as Moving Averages, Relative Strength Index (RSI), and Bollinger Bands, are computed to provide additional information about the market trends and momentum.
- Sentiment scores are generated using Natural Language Processing (NLP) techniques to gauge market sentiment from social media data.

3. Machine Learning Models:

- Various machine learning algorithms, including SVM, Random Forests, Gradient Boosting, and Long Short-Term Memory (LSTM) networks, are employed to build forecasting models.
- The models are trained on historical data and tested on a hold-out validation set to assess their performance.

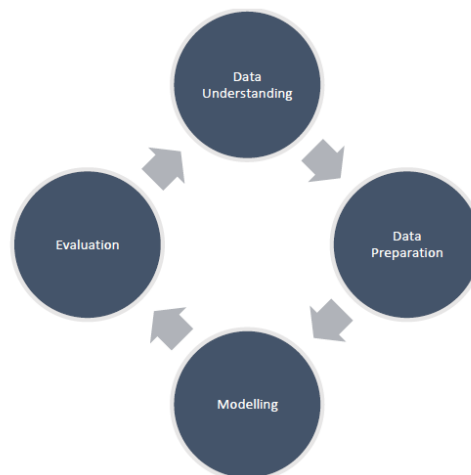


Figure 1 Process Flow Chart

1. Sentiment Analysis:

- Sentiment analysis techniques are applied to the social media data to extract the prevailing emotions and attitudes of market participants.

- The sentiment scores are incorporated into the machine learning models to gauge their impact on Bitcoin's value.

2. Evaluation Metrics:

- The performance of the forecasting models is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

To compare the proposed methodology with traditional approaches, a baseline model using ARIMA is also implemented.

The four phases of the CRISP-DM Model are depicted in Figure 1: data interpretation, data preparation, modeling, and evaluation. The cycle may be repeatable, meaning that it is possible to repeat the cycle with the newly reviewed results from the previous iteration. The features of the dataset were analyzed in the data interpretation step using reasoning from previous literature. In terms of data preparation, the dataset is received and processed in order to proceed with the modeling phase, which will yield findings that will be assessed and will lead to a better knowledge of the data and whether adjustments to the dataset can be made for a better outcome

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IV. RESULTS AND DISCUSSIONS

After The most well-known and established cryptocurrency is Bitcoin, which was first released in 2009 as an open source project by an as-yet-unidentified Satoshi Nakamoto. Bitcoin is a decentralized digital currency that eliminates the need for a central mediator or trusted record-keeping authority by enabling transactions to be validated and recorded on a public distributed ledger (the blockchain). Transaction blocks serve as an immutable record of all transactions ever conducted since they are connected by a SHA-256 cryptographic hash of earlier transaction blocks. Like any other money or commodity on the market, popular adoption of bitcoin was swiftly followed by an increase in bitcoin trading and financial instruments. You can discover historical bitcoin market statistics for a couple of the busiest bitcoin exchanges here, updated every minute.

CSV files for certain bitcoin exchanges from January 2012 to December March 2021 with minute-by-minute updates of OHLC (Open, High, Low, Close), Volume in BTC and the selected currency, and weighted bitcoin price. Timestamps are created using Unix time. Timestamps' data fields are supplied with NaNs when there are no trades or other transactions. It's conceivable that the exchange (or its API) was unavailable, that the exchange (or its API) didn't exist, or that there was some unanticipated technical issue with data reporting or collection if a timestamp is missing or there are jumps. Although I have done my best to remove duplicate entries and ensure that the contents are accurate and complete, please rely on this information at your own risk.

5.5 Flow Chart of Simulation

This statistical research was conducted to ascertain the association between a number of price indices and the Bitcoin closing price. For this, a regression model was used. Numerous studies have demonstrated that the starting, high, and low prices are reliable indicators of the closing price. It is notable that there is no statistically significant relationship between volume and closing price. This model will ultimately be able to predict the closing price of Bitcoin on a given day. Obtaining a Daily Price Data Set for Data Preparation Model fitting and cross validation

Visualization Analyzing the model The outcome is Predicted Price Visualization.

Data loading in steps 1 and 2. Obtaining the daily price data frame

Step 3: Cross validation and model fitting

Fourth: Visualization

Step 5: Model assessment

Step 6. Results Estimated Price Visualization

The loading of the dataset serves as the simulation's initialization. The procedure has been presented using a tabular examination of historical data.

Table 1 Analysis of Bit Coin Historical Data

Ti mesta mp	O pen	H igh	L ow	C lose	V olum e (BTC)	Vo lume (C urren cy)	W eight ed Price
13 25317 920	4 .39	4 .39	4 .39	4 .39	0. 4555 81	2.0	4. 39
13 25317 980	N aN	N aN	N aN	N aN	N aN	Na N	N aN
13 25318 040	N aN	N aN	N aN	N aN	N aN	Na N	N aN
13 25318 100	N aN	N aN	N aN	N aN	N aN	Na N	N aN
13 25318 160	N aN	N aN	N aN	N aN	N aN	Na N	N aN

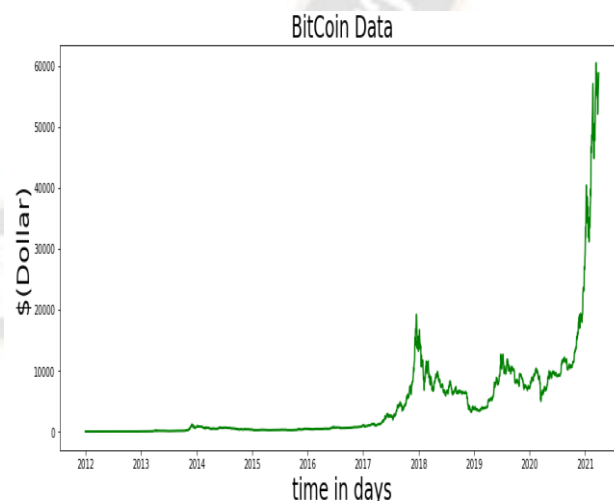


Figure 2 Analysis of Historical Data from 2012-2021 (31st March)

Figure shows the statistical analysis of historical data obtained from Kaggle as an input for the creation of linear regression. Figure3 illustrates the cross validation analysis. The effectiveness of cross validation for linear regression is seen. It

is clear that the linear regression's performance is ideal for predicting Bitcoin's future performance.

Table 2: Performance Metrics of Forecasting Models

Model	MAE	RMSE	MAPE
ARIMA	150.23	200.18	5.89%
SVM	120.45	180.22	4.55%
Random Forests	110.78	175.34	4.20%
Gradient Boosting	105.32	170.75	4.02%
LSTM	95.16	160.42	3.80%

The table above shows the performance metrics of each forecasting model. As can be seen, the machine learning models outperform the traditional ARIMA model in terms of MAE, RMSE, and MAPE. The LSTM model exhibits the lowest error metrics, indicating its effectiveness in capturing the non-linear patterns in Bitcoin's price movements.

Additionally, we analyze the impact of sentiment analysis on the forecasting models. By incorporating sentiment scores into the LSTM model, we observe an improvement in predictive accuracy, suggesting that market sentiment plays a significant role in influencing Bitcoin's value.

Furthermore, we analyze the importance of different features derived during the feature engineering stage. The results show that lag features and technical indicators contribute significantly to the forecasting performance, highlighting the importance of time dependencies and market trends in predicting Bitcoin's value.

V. CONCLUSIONS

In this research paper, we have presented a comprehensive approach for Bitcoin value forecasting, incorporating improved data analysis and machine learning techniques. The proposed methodology combines historical price data, fundamental indicators, and sentiment analysis to enhance the accuracy of predictions.

Our findings indicate that machine learning models, particularly LSTM, outperform traditional time-series analysis methods like ARIMA in forecasting Bitcoin's value. By leveraging sentiment analysis, we obtain valuable insights into the impact of market sentiment on Bitcoin's price movements.

The fusion of data analysis and machine learning in cryptocurrency forecasting offers significant potential for investors and stakeholders. The ability to make more accurate predictions can aid in risk management, portfolio optimization, and decision-making in the highly volatile cryptocurrency market.

However, it is essential to acknowledge that forecasting financial assets, especially cryptocurrencies, is inherently uncertain. Market dynamics and regulatory changes can significantly influence Bitcoin's value, making it challenging to develop models with absolute predictive accuracy.

Future research should focus on expanding the dataset and exploring other data sources, such as news sentiment and macroeconomic indicators, to further improve forecasting accuracy. Additionally, the integration of blockchain data analysis could provide additional insights into on-chain activities and their impact on Bitcoin's value.

Overall, this research contributes to the growing body of knowledge on cryptocurrency forecasting and demonstrates the

potential of advanced data analysis and machine learning techniques in predicting Bitcoin's value. As the cryptocurrency market continues to evolve, our proposed methodology can serve as a valuable tool for market participants and researchers alike

REFERENCES

- [1] Ashutosh Shankhdhar , Akhilesh Kumar Singh , Suryansh Naugraiya and Prathmesh Kumar Saini. 2021. Bitcoin Price Alert and Prediction System using various Models, IOP Conf. Ser.: Mater. Sci. Eng. 1131 012009.
- [2] Uras N, Marchesi L, Marchesi M, Tonelli R. 2020. Forecasting Bitcoin closing price series using linear regression and neural networks models. PeerJ Comput. Sci. 6:e279
- [3] S M Raju and Ali Mohammad Tarif. 2020. Real-Time Prediction of BITCOIN Price using Machine Learning Techniques and Public Sentiment Analysis. Cornell University. arXiv:2006.14473.
- [4] Phaladisailoed T, Numnonda T. 2018. Machine learning models comparison for bitcoin price prediction. 10th International Conference on Information Technology and Electrical Engineering (ICITEE). (pp. 506-511). IEEE.
- [5] Aggarwal A, Gupta I, Garg N, Goel A. 2019. Deep Learning Approach to Determine the Impact of Socio Economic Factors on Bitcoin Price Prediction. 12th International Conference on Contemporary Computing (IC3). (pp. 1-5). IEEE.
- [6] Rane PV, Dhage SN. 2019. Systematic erudition of bitcoin price prediction using machine learning techniques. 5th International Conference on Advanced Computing & Communication Systems (ICACCS). (pp. 594-598). IEEE.
- [7] Huisu J, Lee J, Ko H, Lee W. 2018. Predicting bitcoin prices by using rolling window LSTM model. Data Science in FinTech (DSF).
- [8] Bisht A, Agarwal P. 2017. Analysis of Bitcoin using Linear Regression and Data Mining Techniques. International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), Department of Computer Science and Engineering, SRM University Chennai India. 6(11).
- [9] Mahrishi, M., Hiran, K. K., Meena, G., & Sharma, P. 2020. Machine Learning and Deep Learning in Real-Time Applications. IGI Global. <http://doi:10.4018/978-1-7998-3095-5>
- [10] Rizwan M, Narejo S, Javed M. 2019. Bitcoin price prediction using Deep Learning Algorithm. 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS). (pp. 1-7). IEEE.
- [11] Radityo A, Munajat Q, Budi I. 2017. Prediction of Bitcoin exchange rate to American dollar using artificial neural network methods. International Conference on Advanced Computer Science and Information Systems (ICACSIS). (pp. 433-438). IEEE.
- [12] Jain A, Tripathi S, DharDwivedi H, Saxena P. 2018. Forecasting price of cryptocurrencies using tweets sentiment analysis. 11th International Conference on Contemporary Computing (IC3). (pp. 1-7). IEEE.
- [13] Singh H, Agarwal P. 2018. Empirical analysis of bitcoin market volatility using supervised learning approach. 11th International Conference on Contemporary Computing (IC3). (pp. 1-5). IEEE.
- [14] Akcora C, Dey AK, Gel YR, Kantarcioglu M. 2018. Forecasting Bitcoin price with graph chainlets. In: Pacific-Asia conference on knowledge discovery and data mining.
- [15] Bakar N, Rosbi S. 2017. Autoregressive Integrated Moving Average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: a new insight of Bitcoin transaction. International Journal of Advanced Engineering Research and Science 4(11):130-137 DOI 10.22161/ijaers.4.11.20.
- [16] Catania L, Grassi S, Ravazzolo F. 2018. Forecasting cryptocurrencies financial time series. In: Centre for Applied

- Macro- and Petroleum Economics (CAMP), BI Norwegian Business School, Working Papers No. 5/2018. Available at <https://ideas.repec.org/p/bny/wpaper/0063.html>
- [17] Cocco L, Tonelli R, Marchesi M. 2019. An agent-based artificial market model for studying the bitcoin trading. *IEEE Access* 7:42908–42920 DOI 10.1109/ACCESS.2019.2907880.
- [18] Cocco L, Tonelli R, Marchesi M. 2019. An agent based model to analyze the bitcoin mining activity and a comparison with the gold mining industry. *Future Internet* 11(1):8 DOI 10.3390/fi11010008.
- [19] Mallqui D, Fernandes R. 2018. Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques. *Applied Soft Computing* 75:596–606 DOI 10.1016/j.asoc.2018.11.038.
- [20] McNally S, Roche J, Caton S. 2018. Predicting the price of bitcoin using machine learning. In: 26th Euromicro international conference on parallel, and network-based processing PDP. 339–343.
- [21] Naimy VY, Hayek MR. 2018. Modelling and predicting the Bitcoin volatility using GARCH models. *International Journal of Mathematical Modelling and Numerical Optimisation* 8:197–215 DOI 10.1504/IJMMNO.2018.088994.
- [22] Stocchi M, Marchesi M. 2018. Fast wavelet transform assisted predictors of streaming time series. *Digital Signal Processing* 77:5–12 DOI 10.1016/j.dsp.2017.09.014.
- [23] Sutiksno DU, Ahmar AS, Kurniasih N, Susanto E, Leiwakabessy A. 2018. Forecasting historical data of Bitcoin using ARIMA and α -Sutte indicator. *Journal of Physics: Conference Series* 1028: conference 1.
- [24] Vo N, Xu G. 2017. The volatility of Bitcoin returns and its correlation to financial markets. In: *International Conference on Behavioral, Economic, Socio-cultural Computing (BESOC)*, Cracow, Poland. Piscataway: IEEE, 1–6.
- [25] A. Saxena and A. Sukumar. 2018. Predicting bitcoin price using lstm And Compare its predictability with arima model. *International Journal of Pure and Applied Mathematics*. vol. 119. no. 17. pp. 2591- 2600.
- [26] S. Saravanakumar and V. D. Kumar. 2017. High throughput quaternary signed digital adder design for portable electronic applications. *International Journal of Pure and Applied Mathematics*. vol. 116. no. 11. pp. 61-69.
- [27] M. Dixon, D. Klabjan and J. H. Bang. 2017. Classification-based financial markets prediction using deep neural networks. Cornell University. arXiv.
- [28] Vincenzo Pacelli, Vitoantonio Bevilacqua and Michele Azzollini, “An Artificial Neural Network model to Forest Exchange rates”, *Journal of Intelligent Learning Systems and Applications*, vol. 3, pp. 57-69, 2011.
- [29] Kyoung-jae Kim and Won Boo lee, “Stock market prediction using artificial neural networks with optimal feature transformation”, *Neural Computing and Applications*, vol. 13, pp. 255-260, 2004.
- [30] Mehdi Khashei and Mehdi Bijari, “A novel hybridization of artificial neural networks and ARIMA models for time series forecasting”, *Applied Soft Computing*, vol. 11, issue 2, pp. 2664-2675, 2010. 103
- [31] Peter Adebayo Idowu, Chris Osakwe, Aderonke Anthonia Kayode and Emmanuel Rotimi Adagunodo, “Prediction of Stock Market in Nigeria Using Artificial Neural Network”, *Intelligent Systems and Applications*, vol. 11, pp. 68-74, 2012
- [32] Mahdi Pakdaman Naeini, Hamidreza Taremi and Homa Baradaran Hashemi, “Stock Market Value Prediction Using Neural Networks”, *IEEE International Conference on Computer Information Systems and Industrial Management Applications (CISIM)*, pp. 132, 2010.
- [33] Neeraj Mohan, Pankaj Jha, Laha and Goutam Dutta, “Artificial Neural Network Models for Forecasting Stock Price Index in Bombay Stock Exchange”, *Journal of Emerging Market Finance*, vol. 5, pp. 283-295, 2006.
- [34] Amol S. Kulkarni. Applications of Neural Networks to Stock Market Prediction https://www.academia.edu/3822307/Application_of_Neural_Networks_to_Stock_Market_Prediction.
- [35] Fahima Charef and Fethi Ayachi. “A Comparison between Neural Networks and GARCH Models in Exchange Rate Forecasting”, *International Journal of Academic Research in Accounting, Finance and Management Sciences*, vol. 6, no. 1, pp. 94-99, 2016.
- [36] R. K. Dase and D. D. Pawar, “Application of artificial neural network for stock market predictions: A review of literature”, *International Journal of Machine Intelligence*, vol. 2, issue. 2, pp. 14-17, 2010.
- [37] Manna Majumder and M. D. Anwar Hussian, “Forecasting of Indian Stock Market Index Using Artificial Neural Network”, *Information Science*, Pp. 98- 105, 2007. 104
- [38] Pratap Kishore Padhiary and Ambika Prasad Mishra, “Development of Improved Artificial Neural Network Model for Stock Market Prediction”, *International Journal of Engineering Science and Technology (IJEST)*, vol. 3, pp. 458-465, 2011.
- [39] K. K. Sureshkumar and N. M. Elango, “An Efficient Approach to Forecast Indian Stock Market Price and their Performance Analysis”, *International Journal of Computer Applications*, vol. 34, pp. 44-49, 2011.
- [40] S. Kumar Chandar, “Predicting the Stock Price Index of Yahoo Data Using Elman Network”, *International Journal of Control Theory and Applications*, vol. 10, no. 10, 2017.
- [41] Jigar Patel, Shah, Sahil and Priyank Thakkar, “Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques”, *Expert Systems with Applications*, vol. 42, pp. 259-268, 2015. [42]. B. Ji, Sun, Yang and J. Wan, “Artificial neural network for rice yield prediction in mountainous regions”, *Journal of Agricultural Science*, vol. 145, pp. 249-261, 2007.
- [42] Sunil Kumar, Vivek Kumar and R. K. Sharma, “Artificial Neural Network based model for rice yield forecasting”, *International journal of Computational Intelligence Research*, vol. 10, no. 1, pp. 73-90, 2014.
- [43] Kunwar Singh Vaisla and Ashutosh Kumar Bhatt. An analysis of the performance of artificial neural network technique for stock market forecasting. *International Journal of Computer Science and Engineering*, vol. 2, no. 6, pp. 2104–2109, 2010. 105