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Neural Insights: Optimal Model Selection For Bitcoin And Indian Rupees Analysis

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Abstract:
Cryptocurrencies are virtual underlying asset preferred by young people as their investment choices and entrepreneurs for getting funded for their projects. The aim is to analyse the Price action of BTC-INR for 2015-2022, to visualize the BTC-INR through neural network platform and to predict the BTC-INR price through ANN model. The methodology applied for the study is Exploratory and Experimental in nature and analytical tool applied for prediction is long short-term model of Artificial Neural networks, the outcome of the paper is the BTCINR Prediction Prices for 30 days and the accuracy of the selected model of ANN is 0.9433 and 0.8918 for training and testing the model.

Keywords: *ANN, BTCINR, Cryptocurrencies, Prediction, Visualization.*

JEL Code: C45, C53, F39

Introduction:

Artificial Neural network (ANN) under the stream of Business Analytics has emerged as a special area of study (Aghashahi & Bamdad 2023). How neurons are important and the movement of Blood cells through neurons reaches required place faster, the movement of prices based on various paths helps an investor for optimum Decision making. ANN as an advanced tool of Analytics surpasses other models like Decision tree, Random forest because of its input and output range that ANN picks up for analysing the data (Banjade 2020). A prediction of continuous variable like stocks, Bonds, Currency, Cryptocurrency, GDP, Inflation etc are possible through Econometrics and at advanced level through Artificial Neural Networks for obtaining accurate results than any other model.

As the world evidences the advancement of Blockchain Technology and Entrepreneurs and investors are keen on the movement of Bitcoin prices versus Indian Rupee. Decision making plays a very vital and essential role for any investor and the study on prediction of the most happening variable support all stakeholders for their optimum Decision making (Chinthapalli 2021).

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Cao et.al In their 2009 study, endeavoured to predict shifts in Chinese stock prices by evaluating the efficacy of various established forecasting models. These models encompassed dynamic iterations of a single-factor CAPM-based model and Fama and French's three-factor model. The predictive performance of each model was juxtaposed with that of an artificial neural network (ANN) model employing identical predictor variables. Ultimately, the research concludes that there are no statistically significant distinctions in forecasting accuracy between the CAPM and three-factor models. The study's results, indicating superior performance of the ANN model compared to its linear counterpart, imply that neural networks could serve as valuable tools for predicting stock prices in emerging markets. Different Artificial Neural Networks models that have been tested in stock market forecasts with unique augmentation approaches utilised with them were surveyed by Simon & Raoot (2012). Also investigated were potential research plans for these accuracy-driven ANN models. In order to categorise financial data from Yahoo Inc., Patra et. al. (2015) examined a local linear radial basis functional neural network model. The outcome of the prediction is compared to that of multilayer perceptron’s and radial basis functional neural networks, both of which use gradient descent learning to train their parameters. With a reduced mean squared error, the proposed method can be deemed superior to alternative models. In order to validate the experiment's results, the technique is also assessed using linear data or data from individuals with diabetes.

In 2015, Almeida et.al utilized an artificial neural network (ANN) to predict the future trend of Bitcoin by considering the price and volume data from the preceding day. The study project has been separated into sections, such as Section I as an introduction, Section II as a review of pertinent literature, Section III as prediction networks, followed by Section IV's proposal of an experimental model and Section V's discussion of the findings. In 2018, Senapati et.al examined an intelligent and optimal stock market price model, utilizing a hybrid Adaline Neural Network (ANN) and a modified Particle Swarm Optimization approach (PSO). The predictive performance of the proposed model is compared to various representations, including interval measurements, CMS PSO, and Bayesian-ANN. The results indicate that the proposed scheme surpasses all other approaches when assessed in relation to mean absolute percentage error. In order to forecast the movement of the financial markets, Wang et al. (2018) suggested a novel one-dimensional convolutional neural networks model. Results also demonstrated that the CNN model outperformed earlier machine learning techniques in terms of financial performance, extracting more generic and informative characteristics than standard technical indicators. In 2019, Khaldi et.al investigated the impact of various factors on the price, returns, and volatility of Bitcoin. The paper also investigates the GARCH models' sensitivity to standardized residual distributions in predicting BTC unpredictability. Regarding short- and long-term perspectives, the study contrasted the best GARCH-type model and the best ANN model. The results of the study reveal that APARCH, TGARCH, and EGARCH exhibit high sensitivity to standardized residual distributions, with TGARCH utilizing the normal distribution emerging as the most effective model for capturing Bitcoin (BTC) volatility. In 2020, Liu and So integrated a GARCH model into an artificial neural network (ANN) to model financial volatility and estimated the parameters using TensorFlow. They assessed the model performance by calculating the mean absolute errors of powers of out-of-sample returns from March 2, 2018, to February 28, 2020. The results indicated that the Modeling procedure with an ANN outperformed the standard GARCH (1,1) model with a standardized Student’s distribution. Variable importance analysis revealed that Net Debt/EBITA ranked among the six most significant predictor variables across all neural network models examined. According to Gopal and Senthilkumar (2020), the objective of the study is to analyze the price dynamics of the notably volatile Bitcoin. The ANN model is used in the study to measure the influence of variables on the trade in bitcoin, such as trading volume, money supply, and lag prices. The analysis also showed a strong correlation between the variables used to forecast Bitcoin values. Using the ANN approach, Banjade (2020)'s study forecast the price of Bitcoin. The S&P 500 index, Bitcoin market capitalization, volume, dollar to euro and dollar to pound exchange rates, gold price, and the ability to predict prices are all deemed to be of no use by the author. However, the study

contends that the Bitcoin price lags with four inputs, ten hidden layers, and 200 iterations, which yields a superior result with a root mean square error (RMSE) of 10.20 and a coefficient of determination (R2) of 0.96.
For modelling and forecasting the Bitcoin price, Khedmati et al (2020) study used ARIMA and machine learning techniques together with Kriging, Artificial Neural Networks (ANN), the Bayesian method, Support Vector Machines (SVM), and Random Forests (RF). The study also used the highest, minimum, and daily opening prices to anticipate Bitcoin prices. The study's findings show that, of all the models, Support Vector Machine (SVM) performs the best. In a paper published in 2021, Nayak et al. developed a hybrid ANN using the Rao algorithm (RA + ANN) for the accurate forecast of the prices of six well-known cryptocurrencies: Bitcoin, Litecoin, Ethereum, CMC 200, Tether, and Ripple. Six comparative models, including GA + ANN, PSO + ANN, MLP, SVM, LSE, and ARIMA, are also created and trained concurrently. The study's findings imply that d RA + ANN might be used as a financial tool for cryptocurrency forecasting because it produced the lowest MAPE and ARV values, which were statistically distinct from those produced by the other approaches described above. Chinthapalli (2021) proposed an intriguing approach for assessing the likelihood of clusters of Bitcoin volatility. The study explores exponential hybrid GARCH (EGARCH) techniques, portraying Bitcoin as a financial asset. Analytical insights into the cryptocurrency are provided through the use of artificial neural network (ANN) models. The results illustrate the effectiveness of probability clusters in capturing the influence on both cryptocurrencies and traditional currencies.

Statement of the Problem:
Price action and uptrend on Cryptocurrencies creates interest among investors and firms to know the direction of the BTC. As many companies particularly Unicorns raise money through BTC and young investors wanted to gain out of price action, the prediction of BTC-INR is identified as a problem for the study which caters useful information for these stakeholders.

Objectives of the study:
1. To analyse the Price action of BTC-INR for the period 2017-2022.
2. To Visualize the BTC-INR through neural network platform
3. To predict the BTC-INR Prices through ANN model.

Data Collection and Methodology:
Sample considered is BTC-INR for 2015-2022. Data is collected from Yahoo finance for the period August 2017- September 2022. ANN which is part of deep learning model is applied to predict BTC-INR. The study is analytical in nature, data is divided into training data set and test data set for validating the model.

Results and Discussion
Table 1 is a result of data structure where the data consists of High, Low Open, Close and Adjusted Closing Price along with volume data for a Starting period 2017 which is considered for the study, whereas Table 2 shows the Closing structure without diluting the beginning structure which is in the year 2022 till September. Table 3 depicts the Descriptive statistics which explains the characteristics of the variables considered for the study. The Descriptive statistics shows a mean closing value of 1434001.5939534756 with a deviation of 1303860.7456612343 proving the risk levels higher with a marginally higher return. 1827 days data points are studied within a range of 2017 – 2022.

Table 1 Shows the Structure of Data for the Beginning Period 2017

Index	**Date**	**Open**	**High**	**Low**	**Close**	**Adjusted Close**	**Volume**
0	17-08-	281327.5938	287760.7813	272297.6563	277942.875	277942.875	163836000000.0

	2017						
1	18-08-2017	277471.2813	280147.1875	257346.9844	266654.1563	266654.1563	188534000000.0
2	19-08-2017	265188.4063	271950.5313	254472.5469	268774.25	268774.25	190720000000.0
3	20-08-2017	268492.875	268940.2188	260838.6094	261978.125	261978.125	135215000000.0
4	21-08-2017	262158.875	263354.7813	255689.2031	256531.5469	256531.5469	179551000000.0

Table 2 Shows the Closing Structure of Data for the Ending Period 2022

Index	Date	Open	High	Low	Close	Adjusted Close	Volume
1822	13-08-2022	1943092.5	1979551.125	1938627.5	1944834.75	1944834.75	1830430000000.0
1823	14-08-2022	1945232.125	1988697.5	1927491.25	1936496.25	1936496.25	1830970000000.0
1824	15-08-2022	1936415.25	2002483.375	1896529.25	1920172.25	1920172.25	2794190000000.0
1825	16-08-2022	1919310.125	1927527.625	1882316.375	1890272.75	1890272.75	2196600000000.0
1826	17-08-2022	1888485.875	1937308.25	1855604.375	1860347.25	1860347.25	2433710000000.0

Table 3 Shows the Descriptive Statistics of BTCINR for the Period 2017

Index	Open	High	Low	Close	Adjusted Close	Volume
count	1827.0	1827.0	1827.0	1827.0	1827.0	1827.0
Mean	1433320.5992485494	1470150.9717603177	1392283.430409688	1434001.5939534756	1434001.5939534756	1806527702208.755
Std	1304453.040227235	1337441.1927738262	1266201.3549420408	1303860.7456612343	1303860.7456612343	1497468586294.7415
Min	203023.1563	234932.6563	188797.3125	202295.3906	202295.3906	49759690295.0

25 %	505547.546 89999996	515848.171 89999996	492057.031 25	505884.734 39999996	505884.734 39999996	5068055000 00.0
50 %	719347.812 5	733279.937 5	702727.125	719963.375	719963.375	1604000000 000.0
75 %	2500636.87 5	2577127.87 5	2385259.12 5	2499298.62 5	2499298.62 5	2563770000 000.0
Ma x	4993192.5	5109431.5	4920109.0	4994456.0	4994456.0	2583000000 0000.0

Figure 1 shows the price action of BTCINR from 2017 January till July 2022.The movement in the price is flat for 2018 to 2020 and a surge is seen from January 2021 till July 2022 indicating the confidence in this Crypto by investors even though the volatility is captured. The pattern latter stage provides clue for large investors and stakeholders to jump into this Asset.

Figure 1: Shows the Price Action of BTCINR for the Period 2018 to August 2022

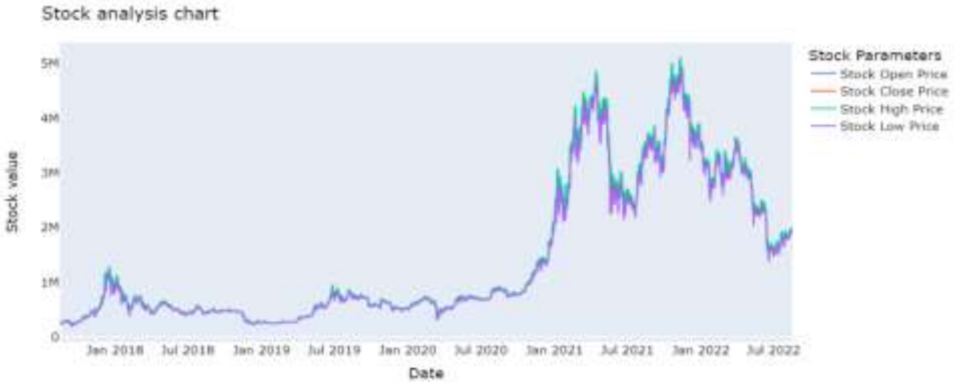


Table 4 indicates the open and high for the period 2017. As the analysts are majorly focussed on the start Price and the landed price which helps them analyse the return from BTCINR and the table explains the closing Prices in few months are traded below opening price, but the margin is very minimal whereas the numbers shows the quantum shift from traditional investments into crypto even after macro shocks affecting the markets. Graph 2 visualises the Open and Close Price whereas graph 3 visualises the High and Low price where it is observed that the High prices are at peak compared to low prices making the movement stronger on bull front.

Table 4 Shows Month wise Open and Close Price Series of BTCINR for the Period 2017

Date	**Open**	**Close**
January	1461689.1349864516	1458774.7286348387
February	1582652.0457702128	1592047.255878014
March	1710015.13166	1715498.9600890323
April	1772424.594594	1771029.0895906666
May	1538847.8455690322	1527047.6889135484
June	1280930.325838	1274676.6450046666
July	1238099.9719793547	1244409.945164516
August	1313065.2442619354	1315793.4392219356
September	1123000.894694	1120534.389172
October	1316165.4500148387	1327605.0915432258
November	1449742.079804	1448745.8385533332
December	1420308.3586832257	1419476.6462787096

Figure 2: Shows Month Wise Direction of Open and Close Price of BTCINR for the Period 2017

Figure 3: Shows Month Wise High And Low Price Of BTCINR For the Period 2017

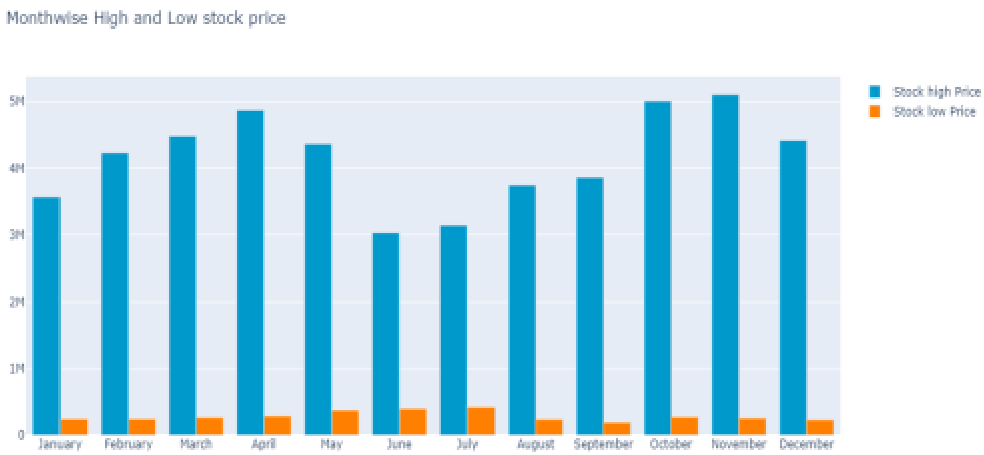


Table 5 depicts the pattern of Open and close unlike 2017 but the Price are high in January and May later has fallen and consolidated in November December avoiding volatility. Graph 4 visualises the Spike in Column bars initially in January and moved to consolidation in November and December. On the other hand graph 5 shows the High and Low price of BTCINR for 2018 and the pattern again suggests the same movement in January whereas the price has reduced in December, It is also observed that the High Price and low difference was far from each other later in December almost reached to same peak. Graph 6 indicates the movement of Open, High, Low and Close price pattern and the chart explains the power of movement of all four prices without any long distance from each other avoiding variance among the prices.

Table 5: Shows Month Wise Open and Close Price of BTCINR for the Year 2018.

Date	**Open**	**Close**
January	840456.074613	832284.832661
February	608970.323664	610213.283486
March	595715.357865	588130.135084

Date	Open	Close
April	523257.609390	528225.451050
May	573586.183474	570216.335690
June	462325.914607	460135.206273
July	487636.166348	490709.127032
August	467022.562523	465981.555471
September	476984.845853	476458.086473
October	477795.421397	477473.360903

Figure 4 Shows Month Wise Direction Of Open And Close Price Of BTCINR for the Period 2018

Graph 5: Shows Month Wise High And Low Price Of BTC-INR for the Period 2018

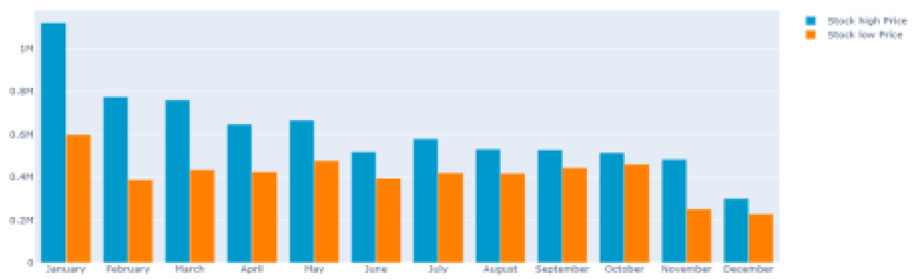
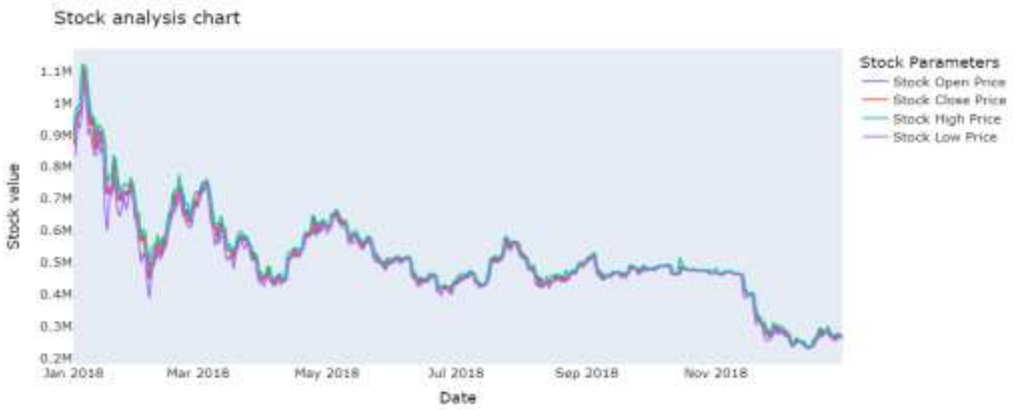


Figure 6: Shows The Price Action of BTC-INR For the Period 2018



The above table 6 indicates the open and Close prices for 2019 and the close prices are on an average started to rise compared to 2017 and 2018, particularly in the month of July, August and September. Graph 7 points the visualization of Open and Close Price month wise suggesting the spike in the above-mentioned months, whereas graph 8 visualizes the High and Low Price where June July and August the prices of BTCINR trading decently and consolidated later month wise. Unlike other years previously mentioned the prices are not distant from each other. Graph 9 shows the movement of all four types of prices i.e Open High, Low and Close Prices. The pattern in Graph 9 indicates the prices rose quickly and shown an opportunity to enter late November December for stakeholders and business who need to alter strategies.

Table 6: Shows Month Wise Open and Close Price Of BTC-INR for the Year 2019

Date	**Open**	**Close**
January	261883.0086	261472.1
February	263219.7327	264245.4
March	276227.2722	276627
April	356636.0354	359559.3
May	502860.8871	510133.9
June	648474.8083	653654
July	734895.2974	733372.4
August	757487.1391	75733.7
September	703893.7958	700428.7
October	595079.5605	597262.8
November	601845.6677	598241.7
December	519471.0444	518480.7

Figure 7 Shows Month Wise Direction Of Open And Close Price of BTC-INR for the Period 2019

Figure 8: Shows Month Wise High And Low Price Of BTCINR for the Period 2019

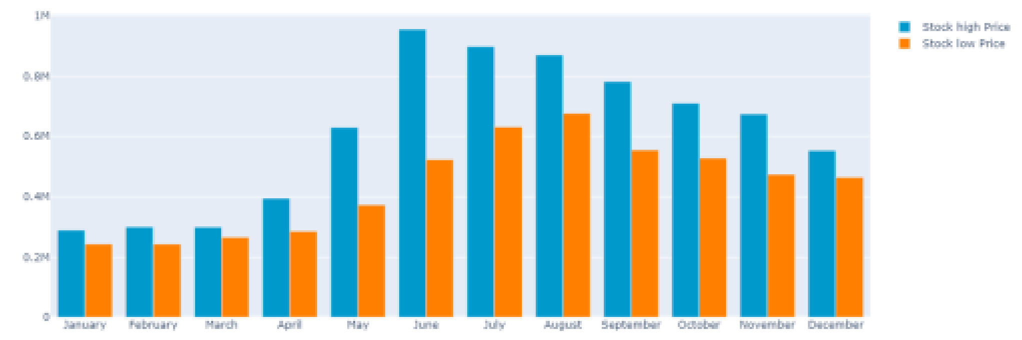
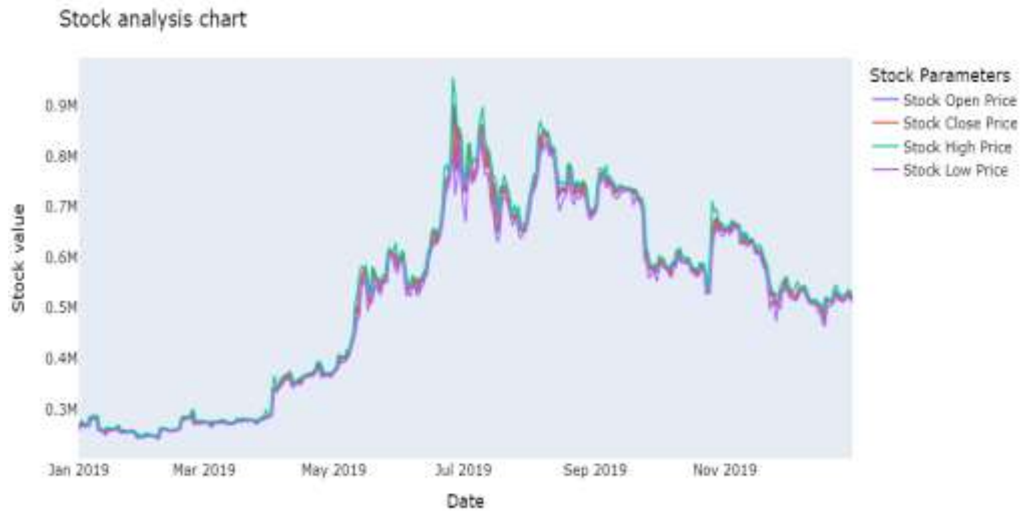


Figure 9: Shows the Price Action Of BTC-INR for the Period 2019



The above table 7 shows the Price action of BTCINR for the year 2021 proving the efficiency at the middle months July August than other months, Graph 10 suggests the Close price has shooted in the above said months whereas graph 6 points that BTCINR had High Price in the month of November and December giving caution on trading the crypto.

Graph 11 shows the high and Low prices of BTCINR for 2020 and graph 12 shows the price action of open, high, low and close prices for 2020.

Table 7: Shows Month Wise Open and Close Price Of BTC-INR for the Year 2018

Date	Open	Close
January	5.930000	5.9800000
February	6.9100000	6.8900000
March	5.1600000	5.1200000
April	5.4500000	5.5100000
May	6.990000	7.0100000
June	7.200000	7.1900000
July	7.1300000	7.1800000
August	8.6900000	8.6900000
September	7.8600000	7.8400000
October	8.6700000	8.7500000
November	1.2200000	1.2400000
December	1.6000000	1.6200000

Figure 10 Shows Month Wise Direction of Open And Close Price Of BTC-INR for the Period 2020

Figure 11: Shows Month Wise High And Low Price Of BTC-INR for the Period 2020

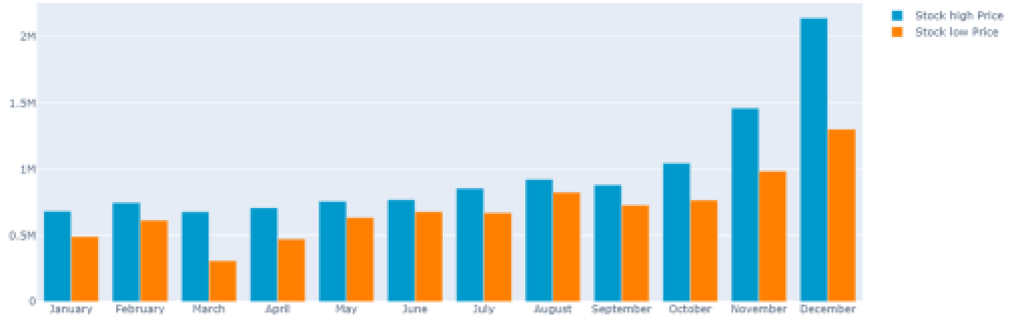
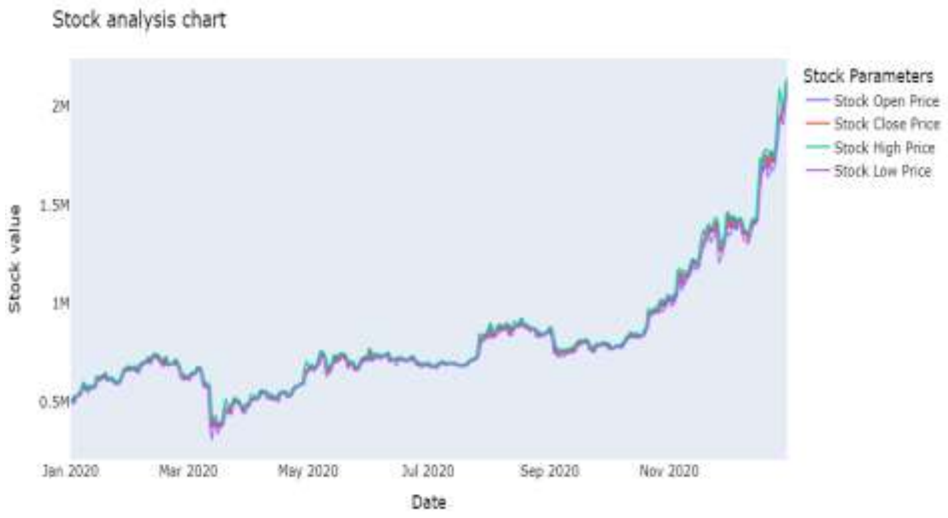


Figure 12: Shows the Price Action Of BTC-INR for the Period 2020.



The table 8 indicates the Price action for the year 2021 and the crypto pattern suggests the confidence of investors moved towards BTCINR from other financial assets because of its continuous price upward movement and 2021 witnessed a fabulous Close prices compared to open prices. On the other hand, graph 4 and 5 suggests the Close, open, High and Low prices of crypto BTCINR. Graph 6 visualizes the price direction of all four types of Prices from Jan 2021 to Nov 2021 indicating the buying behaviour of investors.

Table 8: Shows Month Wise Open and Close Price of BTC-INR for the Year 2018

Date	**Open**	**Close**
January	2.53E+06	2.54E+06
February	3.34E+06	3.37E+06
March	3.97E+06	4.00E+06
April	4.26E+06	4.26E+06
May	3.45E+06	4.26E+06
June	2.64E+06	2.64E+06
July	2.55E+06	2.57E+06
August	3.38E+06	3.39E+06
September	3.39E+06	3.38E+06
October	4.30E+06	4.34E+06
November	4.53E+06	4.51E+06
December	3.75E+06	3.72E+06

Figure 13: Shows Month Wise Direction Of Open And Close Price of BTCINR for the Period 2021

Figure 14: Shows Month Wise High And Low Price Of BTC-INR for the Period 2021

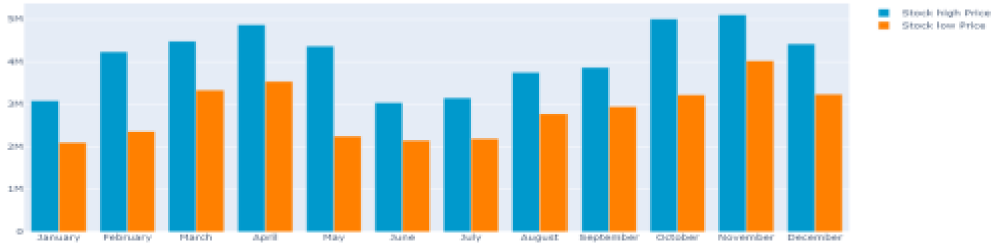


Figure 15: Shows the Price Action of BTC-INR for the Period 2021.

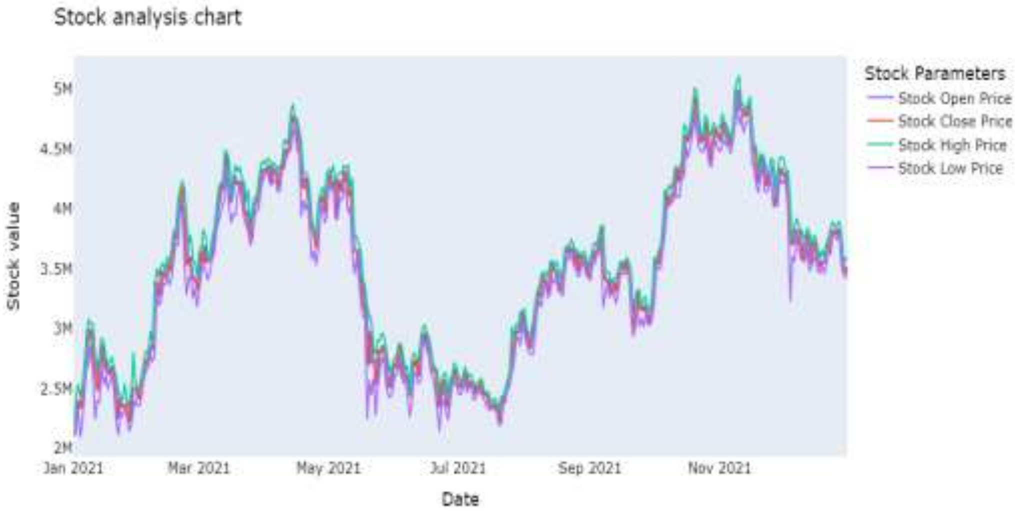


Table 9: Shows Month Wise Open And Close Price Of BTC-INR for the Period 2022

Date	**Open**	**Close**
January	3.08E+06	3.06E+06
February	3.04E+06	3.06E+06
March	3.19E+06	3.20E+06
April	3.18E+06	3.16E+06
May	2.46E+06	2.45E+06
June	1.93E+06	1.90E+06
July	1.70E+06	1.71E+06
August	1.87E+06	1.87E+06

Figure 16 Shows Month Wise Direction Of Open And Close Price of BTC-INR for the Period April 2022

Figure 17: Shows Month Wise High And Low Price of BTC-INR for the Period 2021

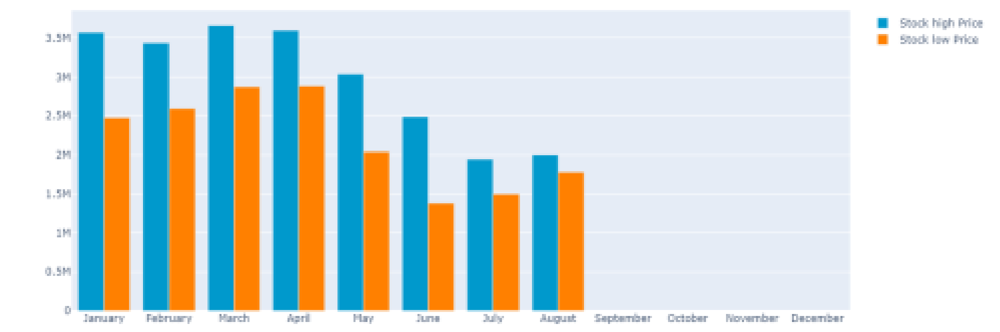
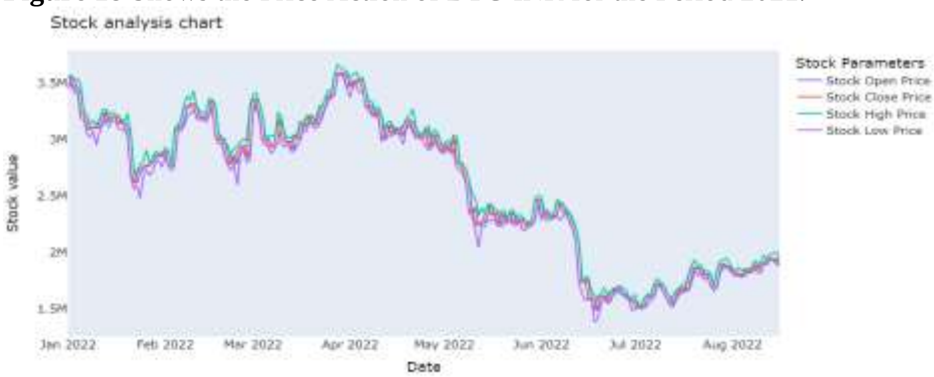


Figure 18 Shows the Price Action of BTC-INR for the Period 2021.



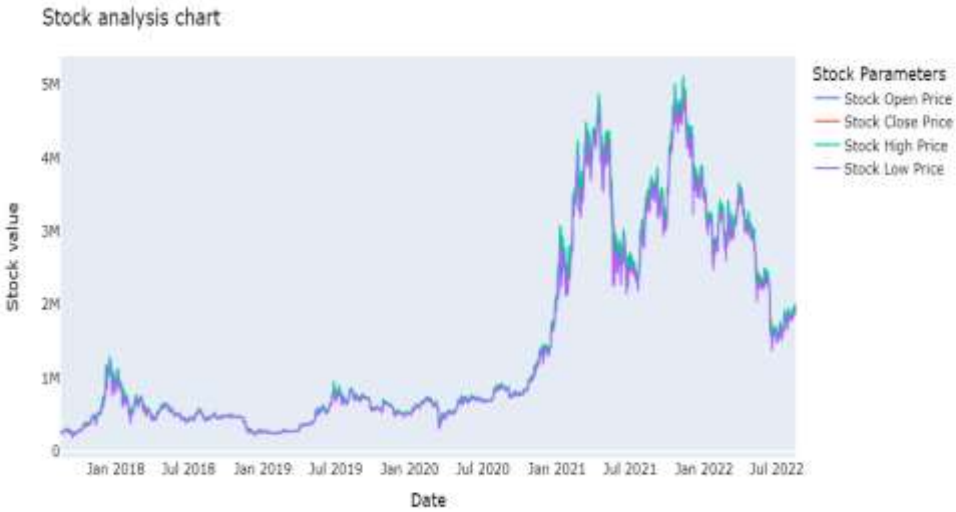
The year 2022 also marked a stupendous return for BTC-INR holders as the movement of 2021 continued for 2022 in the beginning period of January to May whereas later it has diminished in the month of July and August respectively. Figure 5 and 6 showing its Open, Close and High and Low also indicate the initial price movement on upward direction later seen a profit booking for July and August 2022.

The table 10 indicates the average price action of BTC-INR Open and Close for the period 2017 to 2022. The Prices are trading at an increasing pace and with consistent movement every year. Figure 19 shows the directional movement of all four prices from 2017 to 2022 and graph 8 indicates the predicted BTCINR Close Price.

Table 10: Showing the Open and Close Price From 2017 To 2022

Date	Open	Close
January	1.46000001	1.46000001
February	1.58000001	1.59000001
March	1.71000001	1.72000001
April	1.77000001	1.77000001
May	1.54000001	1.53000001
June	1.28000001	1.27000001
July	1.24000001	1.24000001
Augst	1.32000001	1.32000001
September	1.12000001	1.12000001
October	1.32000001	1.33000001
November	1.45000001	1.45000001
December	1.42000001	1.42000001

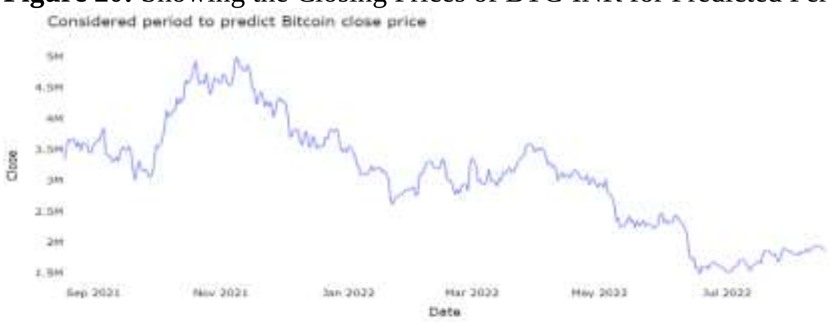
Figure 19 Shows The Stock Analysis Chart For the Period 2018 to 2022



Long short-term model:

Long short term model is applied for predicting BTCINR from 2017 to August 2022. Since BTC changes drastically each year is considered for study and a consolidated data is spilt into training data and test data. First step is dividing the data fir training and testing. Since the BTC fluctuates vs INR these values are approximated and just yearly data is considered to avoid the fluctuations in the data. Since the prediction is on close price the data considered for prediction is Close Price and date. LTSM model of Deep learning provides deep understanding on the predicted variable through providing accuracy in predicting the variable.

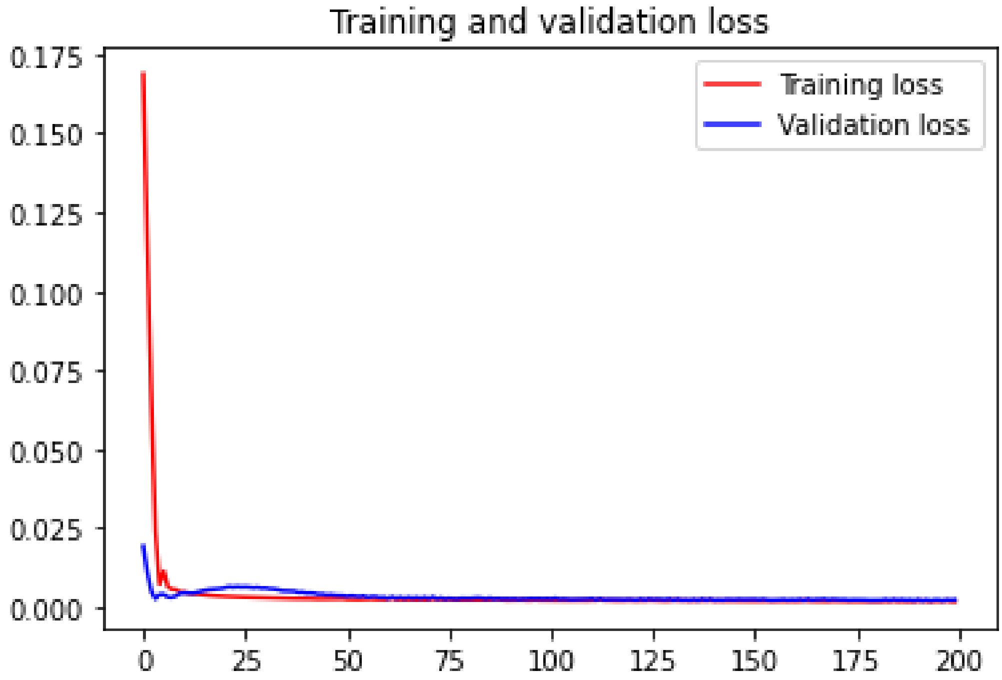
Figure 20: Showing the Closing Prices of BTC-INR for Predicted Period.



Building Long Short-term Memory.
Normalization:
Normalization is a vital and essential technique used in Machine Learning for the preparation of data. The objective of Normalization is to change the value of Numeric Columns to use a common scale. In the process MinMaxScaler subtracts the minimum value in the feature and then divides it by the range. The range is called as the difference between the original maximum and original minimum. MinMaxScaler preserves the shape of the original distribution.

Transformation
Transform the Close price based on Time-series-analysis forecasting requirement. Here The duration considered is 15 days and later 30 days is considered for Prediction
The below graph shows the Training data lost and Validation data lost, there model shows there is minimal loss at validation level ensuring the accuracy of the model considered for the study. The above graph visualizes the training and test moving along without having any dilution in the new data by the model proving its efficiency when new set of data is provided.

Figure 21 Indicating the Actual Model Building for Training and Test Data Set.



The below table shows the results on training and test data sets. The R2 in training data showed a value of 0.9433 whereas the test results showed a value of 0.8918. The results proved the accuracy of the model. The model accuracy has not shrunk with a new set of data.

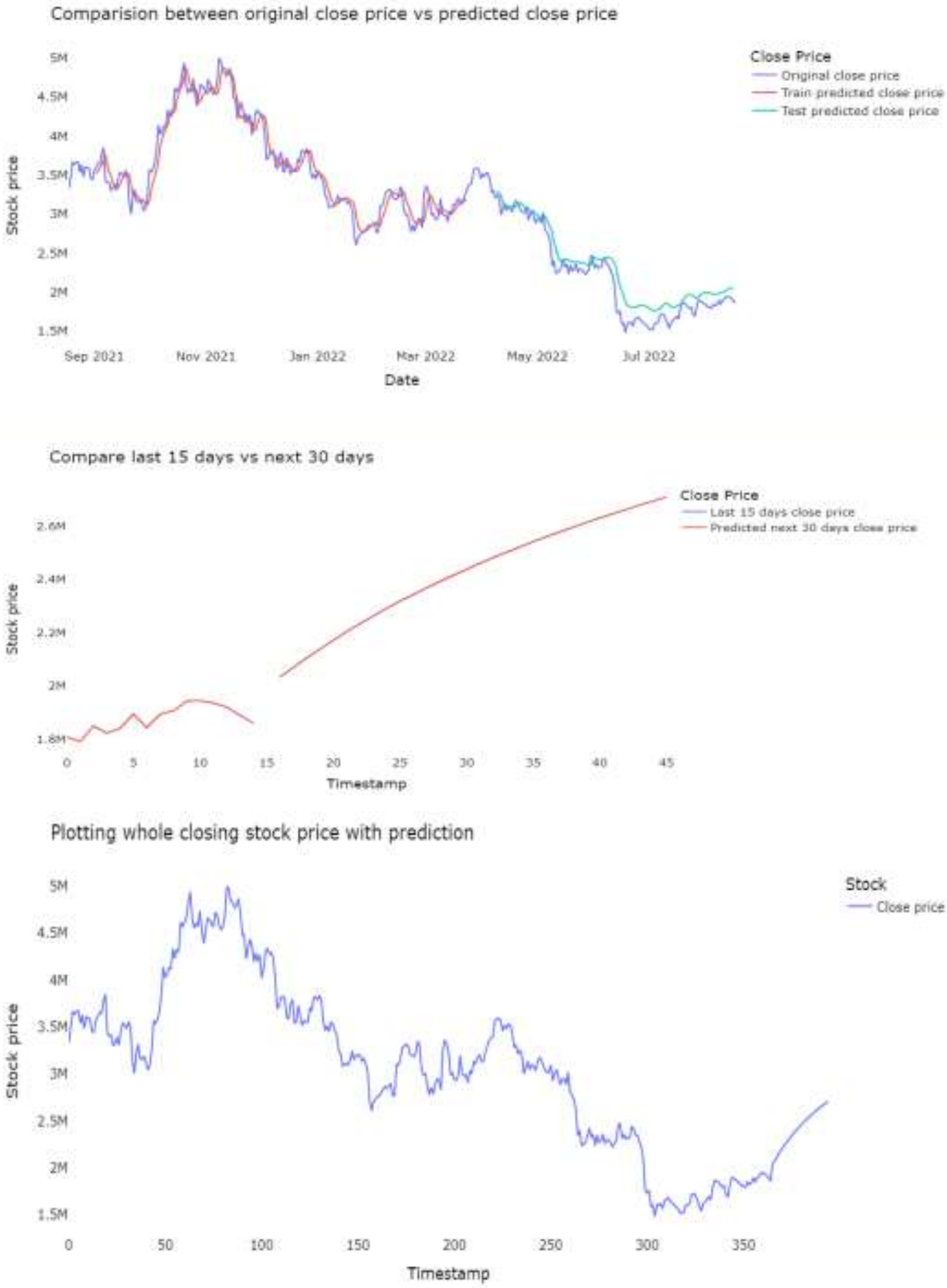
Table 11: Table Showing the Results for Training Data

Training Data					
RMSE	**MSE**	**MAE**	**R2**	**MGD**	**MPD**
148839.2	22153133011	114714	0.9433	0.0018	6220.1

Table 12: Table Showing the Results For Test Data

Test Data					
RMSE	**MSE**	**MAE**	**R2**	**MGD**	**MPD**
173357.1	30052705404	143252	0.8918	0.00763	14948

Figure 22 Indicating the Comparison Between Original Close Price Vs Predicted Close Price



The above graph shows the Original BTCINR, Predicted Training and test Close Prices. The above graph shows the movement of Original stock Price and Predicted Price. It can be visualized that the Predicted and original Prices do not fluctuate at every interval there by making its variance constant. The above graph shows a comparison of 15 days with the predicted prices for next 30 days. The Projection of 30 days is depicted in the graph and the movement is very ideal on the higher side without too many deviations. The above graph shows the movement of Closing Price of BTC-INR for 30 days. The chart shows a study momentum for the period and direction.

Conclusion:

As a part of deep Learning ANN model is accepted widely due its accuracy in predictive analytics and the model proved best in both training and test data sets considered by the authors. ANN networks shows the best neurons which is called an optimum solution out of various neuron or path available. The accuracy is higher compared to any other model due to multiple movements of inputs in reaching the output.

Scope for Further Research

The model can be applied for many financial instruments and the model accuracy can be compared with other models as well.

References

1. Aghashahi, M., & Bamdad, S. (2023). Analysis of different artificial neural networks for Bitcoin price prediction. International Journal of Management Science and Engineering Management, 18(2), 126-133.
2. Almeida, J., Tata, S., Moser, A., & Smit, V. (2015). Bitcoin prediction using ANN. Neural networks, 7, 1-12.
3. Banjade, D. (2020). Forecasting Bitcoin Price using Artificial Neural Network. Available at SSRN 3515702.
4. Behera, S., Nayak, S. C., & Kumar, A. P. (2023). Evaluating the Performance of Metaheuristic Based Artificial Neural Networks for Cryptocurrency Forecasting. Computational Economics, 1-40.
5. Cao, Q., Parry, M. E., & Leggio, K. B. (2011). The three-factor model and artificial neural networks: predicting stock price movement in China. Annals of Operations Research, 185(1), 25-44.
6. Chinthapalli, U. R. (2021). A Comparative Analysis on Probability of Volatility Clusters on Cryptocurrencies, and FOREX Currencies. Journal of Risk and Financial Management, 14(7), 308.
7. Dash, C. S. K., Behera, A. K., Nayak, S. C., & Dehuri, S. (2021, April). QORA-ANN: quasi opposition-based Rao algorithm and artificial neural network for cryptocurrency prediction. In 2021 6th International Conference for Convergence in Technology (I2CT) (pp. 1-5). IEEE.
8. Gopal, N., & Senthilkumar, K. S. (2020). Predicting bitcoin prices-ANN approach. International Journal of Electronic Finance, 10(1-2), 67-78.
9. Ho, A., Vatambeti, R., & Ravichandran, S. K. (2021). Bitcoin Price Prediction Using Machine Learning and Artificial Neural Network Model. Indian Journal of Science and Technology, 14(27), 2300-2308.
10. Jana, R. K., Ghosh, I., & Das, D. (2021). A differential evolution-based regression framework for forecasting Bitcoin price. Annals of Operations Research, 1-26.
11. Jay, P., Kalariya, V., Parmar, P., Tanwar, S., Kumar, N., & Alazab, M. (2020). Stochastic neural networks for cryptocurrency price prediction. Ieee access, 8, 82804-82818.
12. Khalid, R., El Afia, A., & Chiheb, R. (2019). Forecasting of BTC volatility: comparative study between parametric and nonparametric models. Progress in Artificial Intelligence, 8, 511-523.
13. Khedmati, M., Seifi, F., & Azizi, M. J. (2020). Time series forecasting of bitcoin price based on autoregressive integrated moving average and machine learning approaches. International Journal of Engineering, 33(7), 1293-1303.
14. Liu, W. K., & So, M. K. (2020). A GARCH model with artificial neural networks. Information, 11(10), 489.
15. Murugesan, R., Shanmugaraja, V., & Vadivel, A. (2022). Forecasting Bitcoin Price Using Interval Graph and ANN Model: A Novel Approach. SN Computer Science, 3(5), 411.
16. Nayak, S. K., Nayak, S. C., & Das, S. (2021). Modeling and forecasting cryptocurrency closing prices with rao algorithm-based artificial neural networks: A machine learning approach. FinTech, 1(1), 47-62.
17. Nayak, S. K., Nayak, S. C., & Das, S. (2021). Modeling and forecasting cryptocurrency closing prices with rao algorithm-based artificial neural networks: A machine learning approach. FinTech, 1(1), 47-62.
18. Patra, A., Das, S., Mishra, S. N., & Senapati, M. R. (2017). An adaptive local linear optimized radial basis functional neural network model for financial time series prediction. Neural Computing and Applications, 28(1), 101-110.
19. Senapati, M. R., Das, S., & Mishra, S. (2018). A novel model for stock price prediction using hybrid neural network. Journal of the Institution of Engineers (India): Series B, 99(6), 555-563.

20. Sharma, S., & Bhardwaj, I. (2022). Forecasting Returns of Crypto Currency: Identifying Robustness of Auto Regressive and Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs). In Financial Data Analytics: Theory and Application (pp. 183-196). Cham: Springer International Publishing.
21. Simon, S., & Raoot, A. (2012). Accuracy driven artificial neural networks in stock market prediction. International journal on soft computing, 3(2), 35.
22. Sujatha, R., Mareeswari, V., Chatterjee, J. M., Abd Allah, A. M., & Sassanian, A. E. (2021). A Bayesian regularized neural network for analyzing bitcoin trends. IEEE Access, 9, 37989-38000.
23. Tripathi, B., & Sharma, R. K. (2022). Modeling bitcoin prices using signal processing methods, bayesian optimization, and deep neural networks. Computational Economics, 1-27.
24. Vishweswarsastry V.N., Santosh B.R., & Guruprasad Desai D.R. (2023). Impact of Spectrum Allocation on the Top-Line and Bottom-Line of the Indian Telecom Sector. Empirical Economics Letters, 22(10), 175–187. https://doi.org/10.5281/zenodo.10183645
25. Wang, J., Sun, T., Liu, B., Cao, Y., & Wang, D. (2018, December). Financial markets prediction with deep learning. In 2018 17th IEEE international conference on machine learning and applications (ICMLA) (pp. 97-104). IEEE.