Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 10, October 2021: 2282-2291

A Comparative Study On Crypto Currency Prediction Using Modern Deep Learning Techniques

Naveen Ghorpade[1]*, Parashuram Baraki[2], Arun Biradar[3] and Mahesh Kumar M R[4]

[1]Assistant Professor, School of Computer Science and Engineering, Reva University, Bengaluru, naveen.ghorpade@reva.edu.in

[2]Professor, School of Computer Science and Engineering, Reva University, Bengaluru, parashuram.baraki@gmail.com

[3]Professor, School of Computer Science and Engineering, Reva University, Bengaluru, arunpatilm@gmail.com

[4]Assistant Professor, School of Computer Science and Engineering, Reva University, Bengaluru, maheshkumar.mr@reva.edu.in

Abstract: Cryptocurrencies are now well-established and widely accepted as a form of alternative trading money. Because they have invaded nearly all accounting operations, cryptocurrency trading is often regarded as popular and propitious sorts of successful investments. A reliable forecasting and prediction model is essential for predicting the high volatility caused by the increase in financial market. This current work summarises various optimisation techniques by shedding light on the volatility factors like internal competition, market pressure, financial problems, social and political conflicts, etc. A comprehensive study is presented on how to predict the volatility of cryptocurrency and formulate their inter-connections with the parent Cryptocurrencies using various deep learning frameworks. Further, this work focuses on utilising sophisticated models to improve the forecasting performance of cryptocurrency. We are hopeful that this work will provide broader insights in the future research of cryptocurrency.

Keywords: prediction, forecasting, optimisation techniques, currency, volatility

Introduction:

As the economy is getting modernized, the crypto currency is getting digitalized, with the name of digital currency [1]. The most prominent Cryptocurrencies, which including Bit coin, were created for financial transactions, but they are frequently held for speculation in the hopes of a price increase [2-3]. Bitcoin was met with debate, and there are questions about its sustainable feature, yet Cryptocurrencies have gone mainstream since its birth [4]. Cryptocurrencies' rise has significant ramifications for the global economy overall, and emerging nations in particular, some studies also showcased Cryptocurrencies' and Bitcoin as the suitable and complementary of the growing economical market [5]. Cryptocurrencies are essential in ecommerce because they provide a novel value system which effectively serves the influence of social networking.

Cryptocurrency has gained tremendous popularity past few years as a viable option to traditional centralised currencies, this is due to the impact of block chain community and the considerable volatility of its exchange values [6]. The main frame of crypto currency is forecasting of stock data.

The forecasting of stock data includes many big data algorithms alone with the modern artificial intelligence (AI) and machine learning (ML) techniques [7]. Prediction of cryptocurrency is one of the major advantages after crypto currency is got digitalized. Financial forecasting is a difficult area to master. The existence of noise, a high degree of ambiguity, and hidden linkages are common characteristics of data in financial market.

To forecast its price volatility, a hybrid convolutional neural network with generalised auto-regressive conditional heteroskedasticity (ANN-GARCH) was developed, which was trained utilising technical analysis indices [8]. On the basis of user thoughts obtained from internet forums, a deep learning-based algorithm is utilised to anticipate the volatility in the Value of Bitcoin and operations [9]. The main base for crypto currency prediction models is technical indicators [10-11], technical indicators as input parameters to a multilayer layer deep learning framework to forecast crypto currency future return trend. The use of fundamental analysis and technical indicators to forecast market fluctuations can solve financial data noise, ambiguity, linkages impact issue on prediction model [12-13].

Comparative Study:

Cryptocurrency price prediction methodologies:

The Figure 1 and Figure 2 represent the proposed model of the system in [14] and its problem formulation. The main objective is to enhance the scheme of price prediction of Cryptocurrencies and also to formulate their inter-connections with the parent Cryptocurrencies [14]. The model utilizes Bitcoin as the parent currency while anticipating the Litecoin and Zcash prices. In the initial stage of the Litecoin model, the quondam data is gathered and bifurcated into training and testing datasets. These sets are then pre-processed where Z-score normalization of the data takes place in order to discard.

The normalized data is the output of the system. The parent currency's daily data is passed through algorithm 1(direction algorithm) in a concurrent process through which the movement of the Bitcoin is illustrated as the output using two signs +1 and -1. Here, the former represents its hike and the latter is negative closing. For the prediction, the direction of the parent currency is considered because the system evaluates the inter-dependencies between Litecoin, Zcash and Bitcoin [15]. The algorithm uses the average and starting prices of Bitcoin as sources, with a direction output of +1 if the actual cost is greater than the standard price and -1 if the average price is lower.

The normalized training and testing data of Litecoin are integrated with the direction of Bitcoin data. On training the model, the Litecoin price for the next day can be predicted and the comparison of the predicted and actual price helps forecast the price of the following day. The scheme is based on Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) hybrid approach as it can help Recurrent Neural Network (RNN) surpass the gradient vanishing [16]. It functions by processing two distinguished inputs, namely the dataset of the cryptocurrency price and the parent currency direction. These are divided into two networks of LSTM where the first network has 25 neurons succeeded by a dropout layer, a 40 neuron-GRU network and a 5 neuron-dense layer which provides the first output.

The purpose of the dropout layer is to elude overfitting. In the second network, the LSTM branch has 50 neurons which is ensued by a dropout layer and a dense layer which gives the second output [17]. The direction data has to go through a flatten layer and two dense layers with twenty and ten neurons, respectively where the layer with 10 neurons gives the third output. These three outputs have to undergo concatenation in a layer with 20 neurons and then pass through a single neuron-dense layer giving the ultimate output of the proposed scheme. Similarly, the Zcash price can be estimated by employing this model of the proposed system.

A recurring flaw in all of the studies presented and analysed in [18] is that they concentrated on improving forecasting performance by utilising more sophisticated models and methodologies, often overlooking the construction of a sophisticated training dataset with more valuable data. To put it another way, most techniques treat each crypto currency separately, ignoring any potential relationships with other crypto currencies and failing to account for the difficulty and non-stationary of currency data. A current design for the building of accurate and trustworthy prediction model, as well as a new technique, are presented in [18].

Figure 1: Model in [14]. Reproduced from open access article

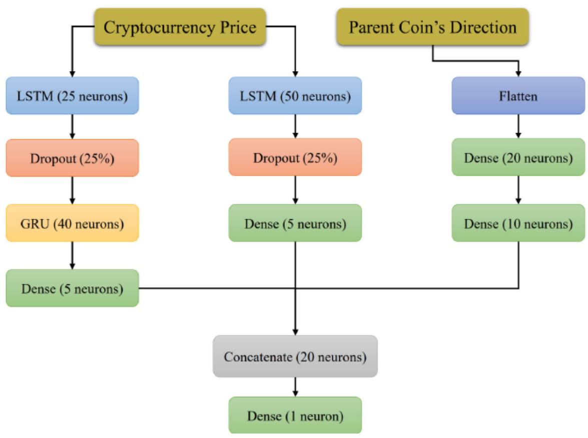


Figure 2: Proposed model in [14]. Reproduced from open access article

The work in [18] uses diverse crypto currency data as inputs and processes them separately in order to exploit and process each crypto currency information separately [19-20]. To issue the final prediction, the processed data from each coin is pooled and further processed. To our knowledge, this is the first time that data from several crypto currencies has been utilised to provide more accurate forecasts.

The proposed approach in [18] is based on the development of a learning model that can independently extract meaningful information from diverse crypto currency data and then analyse that data to produce accurate and trustworthy predictions. The proposed method in [18] involves not collecting all crypto currency data at the same time, but rather processing each crypto currency's data separately and combining them to arrive at a final prediction.

Multiple-input deep neural network (MICDL's) architecture is depicted in Figure 3 [18]. By studying the embedding layer of each crypto currency individually, the proposed technique takes use of convolutional layers' ability to extract meaningful knowledge. A concatenate layer then joins the output vectors of all LSTM layers. After this many layers are used that make up a deep learning neural network's typical structure, such as a dense layer or a dropout layer.

Although every complicated function may be analysed and represented using a typical deep neural network (DNN) model, the training process' convergence can be hampered by the number of weights, and the vanishing gradient problem. The suggested model's design [18] provides more flexibility and adaptively for less computation effort [21-22].

The key parts of the proposed MICRL model in [18], such as convolution and pooling layers, LSTM layers, dense layers, batch normalisation layers, and dropout layers, are then briefly described.

- Convolutional layers are a new type of neural network layer that is distinguished by its capacity to learn the inputs. It can be accomplished by performing convolutional operations on these information and producing new feature values using convolution kernels, often known as "filters"[23].
- Less geographical information means fewer weights, which means less likelihood of overfitting the training data and less computational work. The most often used layers are probably max pooling and average pooling.[23]
- LSTM layers are recurrent neural network layers with a partitioned unit and flexible gate units to control sharing of information. Data may be processed, denied, or updated since all cells includes gates, allowing relevant information to be kept in the cell for longer periods of time [24].
- Dense layers are the most common and extensively used method for building the hidden layer of a DNN. Every layer is made up of neurons that are coupled to every other layer's neurons. Nonlinearity is added by thick layers, and a network with dense layers may possibly simulate any mathematical function. [25-26]
- Batch normalisation is a sophisticated DNN training methodology that relies on stabilising the process of learning by normalising the inputs to the next layer for each mini-batch [23, 27]

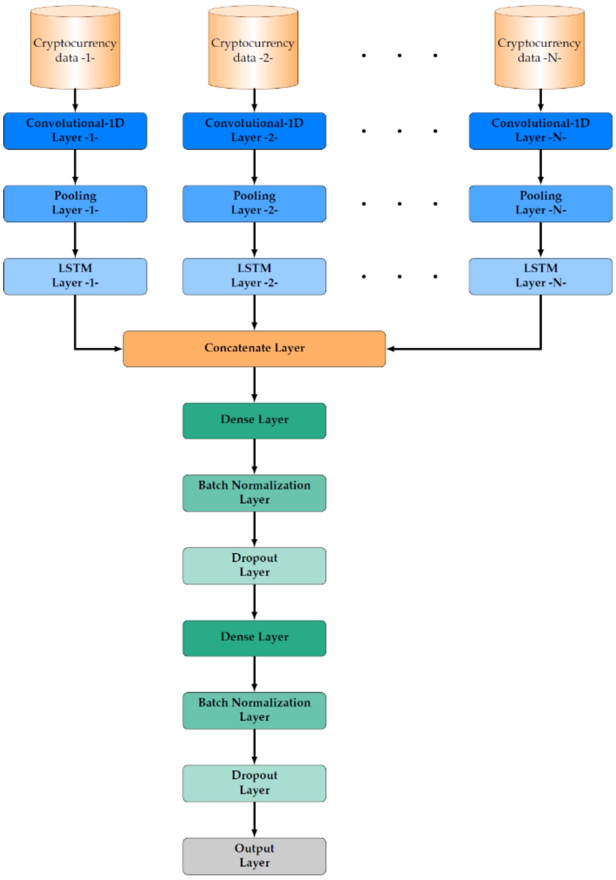


Figure 3: MICDL model [18]. Reproduced from open access article

In order to collect good trading points the scientists started their research based on the changes that happened which hit badly the market [28]. There are five common techniques and strategies namely the double crossover strategy, day trading, swing trading, scalping, position trading has been invented after completion of research work which helps in increasing trading points and market efficiency. It got good output when these strategies worked successfully, and the process of trading completed with an enormous amount of benefit. But several types of Cryptocurrencies are observed in these strategies at some period which brings loss instead earning of profit. One of the reasons to cause loss is when participants leave their temporary position in the trade market and also some people believe in "Random Walk Theory" and do not follow any rules [29-30]. Simultaneously research continued on predicting price fluctuations by testing systems and modules done by other researchers on stock market. Most relevant researches are done on reinforcement learning algorithm like to prove it is capable for learning stock trading [31], compared this algorithm with Q-Learning approach [32].

The study refers to the Deep Reinforcement Learning (DRL) approach [36] which helps in taking right actions based on the reward in the stock market and maximizing short-term investor's profit. This approach belongs to the branch of AI and ML [33]. In this approach, the machine itself performs the actions and compares them with the obtained results in the environment to find out outcome based on past information [34]. The following terms involved in this learning are Agent: the one who performs an action, Action: achieving reward based on the action, Reward: Giving to the agent based on the action performed, Environment: where action performed by agent, State: State of agent [35].

There are two parts of trading process in the deep learning system. The first is Environment, which is in charge of money management, stock asset management, model checking, stock purchasing, holding, and selling, and computing the reward for doing activities. The second type of item is the Agent, which is used to communicate with the environment. It's also in charge of keeping an eye on the environment, deciding what to do with rules, recording and calculating rewards using discounted incentives, computing gradients, and updating the network of systems with gradients. Hourly stock information is taken into account as the environment for agent communication. For stock interaction with the environment, the agent consists of three actions: purchase, hold, and sell. The environment would be observed and monitored using stock closing prices as inputs and action choices by a trained agent. The functioning of the deep reinforcement learning strategy is depicted in Figure 4. Agent starts in state s0 and then chooses one of three actions a0 at random. After acting, it returns to its previous state s1 and performs another action a1. This procedure will continue until all states have been completed, but actions will no longer be performed at random. The agent takes action based on the rewards received from the environment. An agent will always wait for the "sell" action to occur after completing the "buy" action. When the "sell" action is done, the agent subtracts the selling price from the previous buy price. If the subtracted value is larger than zero (r > 0), the trader makes a profit by selling. As a consequence, the agent receives a positive reward for completing the correct action, which is equal to the resultant value. The agent will be rewarded based on the subtracting outcome. If the subtracted value is less than zero (r 0), the agent receives no profit and instead receives a penalty (negative reward) for doing the improper action. As a consequence of following these lines, an agent becomes more "expert" than before and displays evidence of improvement [36].

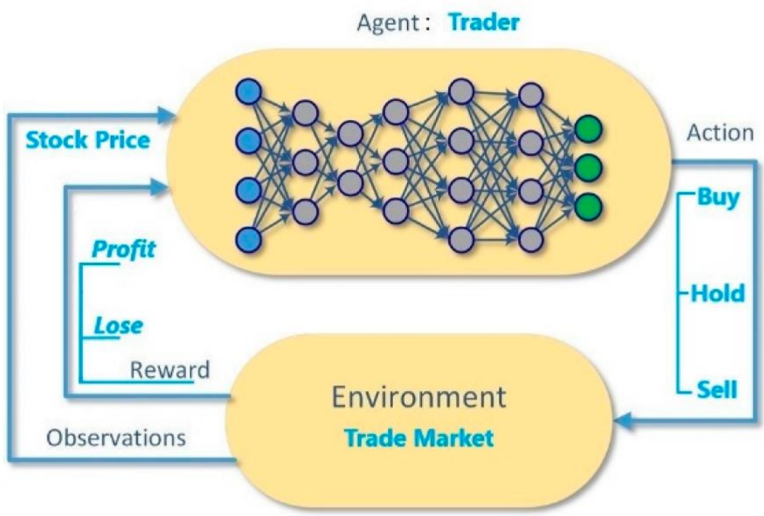


Figure 4: Technique adapted in [36]. Reproduced from open access article

To build three workable future price changes, the set of four multilayer models are constructed is shown in Figure 5. The first and second layer consists of 64 and 32 hidden units. The third layer contains 8 neurons and last layer has possible number of actions along with three units. The activation function, Reclined Liner Unit (ReLU) is used in the first three hidden layers and in the last layer linear function is used. For the error function, Mean Square Error (MSE) function is used. The obtained final results from all four models are considered as the confidence indicators. If the result (confidence indicator) is less than the threshold, it is marked as not good action. Based on the reward function the effectiveness of model is determined. An additional penalty feature is added to prevent the increasing number of rewards which helps to improve agent works and performance by counting sequential purchases. The agent gets negative reward, if the number is greater than the limit. Limit is defined by the data set. Zero feedback will be given to the agent when "hold" action is selected from environment is based on the following algorithm. Simultaneously "hold" action status of status will be under control. In case if the action continues by repeating many times, then agent gets negative reward by punishment. The "hold" actions will be annulled when the agent decides to "buy" the coins from market. Agent gets reward from environment after each "sell" action either positive or negative. The award value depends on the selling action profit. The next step after "sell" action is, annulling of "buy" and "hold" action counter. The algorithm related to the reward function can be seen in [36]. The results obtained showed the better output for trader's financial profit using deep reinforcement learning application.

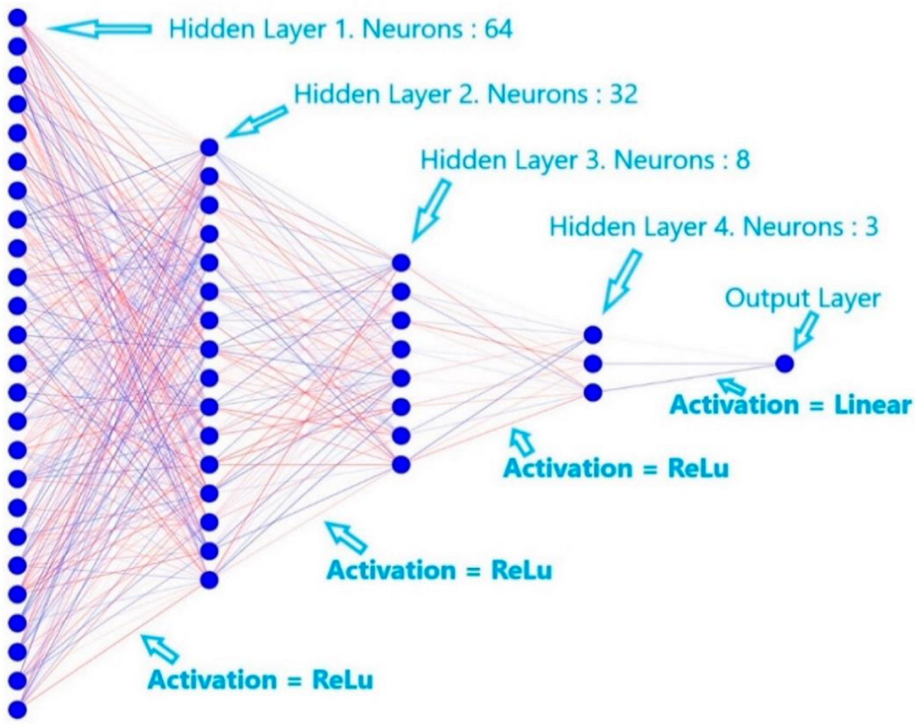
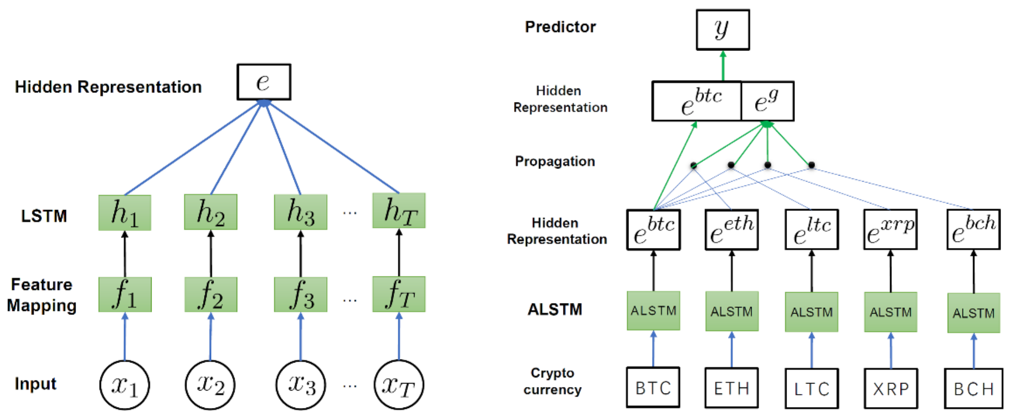


Figure 5: Graphical structure of model in [36]. Reproduced from open access article

The predictor in [37] reduces the possibilities of fading of gradients and maintains time dependencies on long term basis in feature mapping after which it is sent to the LSTM as shown in the Figure 6 (a). Adaptive LSTM is more advantageous. The system reads the document and the less important information is lost. The system extracts the feature, update the system and forgets the least important information. In Figure 6 (b), the various crypto currencies are applied to the ALSTM where the system computes the Latent and hidden representations. The final output is the outcome which is obtained after forgetting the least important information [37]. After the propagation of the information through two hidden layers the proper prediction is achieved.



(a) An attentive LSTM network (ALSTM). (b) Our ALEN model.

Figure 6: (a) ALSTM model. (b) ALEN model in [37]. This image is reproduced from open access article

Conclusion:

Researchers have had a difficult time forecasting bitcoin prices since social and psychological factors influence the price of cryptocurrencies. The Machine learning algorithms highlighted in the study can help to predict the price of cryptocurrencies. The LSTM and GRU hybrid models can be used for predicting Litecoin and Zcash, with the greater accuracy. The CNN based MICRL model, designed with hybrid multilayers had shown the attractive results for Cryptocurrency Forecasting. The Deep Reinforcement Learning methodology aids in adopting the appropriate actions in the financial markets based on the reward and optimising short-term shareholder profit. The cryptocurrency market prediction model with deep reinforcement learning algorithm gives the attractive results for Bitcoin and Litecoin prediction with buying, selling, and holding stock data.

References:

1. Gajardo G, Kristjanpoller WD, Minutolo M. Does bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the Euro, Great British Pound and Yen. Chaos Solitons Fractals 2018; 109:195–205.
2. Kristoufek L, Vosvrda M (2016) Gold, currencies and market efficiency. Physica A: Statistical Mechanics and its Applications 449:27–34
3. Nasir, M.A., Huynh, T.L.D., Nguyen, S.P. et al. Forecasting cryptocurrency returns and volume using search engines. Financ Innov 5, 2 (2019). https://doi.org/10.1186/s40854-018-0119-8
4. Feng, W. Wang Y. Zhang, Z. (2017), Informed trading in the bitcoin market, finance research letters, available online 2 December 2017, ISSN 1544-6123, https://doi.org/10.1016/j.frl.2017.11.009
5. Carrick J (2016) Bitcoin as a complement to emerging market currencies. Emerg Mark Financ Trade 52(10):2321–2334
6. Alonso-Monsalve, S., Suárez-Cetrulo, A. L., Cervantes, A., & Quintana, D. (2020). Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators. Expert Systems with Applications, 149, 113250. doi:10.1016/j.eswa.2020.113250
7. Lahmiri, S., & Bekiros, S. (2019). Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos, Solitons & Fractals, 118, 35–40. doi:10.1016/j.chaos.2018.11.014
8. Kristjanpoller W, Minutolo MC. A hybrid volatility forecasting framework integrating GARCH, artificial neural network, technical analysis and principal components analysis. Expert Syst Appl 2018;109:1–11.

9. Kim YB, Lee J, Park N, Choo J, Kim J-H, Kim CH. When bitcoin encounters information in an online forum: using text mining to analyse user opinions and predict value fluctuation. PLoS ONE 2017;12:e0177630.
10. Huang, J.-Z., Huang, W., & Ni, J. (2018). Predicting Bitcoin Returns Using High-Dimensional Technical Indicators. The Journal of Finance and Data Science. doi:10.1016/j.jfds.2018.10.001
11. Nakano M, Takahashi A, Takahashi S. Bitcoin technical trading with artificial neural network. Physica A 2018;510:587–609.
12. Huang, W., Nakamori, Y., & Wang, S.-Y. (2005). Forecasting stock market movement direction with support vector machine. Computers & Operations Research, 32(10), 2513–2522. doi:10.1016/j.cor.2004.03.016
13. Tay, F. E. ., & Cao, L. (2001). Application of support vector machines in financial time series forecasting. Omega, 29(4), 309–317. doi:10.1016/s0305-0483(01)00026-3
14. S. Tanwar, N. P. Patel, S. N. Patel, J. R. Patel, G. Sharma, I. E. Davidson, "Deep Learning-based Cryptocurrency Price Prediction Scheme with Inter-dependent Relations", IEEE Access, 2016, vol. 4, doi: 10.1109/ACCESS.2021.3117848.
15. V. Derbentsev, N. Datsenko, O. Stepanenko, and V. Bezkorovainyi,``Forecasting cryptocurrency prices time series using machine learning approach," SHS Web Conf., vol. 65, Jan. 2019, Art. no. 02001.
16. D. Vanderbilt, Kun Xie, Wenying Sun. An Applied Study of RNN Models for Predicting Cryptocurrency Prices. Issues in Information System, Volume 21, Issue 2, pp. 135-143, 2020. Accessed October 2021. Available at: https://iacis.org/iis/2020/2_iis_2020_135-143.pdf
17. I. A. Hashish, F. Forni, G. Andreotti, T. Facchinetti, S. Darjani, "A hybrid model for bitcoin prices prediction using hidden markov models and optimized LSTM networks," 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2019, pp. 721–728.
18. Livieris, I.E.; Kiriakidou, N.; Stavroyiannis, S.; Pintelas, P. An Advanced CNN-LSTM Model for Cryptocurrency Forecasting. Electronics 2021, 10, 287. https://doi.org/10.3390/electronics10030287
19. Pintelas, E.; Livieris, I.E.; Stavroyiannis, S.; Kotsilieris, T.; Pintelas, P. Investigating the Problem of Cryptocurrency Price Prediction: A Deep Learning Approach. In IFIP International Conference on Artificial Intelligence Applications and Innovations; Springer: Berlin/Heidelberg, Germany, 2020; pp. 99–110.
20. Livieris, I.E.; Pintelas, E.; Stavroyiannis, S.; Pintelas, P. Ensemble Deep Learning Models for Forecasting Cryptocurrency Time-Series. Algorithms 2020, 13, 121.
21. Livieris, I.E.; Dafnis, S.D.; Papadopoulos, G.K.; Kalivas, D.P. A Multiple-Input Neural Network Model for Predicting Cotton Production Quantity: A Case Study. Algorithms 2020, 13, 273
22. Cai, J.x.; Zhong, R.; Li, Y. Antenna selection for multiple-input multiple-output systems based on deep convolutional neural networks. PLoS ONE 2019, 14, e0215672
23. Goodfellow, I.; Bengio, Y.; Courville, A.; Bengio, Y. Deep Learning; MIT Press: Cambridge, MA, USA, 2016; Volume 1.
24. Greff, K.; Srivastava, R.K.; Koutník, J.; Steunebrink, B.R.; Schmidhuber, J. LSTM: A search space odyssey. IEEE Trans. Neural Netw.Learn. Syst. 2016, 28, 2222–2232.
25. Demuth, H.B.; Beale, M.H.; De Jess, O.; Hagan, M.T. Neural Network Design; Oklahoma State University: Stillwater, OK, USA. 2014.
26. Bennur, A.; Gaggar, M. LCA-Net: Light Convolutional Autoencoder for Image Dehazing. arXiv 2020, arXiv:2008.10325.
27. Livieris, I.E.; Stavroyiannis, S.; Pintelas, E.; Kotsilieris, T.; Pintelas, P. A dropout weight-constrained recurrent neural network model for forecasting the price of major cryptocurrencies and CCi30 index. Evol. Syst. 2020.
28. Campbell, J.Y.; Lo, A.W.; MacKinlay, A.C.; Whitelaw, R.F. The Econometrics of Financial Markets, 2nd ed.; Princeton University Press: Princeton, NJ, USA, 1996.
29. Fama, Eugene F. (1995). Random Walks in Stock Market Prices. Financial Analysts Journal, 51(1), 75–80. doi:10.2469/faj.v51.n1.1861.
30. Fama, Eugene F. "The Behavior of Stock-Market Prices." The Journal of Business, vol. 38, no. 1, University of Chicago Press, 1965, pp. 34–105, http://www.jstor.org/stable/2350752.
31. Azhikodan, A.R.; Anvitha, G.K.; Jadvah, M.V. Stock Trading Bot Using Deep Reinforcement Learning. In Innovations in Computer Science and Engineering; Springer: Singapore, 2019; pp. 41–49. 27.
32. Moody, J.E.; Saffell, M. Reinforcement Learning for Trading; NIPS: San Diego, USA, 1998.

33. Otterlo, M.; Wiering, M. Reinforcement Learning and Markov Decision Processes. In Reinforcement Learning; Springer: Berlin/Heidelberg, Germany, 2012; pp. 3–42.
34. M. M. Ejaz, T. B. Tang and C. Lu, "Autonomous Visual Navigation using Deep Reinforcement Learning: An Overview," 2019 IEEE Student Conference on Research and Development (SCOReD), 2019, pp. 294-299, doi: 10.1109/SCORED.2019.8896352.
35. Ding Z., Huang Y., Yuan H., Dong H. (2020) Introduction to Reinforcement Learning. In: Dong H., Ding Z., Zhang S. (eds) Deep Reinforcement Learning. Springer, Singapore. https://doi.org/10.1007/978-981-15-4095-0_2
36. Sattarov, Otabek, Azamjon Muminov, Cheol W. Lee, Hyun K. Kang, Ryumduck Oh, Junho Ahn, Hyung J. Oh, and Heung S. Jeon 2020. "Recommending Cryptocurrency Trading Points with Deep Reinforcement Learning Approach" Applied Sciences 10, no. 4: 1506. https://doi.org/10.3390/app10041506
37. Li, Y.; Zheng, Z.; Dai, H.-N. Enhancing Bitcoin Price Fluctuation Prediction Using Attentive LSTM and Embedding Network. Appl. Sci. 2020, 10, 4872. https://doi.org/10.3390/app10144872