Analysis and Prediction of the Cryptocurrency Market using Artificial Intelligence

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Faculty: Sharmila Banu K

Name	Reg No
Shreasi Sen	20BCE2738
Shashwat Poudyal	20BCE2746
Ritesh Kolli	20BCE2705
Anmol Srivastava	20BCE2578

Problem Statement

Analysis and Prediction of the Cryptocurrency Market using AI: As of today, there exists a lot of complicated financial indicators and volatile fluctuation of the cryptocurrency market. However, as technology gets more advanced, the opportunity to gain a sizable fortune from the cryptocurrency market has increased and increased knowledge of the industry helps experts to make better predictions. The prediction of the trends of market portfolio is of great importance to help in maximizing the profit of trading while maintaining the low-risk appeal that makes the cryptocurrency market ripe for collecting profits (Klimczuk, C 2020).

Introduction

Significance

Cryptocurrencies are a clever combination of cryptography and game theory, and the first 'currency' – Bitcoin, presented itself as "based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party". Bitcoin was also the first platform, at scale, to rely on decentralized, internet-level 'consensus' for its operations: Without involving a central clearinghouse or market maker, the platform was able to settle the transfer of property rights in the underlying digital token (bitcoin) by simply combining a shared ledger with an incentive system designed to securely maintain it.

The flexibility in terms of what such shared data represents makes the technology extremely versatile, and allows distributed ledgers to track and settle exchanges across multiple types of digital assets. The rules through which the network reaches consensus about the state of the shared data over time are a key aspect of the market design of a crypto token, as they define the incentives for users and contributors of key resources to the platform (Catalini and Gans, 2021).

The distributed ledger where the shared data resides is called a 'blockchain' because it typically constitutes a chain of blocks of transaction data. Each one of the blocks contains valid transaction records for a specific period of time and their attributes. A key attribute of each transaction (and each block) is its timestamp. Blocks are chained together by incorporating a digital fingerprint of the previous block (a hash) in the current block. Any change in the transaction information contained in a specific block would alter such a fingerprint, irreparably breaking the chain of consensus linking that block with all subsequent ones. As a result, one can think of a blockchain not only as a large-scale, distributed database, but also as an immutable audit trail where the 'DNA' of each block is incorporated in all following ones, making it impossible to alter history without being noticed (Aoyagi and Adachi, 2018).

The computationally costly tasks involved in mining are essentially part of a race between miners for the right to add the next block to the chain, and earn the associated reward. The more computing resources a miner dedicates to mining, the higher the chances of winning the race by finding a valid solution for a new block first and broadcasting it to the rest of the network. Each time a miner commits a new block to the chain it can assign a predefined amount of the crypto token to itself as a reward (coin base transaction).

This reward, combined with the transactions fees participants may have included in their individual transactions to incentivize miners to prioritize them over others in the construction of the next block, serves as an incentive for miners for the work they perform. To incentivize a decentralized network of miners to contribute resources to secure and operate the network, blockchain protocols typically rely on a native, built-in "token" (Baur and Dimpfl, 2021).

Motivation

The total market value of all the crypto related assets surpassed $2 trillion as of September 2021—a 1000% increase since January 2020. An entire ecosystem is also flourishing, complete with exchanges, wallets, miners, and stablecoin issuers.

However, the market is highly volatile, due to multiple reasons, including but not limited to, the following factors:

- Entities lack strong operational, governance, and risk practices compared to conventional financial alternatives
- Crypto exchanges face significant disruptions during periods of market turbulence, due to the decentralized and isolated nature of the entity
- Legality of the very fundamentals surrounding the idea of cryptocurrency is something that isn't universal, some nations are accepting of the currency whereas some, as of now, are looking to delegitimize the currency. The stance of the nation's

opposing cryptocurrencies is also understandable, while cryptocurrencies have been a revolutionary and exciting idea from mathematical and technological lens, it is equally important to recognize the threat the (pseudo)anonymity associated with crypto assets carry for regulators and offer alternative routes for illegitimate activities such as money laundering, as well as, terrorist financing.

The risk of financial fraud or malicious actors such as hackers ruining one's savings are not being mentioned, given the fact that in the current financial society, most conventional assets are also digitized and carry the same risk to sabotage and cyber 'warfare'.

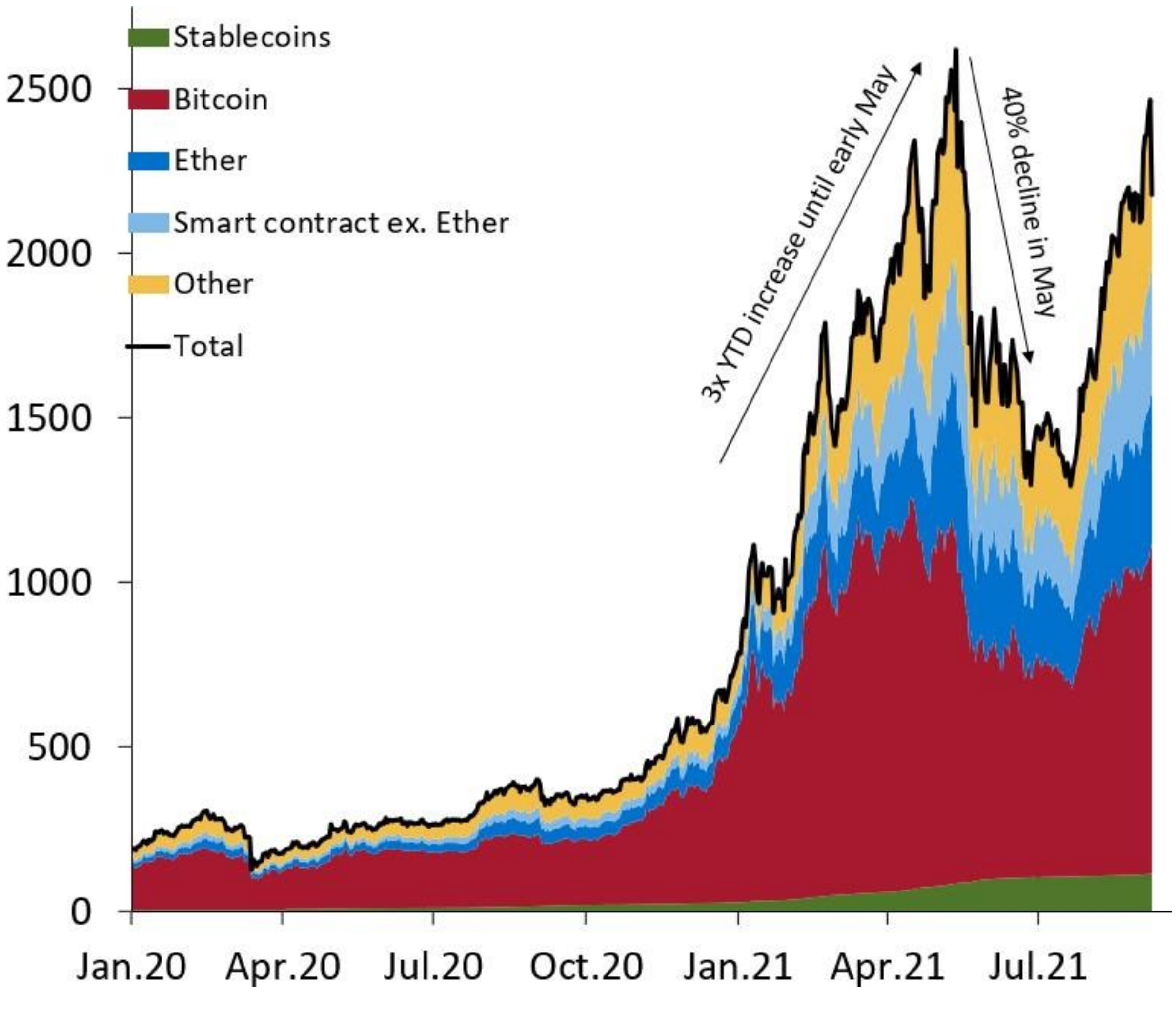


Figure 1 Crypto Assets Market Capitalization [USD, billion]

Therefore, to recapitulate, crypto assets are a relatively new digital phenomenon which have experienced unprecedented growth in short-term and long-term, a 1000% increase in global valuation in 2 years and \$8.27b increase to \$3048.57b global valuation in a 10-year period. Despite the growth in acceptance and valuation, the risks associated with the assets also pose an interesting challenge to the stability in both acceptance and price of the crypto market. The solutions of these will be widely important to the future of the financial market of the world, and will be based upon multiple factors such as the initiatives taken by governments of various nations, private financial institutions and the drivers of cryptocurrency assets. International standards need to be set to address problems such as stability, risks related to foreign investment, tackling malicious and illegitimate actions while also preserving the benefits such as decentralised and anonymous transactions.

For the purposes of the project undertaken, we were motivated by making an attempt to condense the various factors surrounding the crypto assets and making an attempt to predict the trends of a single crypto portfolio.

Scope and Applications

Before discussing the applications and the scope of the project, there’s a need to discuss the objectives that we hope to accomplish, and the objectives are as follows:

- To use AI techniques to evaluate past data pertaining to the cryptocurrency market
- To use the said analysis to make more accurate predictions in the trends of cryptocurrency market
- To make the crypto market more accessible to people who are new to it and attract more traders.
- To provide good and effective prediction systems for the crypto market, help traders, investors, and analysts by providing supportive information like the future direction of the crypto market.

Stock market analysis can be separated into two categories, namely technical and fundamental. Technical analysis looks at the price trend of a stock and uses this data to forecast its future price movement whereas fundamental analysis, on the other hand, looks at economic factors, news surrounding the cryptocurrency.

Text mining techniques can be applied on different articles published by legitimate companies on the internet to extract information to analyse and update our database. We will require a framework for information gathering and processing using an AI tool with our suggested algorithms.

One of the simplest yet most powerful applications can be a cryptocurrency portfolio management algorithm that works in tandem with different profit-making strategies. It'd need to be based on economically sound risk management strategies, and an agent that also applies reinforcement learning instead of only predicting trends might make for an interesting project in the field of financial analysis.

Literature Survey

Sr No	**Author(s)**	**Existing Work**	**Impact on present work**	**Gaps Identified**
1.	• A.U.S.S PRADEEP, • SOREN GOYAL	Statistical arbitrage, market efficiency, Least Square Regression, Neural Networks	Points out the inefficiency of Regression algorithms on sequential data such as stock exchange	Time series = 10 days, single layer with number of neurons varying.

2.	• Z. Asha Farhath, • B. Arputhamary, • Dr. L. Arockiam	ANN, Multilayer Perception (MLP), Deep Belief Net (DBN), Support Vector Machine (SVM)	Seasonal Autoregressive Integrated Moving Average (SARIMA) model.	A purely theoretical analysis of ARIMA and discusses possible implementations.
3.	• Erkam Guresen, • Gulgun Kayakutlu, • Tugrul U. Daim	MLP, Autoregressive Conditional Heteroscedasticity (ARCH), Exponentially Weighted Moving Average (EWMA)	Compares ARCH and it's derivative algorithms with ANNs, while providing literature survey and establishes that ANN triumph over ARCH in financial forecasting.	Single dataset (NASDAQ) and predicted results of both MLP and ANN deviate a lot from actual trends/prices.

4.	• Sornpon Wichaidit, • Surin Kittitornkun,	Correlation Regression Algorithms, Feedforward backpropagation, ARIMA.	Implemented a model called Cross Correlation ARIMA, which saw improvement over previous ARIMA and regression-based models.	3 years of data-set, predicts prices of next days, and the deviation rate when inaccurate is quite high.
5.	• NEELIMA BUDHANI, • Dr. C. K. JHA, • SANDEEP K. BUDHANI.	ANN, Feedforward Networks, Backpropagation algorithm	Discusses benefits and drawbacks of using Neural Networks (ANNs specifically) on commercial problem(s).	A purely theoretical analysis of ANNs and discusses possible implementations.

6.	• Mrs. Nivethitha, • Pavithra, • Poorneshwari, • Raharitha.	Sliding Window Algorithm, applied on Indian Stock Exchange	The authors worked on implementing single layered RNN-LSTM for stock market analysis, A single layer of LSTM and no dropout.	training time series = 7 days and data set = 5 years
7.	• Achyut Ghosh, • Soumik Bose, • Giridhar Maji, • Narayan C. Debnath, • Soumya Sen.	Moving average (MA), autoregression (AR), weighted moving average, ARIMA, CARIMA	Authors implement a basic model on 5 major BSE companies. 3 LSTM Layers, dense activation and final dense layer. No dropout used.	No dropout class used, & Predicted data deviated heavily in few test cases

8.	• Murtaza Roondiwala, • Harshal Patel, • Shraddha Varma	CNN based models applied on time series/sequential data	Authors implement 2 LSTM Layers, dense layer with ReLU activation and dense layer with linear activation model on NIFTY50 Stock Exchange	Error Metric = mean absolute error Time series = 22 days & Data Set = 5 years. No dropout or other mechanism to prevent overfitting
9.	• D. Mahendra Reddy, • H. Veeresh Babu, • K. Ashok Kumar Reddy, • Y. Saileela.	SVM & Backpropagation	Authors utilize a 2-layer LSTM model over ~25 years of dataset of 7 companies and attempted to predict 7 days of price.	No mechanism to prevent overfitting, the test period is of only 1 week which seems relatively short in larger financial context.

10.	• Raghav Nandakumar, • Uttamraj K R, • Vishal R, • Y V Lokeswari	Genetic Algorithms (GA), Artificial Neural Networks (ANN's)	Utilize a robust combination of CNN-LSTM model to predict future stock market prices of 5 different sized companies.	Only 3 layers of LSTM and a single dropout initially that might lead to some contamination of model towards the later layers.
11.	• Emmanouil Christoforou, • Ioannis Z. Emiris, • Apostolos Florakis	Feedforward neural networks (FNNs), gradient-based optimization & Gated Recurrent Units (GRU).	RNN model with 2 layers is used.	No dropout to prevent overfitting, instead of looking at price changes it only considers positive or negative change over a period of 4 years.
12.	• Bruno Spilak	ARIMA, NLARX, RNNs, LSTMs, MLP, CRIX etc.	Author compared various models and various trading strategies	3 Layer LSTM with dropout layers, dataset of only 3 years and time series = 14 days.

13.	• Mohammad J. Hamayel, • Amani Yousef Owda	Support vector machines (SVM), random forests (RF), stochastic gradient boosting machine (SGBM), MLP	Used and compared various LSTM and bi-LSTM models, and their prediction accuracy.	1 year of data set, 3 months of test set.
14.	• Mrs Vaidehi • Alivia Pandit, • Bhaskar Jindal, • Minu Kumari • Rupali Singh	Biological Neural Networks, ARIMA, LSTM, RNN	Used a GRU based Neural Network Model to predict future Bitcoin prices at 35- and 65-day duration.	Only 3 years of data set, and during data pre-processing the nan values are ignored.
15.	• Huisu Jang, • Jaewook Lee	Bayesian Neural Networks, Generalized Autoregressive Conditional Heteroskedasticit y (GARCH), Recurrent neural networks (RNNs) & long short-term memory (LSTM).	Researchers implemented a BNN based model in order to predict future bitcoin prices and compare it to few existing RNN based models.	Researchers chose to focus on macroeconomic variables such as trading volume, hash rate, miners' revenue etc, which might lead to problematic prediction of

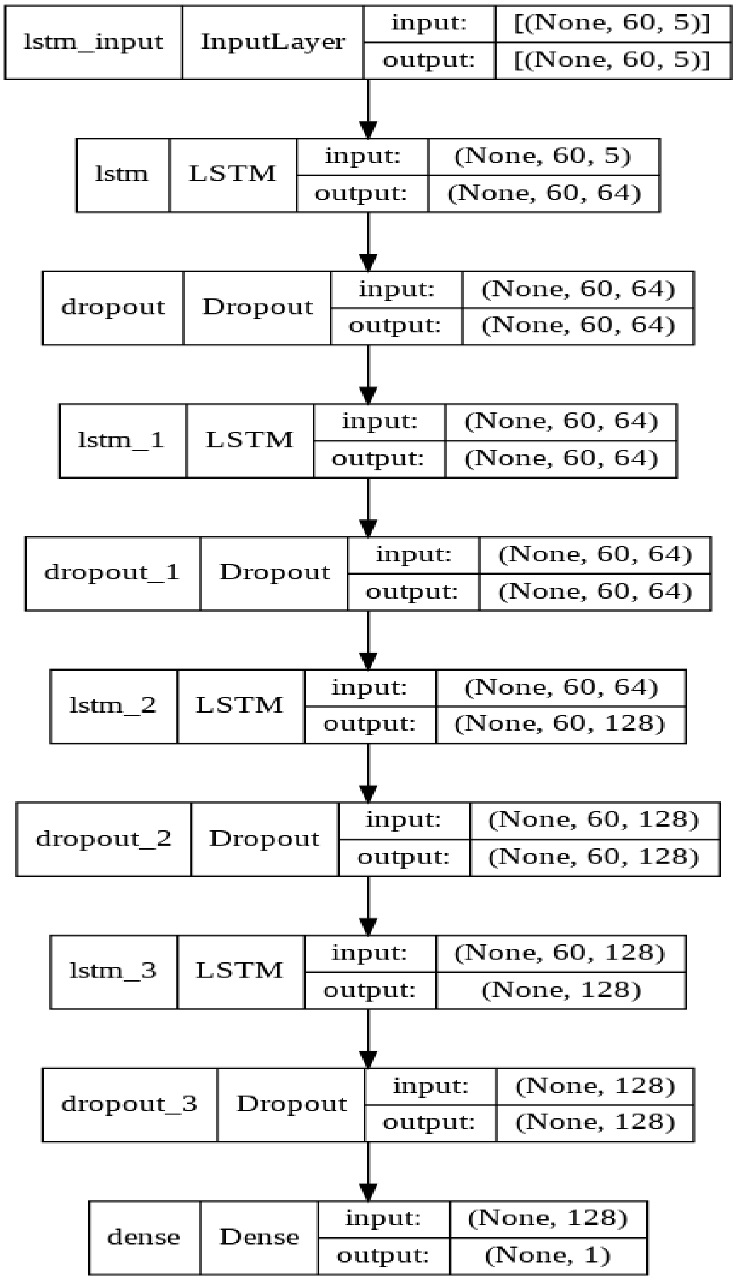
				other cryptocurrencies.
16.	• Kathyayini, R. S., • Jyothi, D. G.	RNN, Artificial Neural Network (ANN), Genetic Algorithm based Selective Neural Network Ensemble (GASEN)	Researchers implement a 3-layer decision tree classifier, Lasso regression model and Linear Regression Model.	The researchers implement a short term prediction mechanism, focusing on data for minute interval for last 7 days.
17.	• Kejsi Struga, • Olti Qirici	RNN, Artificial Neural Network (ANN), GRU, LSTM	Researchers implement a LSTM based model on bitcoin price prediction	Researchers use tanh function which are commonly known to saturate gradients

18.	• Dibakar Raj Pant, • Prasanga Neupane, • Anuj Poudel, • Anup Kumar Pokhrel, • Bishnu Kumar Lama	RNNs, Naive Bayes, Sentiment Analysis	Researchers use tweets from selected accounts in order to perform sentiment analysis and predict the price.	Sentiment analysis on only accounts representing cryptocurrencies or major journalistic social media accounts are considered.
19.	• Stuart Colianni, • Stephanie Rosales, • Michael Signorott	Twitter APIs: Tweepy, Naive Bayes, CNN, NLP	Researchers extract tweets made by media corporations containing the word - “bitcoin”, perform NLP and try to predict whether stock will rise or fall.	Researchers faced a high amount of error due to irrelevant tweets being processed and taken into account from social media websites.
20.	• Isaac Madan, • Shaurya Saluja, • Aojia Zhao,	Bayesian regression, Random Forest, Binomial GLM, artificial neural networks.	Researchers apply Random Forest, SVM and Binomial GLM on per	Highly erratic outputs.

			minute data of bitcoin.	

Implementation

Architecture



Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 64)	17920
dropout (Dropout)	(None, 60, 64)	0
lstm_1 (LSTM)	(None, 60, 64)	33024
dropout_1 (Dropout)	(None, 60, 64)	0
lstm_2 (LSTM)	(None, 60, 128)	98816
dropout_2 (Dropout)	(None, 60, 128)	0
lstm_3 (LSTM)	(None, 128)	131584
dropout_3 (Dropout)	(None, 128)	0
dense (Dense)	(None, 1)	129

Algorithm

Recurrent Neural Network (RNN)

Single feedforward network seems inefficient if we want to modelize sequential data, where the input features are interdependent. If we allow such cyclic connections, we obtain a recurrent neural network, (RNN), which can modelize dynamic processes, for example time series. A common situation, where the order of the input is important, is with time-series data. Examples are measurements of a distant star collected over years or the events recorded in a detector after a collision in a particle collider. The classification task in these examples could be the determination whether the star has an exoplanet, or whether a Higgs boson was observed, respectively. Another example for our purposes, data of financial market in a sequential daily matter.

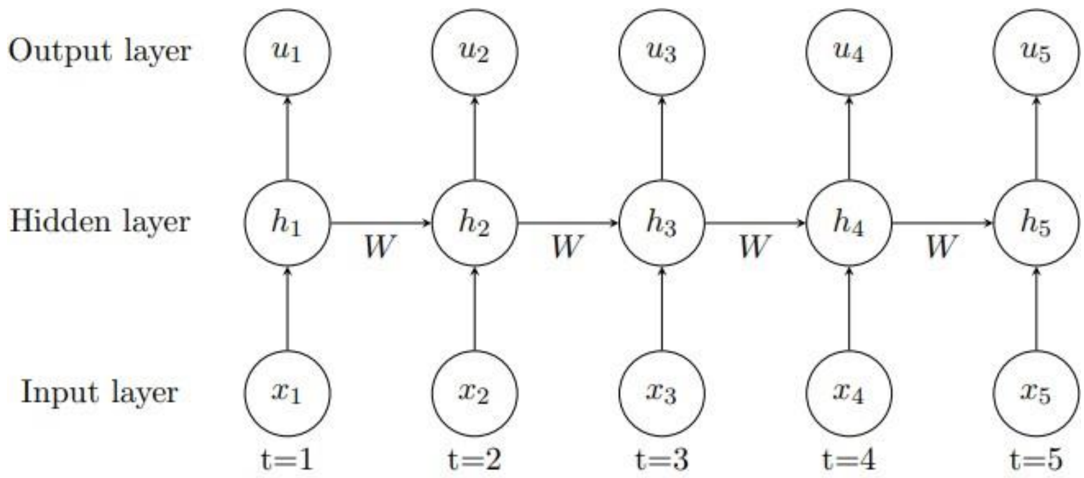


Figure : Unfolded Recurrent Neural Network for 5 time steps

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Compared with the feed-forward networks such as the convolutional neural networks (CNNs), an RNN has a recurrent connection where the last hidden state is an input to the next state. Training of the RNNs suffers from the gradient vanishing and exploding problem due to the repeated multiplication of the recurrent weight matrix, and a proposed solution for the same is implementing LSTM.

LSTM

Another form of RNN is the Long Short-Term Memory (LSTM) network. They differ from Elman RNN in that in addition to having a memory, they can choose which data to remember and which data to forget based on the weight and importance of that feature. Implementation of LSTM for a time series prediction task, we found that the LSTM performed as well as the RNN for this task. This type of model is implemented here also. One limitation in training both the RNN and LSTM is the significant computation required. For example, a network of 50 days is comparable to training 50 individual MLP models.

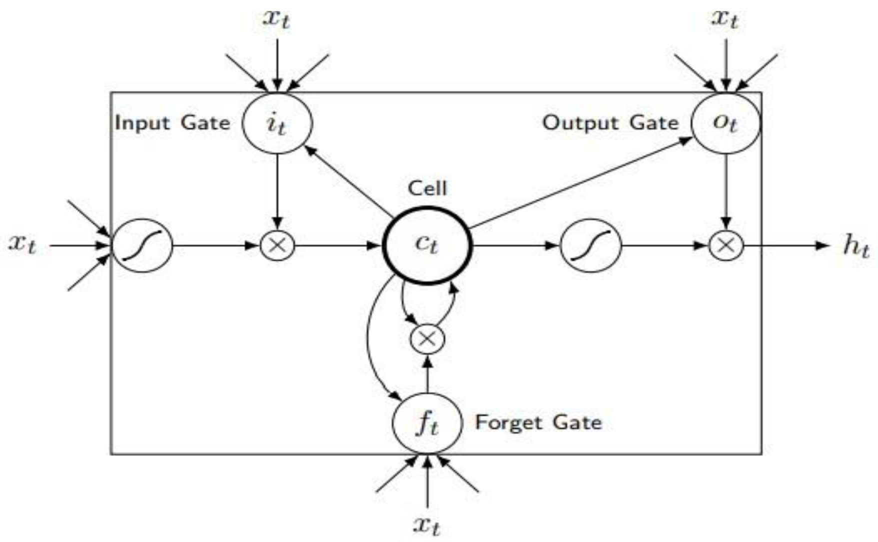

Figure : LSTM cell with a forget gate, source: Graves (2013)

Long Short-Term Memory is an Artificial neural network that has a feedback connection that makes the network work efficiently. LSTM has the advantage of handling sequential time series data not only a single valid data. It has three cells that regulate the functioning, input, and output of the network. This type of network is suitable for classifying and predicting the time series problems which can make things better untestable to a network.

There are several architectures for LSTM but most commonly used are three cell ones that make the network work efficiently and predict the values accurately. An input gate, an output gate and a forget gate.

The Input Gate is the point where we pass the data into the network that we want to teach the model. The output signal is fed to the input of the next gate, and is referred to as ‘feedback signal'. It is responsible for recognizing the value of the loss function in the model and making attempts to correct it. In these input gate, we use the sigmoid function and tanh function to combine the input and hidden value and get the output in the range -1 to 1.

The Output Gate is the last gate in the circuit where it gives the output value and it has an important duty that has to decide what data should be hidden for the next time. First, the previous hidden data and input passed to the sigmoid function then pass the input value and sigmoid output multiply at hyperbolic tangent function that decides what should be stored for the next step.

The Forget Gate is the main gate that stores the previous information for further references. The input from the previous data and the current data to the sigmoid function that gives the value 0 or 1. If we get 1 the forget gate stores the data otherwise it will forget the present data. *(Stock Market Analysis using LSTM in Deep Learning)*.

Bibliography

Analysis. In *2018 IEEE 3rd International Conference on Computing, Communication and Security (ICCCS)* (pp. 128-132). IEEE.

Aoyagi, J. and Adachi, D., 2018. *Fundamental Values of Cryptocurrencies and Blockchain Technology*. SSRN Electronic Journal.

Babu, G.V.P., Sourabh, Y.L.V.S. and Kumar, G.M.,*Analysis Of Stock Market From Investment Perspective*. *Turkish Journal of Physiotherapy and Rehabilitation*, *32*, p.2.

Baur, D. and Dimpfl, T., 2021. *The Volatility Of Bitcoin And Its Role As A Medium Of Exchange And A Store Of Value*. Empirical Economics, 61(5), pp.2663-2683.

Budhani, N., Jha, C.K. and Budhani, S.K. (2014). Prediction Of Stock Market Using Artificial Neural Network. *2014 International Conference of Soft Computing Techniques for Engineering and Technology (ICSCTET).*

Catalini, C. and Gans, J., 2021. *Some Simple Economics of the Blockchain*

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H. and Bengio, Y., 2014. *Learning Phrase Representations Using RNN Encoder-Decoder For Statistical Machine Translation*. *arXiv preprint arXiv:1406.1078*.

Christoforou, E., Emiris, I.Z. and Florakis, A., 2020. *Neural Networks For Cryptocurrency Evaluation And Price Fluctuation Forecasting*. In *Mathematical Research for Blockchain Economy* (pp. 133-149). Springer, Cham.

Colianni, S., Rosales, S. and Signorotti, M., 2015. Algorithmic trading of cryptocurrency based on Twitter sentiment analysis. *CS229 Project*, pp.1-5.

D. Mahendra Reddy, H. Veeresh Babu, K. Ashok Kumar Reddy and Y. Saileela (2020). *Stock Market Analysis using LSTM in Deep Learning*. *International Journal of Engineering Research and*, V9(04).

Detection Of Statistical Arbitrage Using Machine Learning Techniques

Farhath, A. (2016). *A Survey On ARIMA Forecasting Using Time Series Model.*

Ghosh, A., Bose, S., Maji, G., Debnath, N., Sen, S. and Chowdhury, A. (n.d.). *Stock Price Prediction Using LSTM on Indian Share Market*. [online] Available at: https://easychair.org/publications/open/LKgn.

Guresen, E., Kayakutlu, G. and Daim, T.U. (2011). *Using Artificial Neural Network Models In Stock Market Index Prediction. Expert Systems with Applications*, [online] 38(8), pp.10389–10397. Available at:

https://www.sciencedirect.com/science/article/pii/S0957417411002740 [Accessed 2 Sep. 2019].

Hamayel, M.J. and Owda, A.Y., 2021. *A Novel Cryptocurrency Price Prediction Model Using GRU, LSTM and bi-LSTM Machine Learning Algorithms*. *AI*, *2*(4), pp.477-496.

In Indian Stock Markets. (2013). [online] Available at: https://cse.iitk.ac.in/users/cs365/2013/submissions/~deepu/cs365/project/report.pdf [Accessed 8 Dec. 2021].

International Journal of Computer Science and Mobile Computing, [online] 5(8), pp.104–109. Available at: https://www.ijcsmc.com/docs/papers/August2016/V5I8201626.pdf [Accessed 8 Dec. 2021].

Jain, A., Zamir, A.R., Savarese, S. and Saxena, A., 2016. Structural-RNN: Deep Learning On Spatio-Temporal Graphs. In *Proceedings of the ieee conference on computer vision and pattern recognition* (pp. 5308-5317).

Jang, H. and Lee, J., 2017.*An Empirical Study On Modeling And Prediction Of Bitcoin Prices With Bayesian Neural Networks Based On Blockchain Information*. *Ieee Access*, *6*, pp.5427-5437.

Klimczuk, C 2020 ‘*Letting the machines do the maths*’

Laxmi, K.R., Reddy, M.A., Shivasai, C.H. and Reddy, P.S., 2020. *Cryptocurrency Price Prediction Using Machine Learning*. *SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology*, *12*(SUP 3), pp.12-16.

Madan, I., Saluja, S. and Zhao, A., 2015.*Automated Bitcoin Trading Via Machine Learning Algorithms*. *URL: http://cs229. stanford. edu/proj2014/Isaac% 20Madan, 20.*

McNally, S., Roche, J. and Caton, S., 2018, March. *Predicting the price of bitcoin using machine learning*. In *2018 26th euromicro international conference on parallel, distributed and network-based processing (PDP)* (pp. 339-343). IEEE.

Nandakumar, R., Uttamraj, K.R., Vishal, R. and Lokeswari, Y.V., 2018. *Stock Price Prediction Using Long Short Term Memory*. *International Research Journal of Engineering and Technology*, *5*(03).

Nivethitha, P. and Raharitha, P., 2019. *Future Stock Price Prediction Using LSTM Machine Learning Algorithm*. *Int Res J Eng Technol (IRJET)*, pp.1182-1186.

Nivethitha, P. and Raharitha, P., 2019. *Future Stock Price Prediction using LSTM Machine Learning Algorithm. Int Res J Eng Technol (IRJET)*, pp.1182-1186.

Pant, D.R., Neupane, P., Poudel, A., Pokhrel, A.K. and Lama, B.K., 2018, October. *Recurrent Neural Network Based Bitcoin Price Prediction By Twitter Sentiment*

Phi, M., *Illustrated guide to LSTM's and GRU's: A step by step explanation*, 2018. *URL https://towardsdatascience.com/illustrated*-guide-to-lstms-and-gru-sa-step-by-step-*explanation*-44e9eb85bf21.

Roondiwala, M., Patel, H. and Varma, S. (2015). *Predicting Stock Prices Using LSTM. International Journal of Science and Research (IJSR) ISSN*, [online] 6, pp.2319–7064. Available at: https://www.ijsr.net/archive/v6i4/ART20172755.pdf [Accessed 12 Sep. 2021].

Spilak, B., 2018. *Deep neural networks for cryptocurrencies price prediction* (Master's thesis, Humboldt-Universität zu Berlin).

Struga, K. and Qirici, O., 2018. *Bitcoin Price Prediction with Neural Networks*. In *RTA-CSIT* (pp. 41-49).

Vaidehi, M., Pandit, A., Jindal, B., Kumari, M. and Singh, R., 2021. *Bitcoin Price Prediction Using Machine Learning*. *International Journal of Engineering Technologies and Management Research*, *8*(5), pp.20-28.

Wichaidit, S. and Kittitornkun, S. (2015). *Predicting SET50 Stock Prices Using CARIMA (Cross Correlation ARIMA). 2015 International Computer Science and Engineering Conference (ICSEC).*

Williams, G., Baxter, R., He, H., Hawkins, S. and Gu, L., 2002, December. *A Comparative Study Of RNN For Outlier Detection In Data Mining*. In *2002 IEEE International Conference on Data Mining, 2002. Proceedings.* (pp. 709-712). IEEE.