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# Bitcoin price prediction using technical indicators and on-chain analysis

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## I. Introduction

Bitcoin is a peer to peer form of digital money implemented using blockchain technology. The price of Bitcoin has experienced periods of extreme volatility since its inception, offering traders the opportunity to generate substantial returns. Traders use a range of indicators to assess the market. Momentum and trend based technical indicators as commonly used in stock market trading have been employed. Additionally, new indicators have been created based on information obtained from the public blockchain of Bitcoin through a process called on-chain analysis. On-chain analysis encompasses monitoring various aspects such as the number of transactions, the size of transactions, active addresses, the age of coins being traded, exchange inflows and outflows, and monitoring tagged addresses. Indicators calculated from these aid in determining supply and demand, network activity, and help provide a more precise valuation of the network and its underlying asset.

Recent research has focused on training machine learning models to predict Bitcoins price. This research can help traders gain an advantage in the market or help portfolio managers to manage positions. Models have been developed using price, volume and technical indicator data. Supplementary datasets, such as blockchain features, macroeconomic factors, Twitter sentiment analysis and Google search activity have also been used. The purpose of this paper is to evaluate the current state of the art in Bitcoin price prediction. Through this examination, the aim is to identify any gaps in the research and establish the importance of incorporating the newer on-chain analysis based indicators into the training of predictive models.

Section II of this paper is a technical background outlining technical indicators in Section II.A, on-chain analytics in Section II.B and machine learning techniques in Section II.C. Following this will be an analysis of the related literature in Section III. Papers for this literature review were gathered using a variety of search terms. Examples of these terms include: bitcoin price prediction, cryptocurrency price prediction, machine learning price prediction, bitcoin machine learning models, bitcoin price indicators, bitcoin volatility prediction, bitcoin statistical forecasting. The resulting papers were read and divided into four categories, statistical forecasting, machine learning, feature selection, and deep learning. Section III.D focuses on making price or volatility predictions using traditional statistical methods as employed commonly in the financial industry. Section III.E focuses on making predictions by training machine learning models. Section III.F highlights the various features used for training models and how they can be evaluated. Section III.G focuses on predictions using more advanced deep learning techniques. The paper concludes with a summary of the findings.

## II. Technical Background

### A. *Technical indicators*

In order to evaluate the proposed model, which will use the on-chain indicators outlined in Section III.B, we will need a baseline with which to compare it to. To create the baseline model a combination of price and technical indicators will be used for training. The proposed model will then be created with the same combination of price and technical indicators, but will also include the on-chain indicators. In this way it will be possible to evaluate the models against each other.

Technical indicators are mathematical calculations used to provide information such as trend direction, momentum, volatility, and support and resistance levels based on the price, volume, or open interest of an asset. This asset could be stocks, cryptocurrencies, or commodities. The use of these indicators to identify trading opportunities is well documented in the literature. Examples of common technical indicators used in bitcoin trading include: Moving Averages, Relative Strength Index (RSI), On Balance Volume (OBV), Moving Average Convergence Divergence (MACD), Bollinger Bands.

### B. *On-chain analysis*

On-chain analysis refers to the analysis of transaction data and other activity on the bitcoin network. This data can be used to study various aspects of the network, such as transaction volumes, user behaviour, and network health. There are several base level features which can be examined including: transaction fees, hash rate, miner revenue, number of transactions, number of addresses. There is also a newer class of indicator calculated from the above often in combination with price information in USD. This combination results in a very rich source of information about the bitcoin system as a whole. To the best of my knowledge these indicators are not documented in the literature and the aim here is to establish the need for their examination in relation to Bitcoin price prediction. Some important on-chain indicators as outlined in [16] are described here:

*Spent Output Profit Ratio (SOPR)* is an indicator that gives a measure of the realised profit for all coins moved on chain within a specific period. Values greater than 1 indicate coins are selling at a profit while values less than one indicate coins are selling at a loss.

$$SOPR = \frac{Value\ x\ Price_{spent}\ (in\ USD\ of\ all\ spent\ outputs)}{Value\ x\ Price_{created}\ (in\ USD\ of\ all\ spent\ outputs)}$$

*Realised Capitalisation (Realised Cap)* is a variation of Market Capitalisation that values each coin at the point at which it was last moved rather than at the current market price. An issue with Market Capitalisation is that it includes lost or inactive coins in its calculation at the same value as active coins. Realised cap reduces the impact that lost and inactive coins have on the overall total as they are valued at the point at which they last moved. If an inactive coin becomes active again the Realised Cap is adjusted with its current value.

$$Realised\ Cap = Value\ x\ Price_{created}\ (in\ USD\ of\ all\ UTXO)$$

*Net Unrealised Profit/Loss (NUPL)* is an analysis of whether the entire network is in a state of profit or loss based on the difference between Unrealised Profit and Unrealised Loss. Values greater than 0 indicate the network is in a state of net profit while values less than zero indicate the network is in a state of net loss.

$$NUPL = \frac{Market\ Cap - Realised\ Cap}{Market\ Cap}$$

*Net Realised Profit/Loss (NRPL)* is a measure of the net profit or loss for all coins spent in a specific timeframe, measured in USD. Positive values indicate capital is flowing into the system while negative values indicate capital outflows. It is calculated as follows:

$$NRPL = (1 - \frac{1}{SOPR})\ x\ Transaction\ Volume\ in\ USD$$

*Puell Multiple* is an examination of the profitability of mining and is calculated as a ratio of daily coin issuance in USD and a 365 day moving average of daily coin issuance in USD. High values indicate that mining is very profitable when compared to the yearly average. This incentivises the miners to sell their holdings and so increased sell pressure can be expected. Low values indicates mining is less profitable and some miners may need to switch off their rigs. This increases the hash share of the remaining miners and so they may not need to sell as many coins as usual which in turn reduces sell pressure.

$$Puell\ Multiple = \frac{Daily\ Coin\ Issuance\ (USD)}{MA_{365}\ Daily\ Coin\ Issuance\ (USD)}$$

*Coin Days Destroyed (CDD)* is a richer way of analysing transaction volume. Transaction volume gives the same weight to all coins where CDD gives more weight to coins that have not moved in a long time. It is calculated by multiplying the value of the spent output by the number of days since it last moved. A 0.5 BTC transaction that last moved 200 days ago would destroy 100 coin days. Coin days destroyed for a given period is calculated as follows:

$$CDD = Value\ x\ Lifespan\ (for\ all\ spent\ outputs)$$

### *C. Machine learning algorithms*

The most commonly used algorithms for bitcoin price prediction from the literature reviewed are briefly described below.

*Auto-Regressive Integrated Moving Average (ARIMA)* is a statistical model commonly used for time series forecasting. It is a moving average model which means that the result depends linearly on the past values.

*Generalised Autoregressive Conditional Heteroskedasticity Model (GARCH)* is a statistical model typically used to model volatility in time series data.

*Support Vector Machine (SVM)* models are typically used for classification and regression analysis.

*Long Short Term Memory Network Model (LSTM)* is a type of recurrent neural network. They are particularly well suited to making predictions based on time series data.

*Nonlinear Auto-Regressive with Exogenous Input Model (NARX)* is a model used for time series forecasting based on current and past values of the exogenous variables. It is well suited to forecasting values where the relationship between the inputs and the output may be complex and nonlinear.

*MultiLayer Perceptron Model (MLP)* is a fully connected feedforward artificial neural network which uses backpropagation for training. Capable of modelling complex nonlinear relationships between the input and output data.

*Random Forest* models are made up of multiple decision trees. The result is the aggregate of the multiple trees. They are suited to regression and classification problems.

*Naïve Bayes (NB)* models are probabilistic classifiers based on Bayes theorem. They are typically used for classification problems.

## III. Related Literature

### *D. Statistical Forecasting*

Statistical forecasting involves building mathematical models that allow the prediction of future values based on historical data. Statistical forecasting is well established and has been used in the financial industry for almost a century. As highlighted in [23] some corporate investors have obligations to disclose how investment decisions are made to their customers. This excludes them from using certain machine learning models as the decision making process within the model can not be explained easily by the institution. For this reason statistical forecasting is an active area of research in bitcoin price prediction.

In [1] bitcoin volatility forecasting is studied using historical volatility and the bitcoin order book from an exchange as the datasets. Features captured from the order book include volume, spread, depth, and slope for both the ask and the bid sides of the book. Individual component models are created to specialise on different sections of the data and then a temporal mixture model is created using these component models. The temporal mixture model can be described as a weighted sum of the component models. The model is found to perform better than standard statistical models that focus on one set of data. The results suggest that including more datasets can increase the accuracy of the models predictions. However when the ARIVAX and STRX use both sets of data they fail to outperform their counterparts. This suggests that when attempting to make forecasts or predictions in bitcoin it is not just the feature selection that is important but also the model selection. Several attempts using combinations of different features and models may be necessary in order to achieve satisfactory forecasts. It is suggested that including further datasets such as social media data, blockchain data, and data from exchanges should be attempted and their effects on volatility measured using the temporal mixture model.

In [2] the empirical linkages between bitcoin returns and transaction activity is examined using two separate bivariate vector autoregressive (VAR) models. The first model is between bitcoin returns and the percent change in total number of transactions. The second is between bitcoin returns and the percent change in total number of bitcoin addresses. The research shows strong links between bitcoin returns and its transaction activity. It is suggested that future work concentrate on exploring bitcoin's microstructure instead of relying on the traditional economic variables that are typically used to explain returns in conventional assets. Similarly in [3] quantile on quantile regression is used to evaluate the predictive power of transaction activity on bitcoin returns. It is found that higher transaction activity predicts higher returns when bitcoin is in a bull market and lower returns when bitcoin is in a bear market. Reference [4] also recognises the importance of the bitcoin microstructure and proposes a framework for analysing the local topography of the bitcoin transaction graph through chainlet motifs. These chainlets are recurring topographical structures which are defined with a heterogeneous graph model. Important chainlets can be categorised as those that have a large impact on price dynamics and thus can be used to facilitate price prediction. It is found that utilising chainlets results in more competitive pricing models when compared to state of the art time series models. It is clear from [2], [3] and [4] that analysing the information from the blockchain itself will form an important part of building a pricing model.

### *E. Machine learning*

Machine learning involves developing algorithms and models that enable computer systems to learn and improve from datasets, without being explicitly programmed. It involves the use of statistical and mathematical techniques to automatically identify patterns and relationships in the data, and make predictions or decisions based on that analysis. Research in the area of bitcoin has focused heavily on training models based on historical price data. Linear regression, decision trees, random forests and neural network techniques have been studied as means to forecast bitcoins price. An important area of research is identifying which machine learning techniques offer the best results for forecasting bitcoin price. In [5] a review of the machine learning algorithms used in price prediction is carried out. These include ARIMA, Linear Regression, LSM, BGLM, GARCH, SVM, LSTM, NARX, and MLP. The NARX model was found to have the most accurate predictions achieving 62% accuracy. Unfortunately it is difficult to further interpret these results as the testing and evaluating process is not documented. In [6] a more thorough examination of the various models is documented. A variety of nonlinear models are trained using a large range of technical indicators representing market momentum, trend, sentiment, and volume. A nonlinear Random Forest model is found to be the best performing model. This seems to go against the logical assumption that a time series style model would perform better than a classification style model. However there is literature to support this finding. In [7] Random Forests were found to outperform existing models when predicting stock prices. In [9] Random Forest models are created using a range of technical indicators and are found to have accuracy of 92%, 85%, 87% for 3 day, 5 day, 10 day directional predictions. In [10] SVM, ANN, NB, and Random Forest models are compared and the Random Forest is found to have the highest forecasting performance in the continuous dataset. Reference [8] gives a possible explanation for the advantage that Random Forests have. It attributes the advantage to the fact that they allow nonlinear predictor interactions that are missed by other style models. The research in [6] is very useful, not only in the way that it highlights the Random Forest model as one suitable for further examination, but also in that it provides a clear overview of how the effectiveness of models and features can be tested.

### *F. Feature selection*

An important part of developing a machine learning prediction model is the selection of its input variables, which are also known as features. In order for a model to perform well it is important that it is only trained using important features. If a model is trained using too many features it can begin to identify patterns that are not important which results in less accurate predictions.

In [6] a quantitative analysis is carried out with regards to the impact the individual features have on the model's accuracy. Through this analysis a shift is identified in the bitcoin market from being dominated by trend following and momentum in earlier years to one driven by sentiment: fear, greed, and google search activity in more recent years. This finding strengthens our position that including features beyond the typical price and volume information in the training of models may lead to enhanced accuracy in forecasts. A number of researchers have included non-typical features in their training data. Reference [11] documents an LSTM model trained using bitcoin price and social sentiment gathered from twitter and analysed using Apache Flume. Results were not satisfactory at 50% accuracy and 60% precision. An explanation for these unsatisfactory results may be found in [15] where it is found that it is not the sentiment that is a highly predictive feature for price but rather the overall volume of tweets or google searches. This highlights the importance of examining the data and trying different variations of the same feature in order to arrive at the optimal combination for training the model.

In [12] an attempt is made to quantify the importance of business cycle variables like interest rates, inflation, and market volatility for predicting bitcoin price. To do so Random Forest models are trained using bitcoin price, a variety of technical indicators, and macroeconomic variables. It is found that yield on the US ten-year bond and the oil volatility index are the most important when predicting price direction. These results highlight the impact that the broader macroeconomic climate has on bitcoin price. However it raises a question. Is it worthwhile including macro variables in the training data if the prediction horizon is short? In [13] this problem is addressed and it is suggested that for low frequency daily price prediction, less complex algorithms should be used but with several higher dimension features. For high frequency price prediction a low amount of features should be used but with a complex algorithm. These findings are echoed in [14] where it is found that as the prediction horizon increases the importance of features other than the bitcoin price increase. This paper is a valuable contribution to the literature as it documents a process for quantifying the impact of individual features in a bitcoin prediction model. Impact is quantified by randomly permuting every feature vector with a standard normalised vector and then measuring the decrease in prediction accuracy. If there is a large drop in accuracy then it means that the prediction model relies heavily on that feature for predictions. This process could be implemented when evaluating the impact that the on-chain indicators have on the accuracy of the proposed models predictions.

### *G. Deep learning*

Deep learning is a subset of machine learning and is based on multilayer neural networks. It involves more sophisticated techniques than the ones discussed so far and is more expensive computationally. The process of deep learning involves training the neural nets on a large dataset during which the weights of each neuron are adjusted to bring the prediction output in line with the actual output. Training deep learning models is a longer process than for the simpler machine learning techniques but typically results in models that are capable of making complex nonlinear correlations between the input features. Recently several papers have focused on using deep learning techniques to forecast bitcoin price.

In [18] several models were created using different techniques and several features. The techniques used were Artificial neural network, Stacked artificial neural network, Support vector machines, and Long short-term memory. The features included Simple Moving Average, Exponential Moving Average, Relative Strength Index, Weighted Moving Average, Standard Deviation, Variance, Triple Moving Exponential and Rate of Change. The importance of feature selection and its relation to data frequency was highlighted. Several techniques were used to identify the important features and these were carried out separately for each prediction horizon. Overall the LSTM was found to have the best performance with next day prediction accuracy of up to 65%. Reference [17] studied a hybrid approach of LSTM and Bayesian Optimisation. They made the novel choice to use weekly data in order to try to minimise the detrimental effect of bitcoins volatility on the quality of their models predictions. Most research up to this point had used minute range or daily range data. In [19] LSTM and MLP models were trained with exchange activity and social features. It was found that the accuracy of the models increases with the additional features and that the LSTM is the best model of the two for price prediction. Similarly [20] compared LSTM with a Gradient Boosting Model and found that the LSTM performs 7% better. The research presented in [17], [18], [19], and [20] all point to LSTM models as being worthy of future examination with regard to bitcoin price prediction.

A novel approach was taken in [21] where the most frequent edges of the bitcoin transaction network were used to make predictions about bitcoins price. The process of creating the transaction network for this study involved creating a node for every address in the bitcoin blockchain and a directed link between two nodes for each transaction as outlined in [22]. The frequency of use of each edge was quantified daily and then the most frequently used ones were taken for further examination. This group of the most frequently used edges was further narrowed down using a Random Forest classifier which eliminated the edges that had a weak impact on price. The remaining edges were used to train a single-hidden layer feedforward neural network (SLFN) alongside the log of bitcoin returns. The model achieved 60.05% accuracy. An interesting finding is that the model achieved this result using only the most active 0.45% of edges in the transaction network. These findings show that the bitcoin transaction set holds valuable predictive power over price. As most of the on-chain indicators are drawn from the transaction set these findings justify their further examination in relation to bitcoin price prediction.

## IV. Conclusion

In this paper a brief technical background of bitcoin indicators and machine learning techniques was followed by a review of the bitcoin price prediction literature. The literature was reviewed across four topics namely Statistical Forecasting, Machine Learning, Feature Selection, and Deep Learning. It is noted that throughout the literature there is a tendency to increase the number of predictive features included in datasets in an attempt to train more accurate models. The motivation for this is that including these features may explain some unknown cause and effect or help identify a certain pattern that has a predictive value in relation to price. The on-chain indicators outlined in Section II.B which fuse important aspects of price, blockchain features, supply and demand, are the ideal candidates for further enhancing the state of the art models. However as highlighted in Section III.F it will be important to select only quality features for training our models in order to avoid introducing noise. Another important finding was that short range forecasting models performed better using complex algorithms with a smaller amount of key features while longer range models performed better with simpler algorithms and a broad spectrum of features. This will be useful when selecting features and algorithms for the proposed model. In this review it was shown that both the Random Forest machine learning model and the LSTM deep learning models are well studied and perform well in comparison to their alternatives. It has also been found that the bitcoin transaction set has proven predictive power with relation to price which lends credibility to our assumption that indicators drawn from the blockchain itself will have predictive power. Overall this review of the Bitcoin price prediction literature provides a strong foundation for further research by providing key insights in model algorithm and feature selection while providing evidence that machine learning models with higher dimension features, including those drawn from the transaction graph, have proven increases in predictive power.

## References


[1] Guo, Tian, A. Bifet, and N. Antulov-Fantulin. "Bitcoin volatility forecasting with a glimpse into buy and sell orders." 2018 IEEE international conference on data mining (ICDM), pp. 989-994. IEEE, 2018, doi: https://doi.org/10.1109/ICDM.2018.00123.

[2] D. Koutmos, "Bitcoin returns and transaction activity," *Economics Letters*, vol. 167, pp. 81–85, 2018, doi: https://doi.org/10.1016/j.econlet.2018.03.021.

[3] L. Hau, H. Zhu, M. Shahbaz, and W. Sun, "Does transaction activity predict Bitcoin returns? Evidence from quantile-on-quantile analysis," *The North American Journal of Economics and Finance*, vol. 55, p. 101297, 2021, doi: https://doi.org/10.1016/j.najef.2020.101297.

[4] C. G. Akcora, A. K. Dey, Y. R. Gel, and M. Kantarcioglu, "Forecasting bitcoin price with graph chainlets", *Advances in Knowledge Discovery and Data Mining*, Cham: Springer International Publishing, pp. 765–776. 2018, doi: https://doi.org/10.1007/978-3-319-93040-4_60.

[5] Rane, Prachi Vivek, and Sudhir N. Dhage. "Systematic erudition of bitcoin price prediction using machine learning techniques." In *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, pp. 594-598. IEEE, 2019, doi: https://doi.org/10.1109/ICACCS.2019.8728424.

[6] Gradojevic, Nikola, Dragan Kukolj, Robert Adcock, and Vladimir Djakovic. "Forecasting Bitcoin with technical analysis: A not-so-random forest?." *International Journal of Forecasting* 39, no. 1, pp. 1-17, 2023, doi: https://doi.org/10.1016/j.ijforecast.2021.08.001.

[7] Khaidem, Luckyson, Snehanshu Saha, and Sudeepa Roy Dey. "Predicting the direction of stock market prices using random forest." *arXiv preprint arXiv:1605.00003*, 2016, doi: https://doi.org/10.48550/arXiv.1605.00003.

[8] Gu, Shihao, Bryan Kelly, and Dacheng Xiu. "Empirical asset pricing via machine learning." *The Review of Financial Studies* 33, no. 5, pp. 2223-2273, 2020, doi: https://doi.org/10.1093/rfs/hhaa009.

[9] Inder, Shivani, and Sandhir Sharma. "Predicting the Movement of Cryptocurrency "Bitcoin" Using Random Forest." In *Data Science and Computational Intelligence: Sixteenth International Conference on Information Processing, ICInPro 2021, Bengaluru, India, October 22–24, 2021, Proceedings 16*, pp. 166-180. Springer International Publishing, 2021, doi: https://doi.org/10.1007/978-3-030-91244-4_14.

[10] Pabuçcu, Hakan, Serdar Ongan, and Ayse Ongan. "Forecasting the movements of Bitcoin prices: an application of machine learning algorithms." *Quantitative Finance and Economics* 4, no. 4, pp. 679-692, 2020, doi: https://doi.org/10.3934/QFE.2020031.

[11] Mohanty, Pavitra, Darshan Patel, Parth Patel, and Sudipta Roy. "Predicting fluctuations in cryptocurrencies' price using users' comments and real-time prices." *2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*, pp. 477-482. IEEE, 2018, doi: https://doi.org/10.1109/ICRITO.2018.8748792.

[12] Basher, Syed Abul, and Perry Sadorsky. "Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility?." *Machine Learning with Applications* 9, 100355, 2022, doi: https://doi.org/10.1016/j.mlwa.2022.100355.

[13] Chen, Zheshi, Chunhong Li, and Wenjun Sun. "Bitcoin price prediction using machine learning: An approach to sample dimension engineering." *Journal of Computational and Applied Mathematics* 365, 112395, 2020, doi: https://doi.org/10.1016/j.cam.2019.112395.

[14] Jaquart, Patrick, David Dann, and Christof Weinhardt. "Short-term bitcoin market prediction via machine learning." *The journal of finance and data science* 7, 45-66, 2021, doi: https://doi.org/10.1016/j.jfds.2021.03.001.

[15] A. Mittal, V. Dhiman, A. Singh and C. Prakash, "Short-Term Bitcoin Price Fluctuation Prediction Using Social Media and Web Search Data", *2019 Twelfth International Conference on Contemporary Computing (IC3)*, pp. 1-6, 2019, doi: https://doi.org/10.1109/IC3.2019.8844899.

[16] "Glassnode Academy" Glassnode. https://academy.glassnode.com/ (accessed Jan 30, 2023).

[17] Pour, Ehsan Sadeghi, Hossein Jafari, Ali Lashgari, Elaheh Rabiee, and Amin Ahmadisharaf. "Cryptocurrency price prediction with neural networks of LSTM and Bayesian optimization." *European Journal of Business and Management Research* 7, no. 2, pp. 20-27, 2022, doi: https://doi.org/10.24018/ejbmr.2022.7.2.1307.

[18] Mudassir, Mohammed, Shada Bennbaia, Devrim Unal, and Mohammad Hammoudeh. "Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach." *Neural computing and applications*, pp. 1-15, 2020, doi: https://doi.org/10.1007/s00521-020-05129-6.

[19] Misnik, Anton, S. Krutalevich, Siarhei Prakapenka, P. Borovykh, and M. Vasiliev. Neural Network Approximation Precision Change Analysis on Cryptocurrency Price Prediction, Proceedings of the II International Scientific and Practical Conference, pp. 96–101, 2018.

[20] Kwon, Do-Hyung, Ju-Bong Kim, Ju-Sung Heo, Chan-Myung Kim, and Youn-Hee Han. "Time series classification of cryptocurrency price trend based on a recurrent LSTM neural network." *Journal of Information Processing Systems* 15, no. 3, pp. 694-706, 2019, doi: https://doi.org/10.3745/JIPS.03.0120.

[21] Kurbucz, Marcell Tamás. "Predicting the price of bitcoin by the most frequent edges of its transaction network." *Economics letters* 184 p. 108655, 2019, doi: https://doi.org/10.1016/j.econlet.2019.108655.

[22] Kondor D, Po´sfai M, Csabai I, Vattay G, "Do the Rich Get Richer? An Empirical Analysis of the Bitcoin Transaction Network", PLoS ONE 9(2): e86197, 2014, doi: https://doi.org/10.1371/journal.pone.0086197

[23] Dolatsara, Hamidreza Ahady, Eyyub Kibis, Musa Caglar, Serhat Simsek, Ali Dag, Gelareh Ahadi Dolatsara, and Dursun Delen. "An interpretable decision-support systems for daily cryptocurrency trading." *Expert Systems with Applications* 203, p. 117409, 2022, doi: https://doi.org/10.1016/j.eswa.2022.117409.