

Cryptocurrencies Price Prediction Using Deep Learning Models (Gated Recurrent Unit And Recurrent Neural Network)

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Abstract

Background: With their volatile prices, cryptocurrencies have become valuable assets in the financial market. Predicting cryptocurrency prices accurately is essential for making well-informed investment decisions. Time series prediction models, like Gated Recurrent Unit (GRU) and Recurrent Neural Networks (RNN), are popular tools for financial data forecasting because they can capture sequential dependencies in data. **Aim:** This study aims to predict the average monthly closing prices of five major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Litecoin (LTC), and Ripple (XRP)—using GRU and RNN models and evaluate their performance in forecasting these prices. **Method:** Time series input sequences were produced and historical price data for the chosen cryptocurrencies were preprocessed using Min-Max Scaling. This data was divided into training and test sets, and it was used to train both the GRU and RNN models. The Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) were used to assess the performance of the model. **Results:** For the majority of cryptocurrencies, the RNN model exhibited better predicted accuracy and consistently outperformed the GRU model. For instance, the RMSE for Ripple was 0.06 for the RNN model and 0.09 for GRU. In a similar vein, the RNN model outperformed the GRU model with a MAPE of 12.97% for Ethereum. These results imply that RNN models are more suitable for financial forecasting in this sector, as they yield more accurate predictions for cryptocurrency values.

Keywords: Cryptocurrency, Price, Bitcoin, Blockchain, Fluctuations.

1. Introduction

The explosive growth of virtual currencies over the past ten years is one of the most contentious and confusing developments in the contemporary world trade. The financial markets, payment systems, and economic structures are all altered by emerging technology. The global financial markets are now more digitized than they have ever been, and a cashless society is quickly approaching. These days, people can create their own money (digital cryptocurrencies), and questions are raised about the role of central banks as last-resort lenders (Pabuçcu, Ongan, & Ongan, 2020). The Study of Monish, Mohta, & Rangaswamy (2022) states that Blockchain is a powerful technology that can access any banking or financial institution. Due of its diversity, computer science, cryptography, and the expansion of communications have all expressed interest in it. Blockchain technology can offer a platform for money exchange without the need for a middleman like the government or other financial institutions. One such application that was developed on the Blockchain and has an effect on the financial industry is cryptocurrency. Numerous nations, including the United States, Canada, and Europe, have recognized cryptocurrencies as legitimate forms of payment. Price-prediction models and their direct impact on trading efficacy require a thorough

understanding due to the swift evolution of cryptocurrency markets and the growing intricacy of trading tactics (Otabek & Choi, 2024). Precise predictions affect economies, shapes policies, and aids in preparedness for emergencies. But because the world's systems are so complicated, making predictions is still a difficult task that calls both interdisciplinary collaboration and creative thinking (Kishore, Nayak, & Behera, 2020). As the world gets more interconnected, the need for accurate predictions only increases.

In 2009, the first cryptocurrency Bitcoin was released as an electronic payment system based on cryptographic evidence. There are currently about 10,000 digital coins available on the cryptocurrency market. Cryptocurrency is a type of digital resource that is maintained and verified through transactions using blockchain technology and cryptography. Because of its digital asset's unpredictable behavior, decentralized structure, and liquidity, trading in it is becoming more popular. Transacting with this digital asset offers transaction security and anonymity. Its trade is riskier due to its price's irrational oscillations (Yamin & Chaudhry, 2023). The most widely used decentralized virtual money is called Bitcoin, and it plays a significant role in a free market economy by removing the need for a middleman between consumers and other parties (Shruthi, Anbarasu, Sabarish, & Anand, 2023). Ethereum is the second most well-known cryptocurrency after Bitcoin, and its use and popularity have grown in recent years along with their prices. It has grown to be a desirable investment for both traders and first-time buyers. The supply and demand of Ethereum, as well as the cryptocurrency market in which it is traded all influence its fluctuating price. Because Ethereum is readily guaranteed by the blockchain, it can be used as cash and we can even pay someone with some or all of it in return. These features make Ethereum extremely valuable. Ethereum's price fluctuates significantly higher than that of equities since it is traded continuously, around-the-clock, without a set closing time. (Monish et al., 2022). Cryptocurrencies, like Bitcoin, are among the most intricate and contentious technological advancements in the modern financial system (Pabuçcu et al., 2020). The reason why market predictions for cryptocurrencies are popular is that they lower the chance of trading losses. There is a wealth of publicly accessible data about this sector on the internet (Yamin & Chaudhry, 2023). For almost a decade, the bitcoin sector has flourished and undergone significant transformation. The global community was concerned about and examined the success of cryptocurrencies (Liao, Lu, & Zhang, 2023). The variations in cryptocurrency prices could also be attributed to macroeconomic factors, since the price of Bitcoin aligns with the monetary policies of nations that have established regulations pertaining to cryptocurrencies (Ani et al., 2024). The three most widely used cryptocurrencies are Litecoin, Ethereum, and Bitcoin; each has a distinct value that is very unpredictable. Because of this volatility, data analysis is necessary to accurately estimate prices, allowing investors to trade these currencies profitably. Five machine learning algorithms were effectively applied in previous studies to assess transaction history data, with noteworthy accuracy in price estimation (Sahi, Saluja, & Nargotra, 2023). Expanding upon these findings, a gap exists in the present research concerning the application of extra predictive variables like the average price, price rate of change and the index of relative strength. The purpose of this study is to increase the prediction accuracy of cryptocurrency prices using the GRU and RNN models by integrating supplementary variables such as average prices, and rate of change in price.

2. Related Works

The concept of a cryptocurrency was first proposed in 1990 as a way to have an untraceable currency that was not controlled by centralized organizations like banks. The history of this new market started in 2008 when Satoshi Nakamoto purchased bitcoin.org, published a description of the Bitcoin blockchain network, and mined the network's first block in 2009. As a result, Bitcoin is the most well-known and well-liked kind of cryptocurrency. It is also being widely recognized as a form of payment for many businesses, and it is regarded as a genuine medium

of exchange. A single Bitcoin's value increased 20 times in 2017 from about \$800 in January to almost \$17,000 in only a single year; two months later, though, its value dropped to about \$8,000 per Bitcoin. A number of new cryptocurrencies have emerged and gained popularity in the last ten years. Cryptocurrency types and attributes differ, and there is no clear association between them or with eternity, which leads to abrupt price changes. For this reason, it is important for researchers and investors to study and forecast the market (Liao et al., 2023).

A cryptocurrency is a decentralized, digital, encrypted electronic money that cannot be double-spent or counterfeited. One of the most well-liked financial tools, its volume on blockchain-based cryptocurrency exchanges is constantly increasing. Due to supply and demand imbalances, governmental restrictions, investor mood, and most importantly, media hype, it is very volatile (Rafi et al., 2023). Transactions involving cryptocurrency take the form of forwarding from one individual to another individual online, so they deal directly without a middleman (Amsyar, Christopher, Dithi, Khan, & Maulana, 2020).

The field of digital currency price prediction faces numerous obstacles due to the inherent volatility of cryptocurrencies, which can be attributed to various factors such as economic, technical, market sentiment, and political issues. Because of this volatility, cryptocurrency values are highly unpredictable, which emphasizes the need for more accurate and reliable prediction models to support investors. (Zubair et al., 2024).

Through online cash transfers using cryptocurrencies, people can send money to one another without the use of middlemen. By avoiding the involvement of a third party, this decentralized procedure streamlines transactions by enabling direct peer-to-peer contacts (Amsyar et al., 2020). Trading takes place via a centralized third-party platform for currencies (Tian et al., 2020).

Crypto exchange services are decentralized, meaning all orders are visible to the public before they are resolved, or they are trusted central institutions that have been regularly attacked. The latter enables what is known as "front running" amongst market players, which is prohibited in most jurisdictions (Baum, David, & Frederiksen, 2021).

Researchers and investors alike have expressed a great deal of interest in precise cryptocurrency price prediction algorithms. Deep Learning models are well-known machine learning approaches that have revolutionized a number of industries and have demonstrated promise in the fields of economics and finance. Due to the extreme market volatility, a number of deep learning models have been investigated for cryptocurrency price predictions; nevertheless, it is unclear which models are appropriate (Wu, Zhang, Huang, Zhou, & Chandra, 2024).

3. Methodology

3.1 Data Collection and Preprocessing

The Bitcoin, Ethereum, Litecoin, Ripple, Binance Coin datasets were obtained from the Kaggle machine learning repository for the deep learning study on cryptocurrency price prediction. The data consists of attributes like Price, Open, Close, High and Low.

3.2 Data Cleaning and Transformation

The initial steps involved cleaning the dataset to ensure consistency and accuracy:

- **Time Column Conversion:** Pandas was used to change the "date" column from a string structure to a datetime structure, allowing for easier time-based operations and resampling.
- **Monthly Resampling:** The average close prices for each month were computed after the dataset was resampled with a monthly frequency. This process assisted in eliminating noise from the data and identifying long-term trends.

- **Conversion and Aggregation:** To determine the average close prices, A monthly frequency of sampling was applied to the data and the “date” column changed to a datetime structure. Long-term patterns were captured and noise in the data was decreased thanks to this aggregation.

3.3 Normalization

The Min-Max Scaler was used for the data to be scaled between 0 and 1 in order to normalize the monthly average close prices. Normalization guarantees that each input feature contributes in line with the model during training, which is essential to neural network success.

Min-Max Scaling: The Min-Max Scaler was applied to the monthly average close prices.

Sequence Creation: The creation of input sequences containing past price data made it easier for both models to anticipate time series. Three previous monthly price points made up each sequence, which was used to forecast the price for the following month. With this configuration, the models were able to efficiently learn temporal dependencies.

3.4 Model Selection

Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU) were chosen as the main forecasting models in this study in order to estimate the average close prices and price rate of change for Litecoin, Ripple, Bitcoin, Ethereum, and Binance Coin, the five major cryptocurrencies.

Recurrent Neural Networks (RNN): RNNs' capacity to identify temporal connections in sequential data makes them ideal for time series forecasting. They are useful for long-term price trend prediction because they process inputs sequentially and keep a state that incorporates data from earlier time steps. RNNs were selected in order to take advantage of their innate capacity to understand the dynamics of bitcoin price fluctuations because of their track record of performance in sequence prediction tasks.

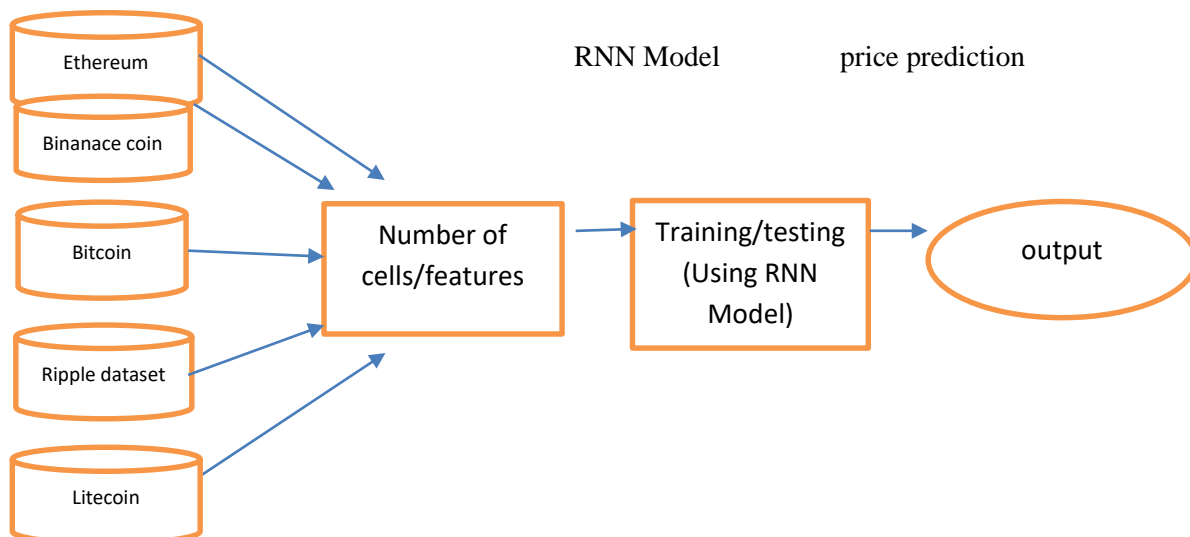


Figure 1: Diagrammatic Representation of RNN-based Model

Gated Recurrent Units (GRU): A variant of RNNs called GRUs was created to overcome some of the drawbacks of conventional RNNs, such as the inability to capture long-term relationships because to vanishing gradient issues. By introducing gating methods to regulate input flow, GRUs improve their computing efficiency while remembering long-term trends. Because of this, GRUs are especially well suited for time series data containing intricate patterns and lengthy sequences.

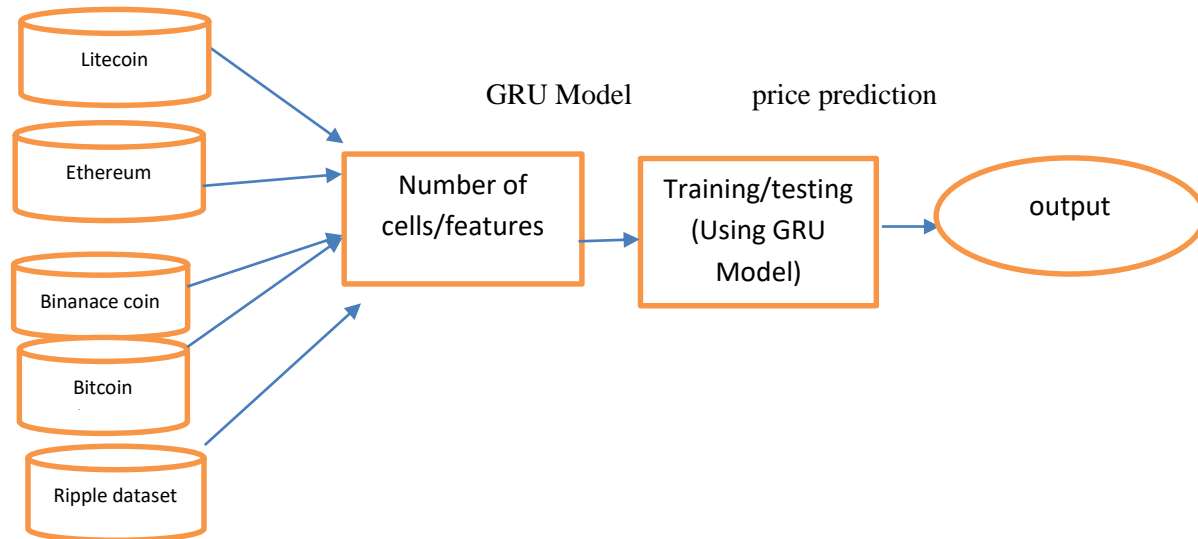


Figure 2: Diagrammatic Representation of GRU-based Model

3.5 Justification for Model Choice

The RNN and GRU models were chosen because they have a track record of managing time-varying data and modeling non-linear connections. For sequence prediction, RNNs give a basic method, while GRUs perform better when handling longer-term dependencies. The purpose of this study is to compare these two models in order to assess how well they each predict cryptocurrency values and determine which model better reflects the complex patterns of price fluctuations.

This research study has incorporated a few preset Python libraries—like pandas, NumPy, matplotlib, TensorFlow, etc.—that facilitate data visualization and make it simpler to understand the essential functionalities required by the system.

3.6 Proposed Model(s)

The proposed model includes properties of average price and price rate of change, which improve prediction skills by smoothing out short-term swings and capturing market momentum. These improvements provide a more thorough knowledge of cryptocurrency patterns than existing models which rely largely on closing prices.

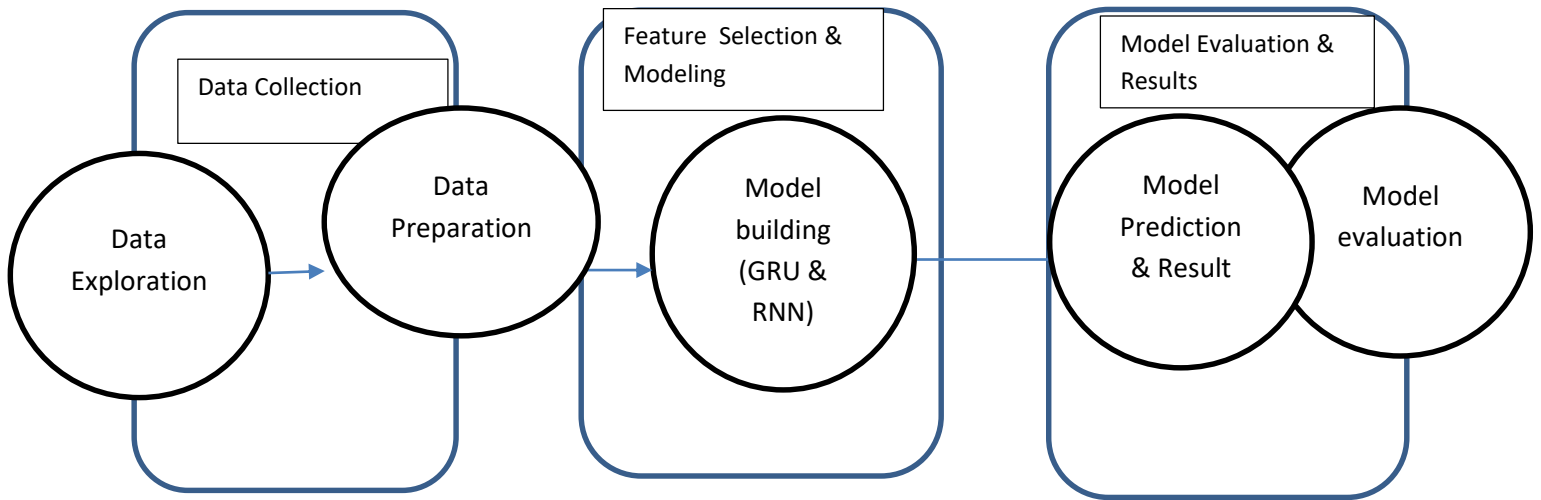


Figure 3: Proposed Model(s)

3.6 Evaluation

The efficacy of the model was evaluated using RMSE and MAPE;

Root Mean Square Error

The standard deviation of the residuals is called the Root Mean Square Error, or RMSE. The spread or dispersion of these points is assessed by RMSE, while residuals are defined as the difference between the actual and anticipated value. The RMSE is sensitive to data outliers. It is assessed in the same units as the response variable and does not penalize excessive errors made during prediction.

$$RMSE = \sqrt{\frac{1}{m \times \Pi} \sum_{i=1}^N \sum_{j=1}^M (y_{ij} - \hat{y}_{ij})^2}$$

----- (1)

Mean Absolute Percentage Error

The MAPE can be referred to as the metric to evaluate how accurate the forecast model performed. This accuracy measures as a percentage.

$$M = \frac{1}{v} \sum_{i=1}^v \left| \frac{A_i - F_i}{A_i} \right|$$

----- (2)

4. Results and discussion

For the selected coins, short-term forecasts were made using the normalized prices. The average monthly close price projection value for each cryptocurrency—Bitcoin, Ethereum, Binance Coin, Ripple, and Litecoin—is the objective or target variable.

4.1 GRU Model Performance

The MAPE and RMSE values for the GRU model are shown in this table for the five main cryptocurrencies: Ethereum, Litecoin, Binance Coin, Ripple, and Bitcoin. The findings show that while the GRU model's performance was inconsistent, it was notably accurate in predicting the price of Binance Coin, which had the lowest MAPE and RMSE values.

Cryptocurrency	MAPE	RMSE
Bitcoin	20.22%	7332.85
Ethereum	17.99%	392.12
Binance Coin	11.56%	43.54
Litecoin	17.99%	16.56
Ripple	17.30%	0.09

4.2 RNN Model Performance

The RNN model's performance metrics are displayed in this table. In comparison to the GRU model, the RNN consistently performed better in predicting average monthly close prices, especially for Ethereum, Binance Coin, and Ripple. The RNN model appears to have better caught price variations and produced more accurate forecasts based on its reduced MAPE and RMSE values.

Cryptocurrency	MAPE	RMSE
Bitcoin	14.91%	7954.53
Ethereum	12.97%	322.92
Binance Coin	7.54%	28.70
Litecoin	15.63%	14.54
Ripple	11.35%	0.06

5. Conclusion

The findings show that for the majority of cryptocurrencies, including Ethereum, Binance Coin, Litecoin, and Ripple, the RNN model fared better in predicting average monthly close prices than the GRU model. With lower MAPE and RMSE values and more accurate predictions, the RNN model may be able to better capture the subtleties of fluctuations in cryptocurrency prices. Even though the GRU model was marginally less accurate, it nevertheless performed competitively and might use more fine-tuning and optimization. The study is recommended to researchers interested in machine learning and cryptocurrency price prediction, as well as financial analysts and data scientists. Through the use of Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU), this study offers significant understanding into predicting the average closing prices and rate of change of major cryptocurrencies like Ethereum, Bitcoin, Binance Coin, Litecoin, and Ripple. Those looking to comprehend and increase prediction accuracy in the turbulent cryptocurrency market may find the work especially helpful. Future studies may focus on improving prediction models' applicability in real-world scenarios by creating real-time predictive systems that adjust to shifting market circumstances. In order to provide more accurate and timely insights in volatile markets such as cryptocurrency, models might incorporate real-time learning and dynamic updating approaches, which would allow them to continuously change their predictions as new data becomes available. This would greatly increase their suitability for use in real-time trading situations and decision-making procedures.

References

- Amsyar, I., Christopher, E., Dithi, A., Khan, A. N., & Maulana, S. (2020). The Challenge of Cryptocurrency in the Era of the Digital Revolution : A Review of Systematic Literature. *Aptisi Transactions on Technopreneurship (ATT)*, 2(2), 153–159.
- Ani, C. L., Mashood, L. O., Anche, J. Y., Adikwu, S., Aderupatan, E., & Bart, M. G. (2024). Crypto Assets Indicators and their Effect on the Market Capitalization : A Panel Data Analysis. *KASU Journal of Computer Science*, 1(2), 200–217.
- Baum, C., David, B., & Frederiksen, T. K. (2021). P2DEX : Privacy-Preserving Decentralized Cryptocurrency Exchange Full version. *In International Conference on Applied Cryptography and Network Security*, (9040), 1–42.
- Kishore, K. S., Nayak, S. C., & Behera, H. S. (2020). FORECASTING CURRENCY EXCHANGE RATE TIME SERIES WITH FIREWORKS ALGORITHM-BASED HIGHER ORDER NEURAL NETWORK , WITH SPECIAL ATTENTION. *Computer Science*, 21(4), 463–488.
- Liao, C., Lu, K., & Zhang, J. (2023). Cryptocurrency Price Tendency Analysis Using Conventional Statistical Model and Machine Learning Approach. *In Proceedings of the International Conference on Financial Innovation, FinTech and Information Technology*. <https://doi.org/10.4108/eai.28-10-2022.2328451>
- Monish, S., Mohta, M., & Rangaswamy, S. (2022). ETHEREUM PRICE PREDICTION USING MACHINE LEARNING TECHNIQUES – A COMPARATIVE STUDY. *International Journal of Engineering Applied Sciences and Technology*, 7(2), 137–142.

- Otabek, S., & Choi, J. (2024). From Prediction to Profit : A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques. *IEEE Access*, 12(May), 87039–87064. <https://doi.org/10.1109/ACCESS.2024.3417449>
- Pabuçcu, H., Ongan, S., & Ongan, A. (2020). Forecasting the movements of Bitcoin prices : an application of machine learning algorithms. *Quantitative Finance and Economics*, 4(November), 679–692. <https://doi.org/10.3934/QFE.2020031>
- Rafi, M., Mirza, Q. A. K., Sohail, M. I., Aliasghar, M., Aziz, A., & Hameed, S. (2023). Enhancing Cryptocurrency Price Forecasting Accuracy: A Feature Selection and Weighting Approach With Bi-Directional LSTM and Trend-Preserving Model Bias Correction. *IEEE Access*, 11(July), 65700–65710. <https://doi.org/10.1109/ACCESS.2023.3287888>
- Sahi, G., Saluja, T., & Nargotra, P. (2023). Predicting Cryptocurrency Price Using Machine Learning. *European Economic Letters ISSN Http://Eelet.Org.Uk Predicting*, 13(1), 2323–5233. https://doi.org/10.1007/978-981-19-2225-1_25
- Shruthi, C. K., Anbarasu, Sabarish, & Anand, B. (2023). Cryptocurrency price prediction using machine learning. *World Journal of Advanced Engineering Technology and Sciences*, 8(1), 251–257. <https://doi.org/10.30574/wjaets.2023.8.1.0032>
- Tian, H., Xue, K., Li, S., Xu, J., Liu, J., & Zhao, J. (2020). Enabling Cross-chain Transactions: A Decentralized Cryptocurrency Exchange Protocol. *IEEE Transactions on Information Forensics and Security*, 16, 3928–3941.
- Wu, J., Zhang, X., Huang, F., Zhou, H., & Chandra, R. (2024). *Review of deep learning models for crypto price prediction: implementation and evaluation*. Retrieved from <http://arxiv.org/abs/2405.11431>
- Yamin, M. A., & Chaudhry, M. (2023). Cryptocurrency market trend and direction prediction using Machine Learning : A Comprehensive Survey Cryptocurrency market trend and direction prediction using Machine Learning : A Comprehensive Survey. *Vertechx Technologies*.
- Zubair, M., Ali, J., Alhussein, M., Hassan, S., Aurangzeb, K., & Umair, M. (2024). An Improved Machine Learning-Driven Framework for Cryptocurrencies Price Prediction with Sentimental Cautioning. *IEEE Access*, 12(February), 51395–51418. <https://doi.org/10.1109/ACCESS.2024.3367129>