EVALUATING THE PRICE DYNAMICS OF CRYPTO CURRENCY USING ANN, AI AND LSTM RECURRENT NEURAL NETWORKS

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Abstract
Cryptocurrency is becoming more and more important in changing the financial system as a result of its rising adoption by merchants and popularity. Despite the fact that many people are investing in cryptocurrencies, it is still difficult to forecast their dynamical characteristics, unpredictability, and predictability, which raises the risk of the investment. Understanding the factors that affect the creation of value is essential. Using cutting-edge artificial intelligence frameworks like as fully connected Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Networks, we assess the price dynamics of Bitcoin, Ethereum, and Ripple in this study. We find that LSTM is more effective than ANN at leveraging significant information concealed in historical memory long-term history because it tends to depend more on short-term dynamics. However, given sufficient historical data, ANN can attain comparable precision as LSTM. This study gives a novel illustration of the predictability of the Cryptocurrency market price. However, the explanation for predictability may differ depending on the type of the machine-learning model employed.

Introduction
A regulated algorithm powers the peer-to-peer electronic money and payment system known as cryptocurrency. The cryptocurrency is created when a miner successfully decodes an algorithm to add a block of transactions to the blockchain, a public ledger. It lets users to store and transport data utilizing a decentralized network and an encryption mechanism. A crucial and competitive component of the bitcoin system is mining. The likelihood of finding a new currency is higher for the miner with the highest processing power than the miner with the least. The earliest and most well-known digital currency is Bitcoin, which was released in 2009. Its market capitalization peaked in 2014 at over $7 billion before skyrocketing to $29 billion in 2017 and it was introduced in 2008 by Satoshi Nakamoto. The most amazing characteristic of bitcoin is its decentralization, which may effectively remove the influence of traditional financial sectors and monetary authorities due to its blockchain network features. Furthermore, Bitcoin's electronic payment system is based on cryptographic proof rather than trust between each other because its transaction historycannot be changed without redoing all proof of work of all blockchain, which plays a critical role of being a trust intermediary and can be widely used in reality such as recording charitable contributions to avoid corruption. Furthermore, bitcoin has introduced the adjustable anonymity scheme, which improves users' safety and anonymity when using this technology. For example, we may use this property of blockchain to create identification cards, which not only protects our privacy but also verifies our identity. Investing in cryptocurrencies, such as Bitcoin, is now one of the most effective methods to make money. For example, the price of Bitcoin increased significantly in 2017, from a relatively low position of 963 USD on January 1ST 2017 to a top of 19186 USD on December 17th 2017, and it completed the year with 9475 USD. As a result, the rate of return on bitcoin investmentin 2017 was more than 880%, which is an outstanding and unexpected scenario for most investors. While a rising number of people are investing in cryptocurrency, the bulk of investors will not benefit because they are unconcerned with cryptocurrency dynamics andthe crucial aspects that drive bitcoin movements. As a result, increasing people's awareness ofcritical issues can assist us in becoming savvy investors. Although market prediction is difficult due to its complexity, the dynamics are predictable and intelligible to some extent. When there is a scarcity of bitcoin, for example, its price will rise because investors who see bitcoin as a viable investment opportunity will have a strong desire to pay for bitcoin. Furthermore, the price of bitcoin can be readily influenced by external variables such as political considerations. Despite the fact that present efforts on cryptocurrency analysis and prediction are limited, a few researches have been conducted with the goal of understanding cryptocurrency time series and developing statistical models to replicate and predict price movements. For example, Madan et al. collected bitcoin prices over time intervals of 0.5, 1, and 2 hours and integrated them with the blockchain network, bitcoin's underlying technology. Their predictive algorithm uses random forests and binomial logistic regression classifiers, and its precision in predicting bitcoin's price is roughly 55%. Shah et al. employedBayesian regression and high frequency (10-second) Bitcoin price data to improve their bitcoin investment strategy. Their models have also had a lot of success. An MLP-based prediction model was provided to estimate the following day price of bitcoin using two

types of input: the first kind of input: the opening, minimum, maximum, and closing price, and the second type of input: Moving Average of both short (5, 10, 20 days) and long (100, 200 days) windows. During validation, their model was shown to be 95% accurate. Many academic studies have been conducted on exchange rate forecasting, such as the monetary and portfoliobalance models investigated by Meese and Rogoff (1983, 1988).

Literature Survey

The field of artificial intelligence known as machine learning (ML) is particularly useful for making forecasts by analyzing historical data. Prior research has shown that ML-basedmodels not only give a result that is nearly or exactly the same as the real result, but also improve the accuracy of the result [25], which is only one of the many ways in which they excel over traditional forecasting models. Neural networks, support vector machines, anddeep learning are all examples of machine learning. Two ways in which the authors of [26] show that a portfolio benefits from the addition of cryptocurrencies. The primary goal is to lower the standard deviation, and the secondary goal is to give investors more leeway in how they allocate their capital. Experts say the optimal cryptocurrency allocation lies between 5 and 20 percent, depending on the investor's comfort level with risk. In [27], the authors employ two machine learning algorithms—random forests (RF) and stochastic gradient boosting machine learning—to the problem of forecasting time series data (SGBM). The findings demonstrate the viability of using the ML ensemble method to forecast Bitcoin prices. The investing process can be safer if the proper decision is made at the right time, and that's why good decision making is so important. In [28], we see a Litecoin and Monero- specific LSTM-GRU hybrid prediction system introduced. The authors of [29] combine RV data from Bitcoin returns taken every minute during durations of 3 hours. The heterogeneous auto-regressive realized volatility (HARRV) model with optimized lag parameters is compared to the results of several machine learning techniques for predicting future values based on past samples. These techniques include artificial neural networks (MLP and LSTM), support vector machines (SVMs), and ridge regression. The results demonstrate the effectiveness of the proposed methodology in predicting future prices, suggesting it might be used to the prediction of a wide range of cryptocurrency markets. In [30], the authors make Bitcoin price predictions using time-honored techniques like support vector machines and linear regression. In this study, the Bitcoin closing price is used as a time series predictor to develop Bitcoin price forecasting models. In [31], the authors employ machine learning to tackle a multiple regression technique that depends on highly correlated attributes and a deep learning mechanism that employs a conjugate gradient mechanism in conjunction with a linear search for BTC price prediction. Bitcoin, Ethereum, and Ripple price dynamics are examined in [32]. The authors use robust AI frameworks, such as a fully linked artificial neural network (ANN) and a long short-term memory (LSTM) recurrent neural network, and find that ANN relies more on long-term history while LSTM relies more on short-term dynamics, suggesting that LSTM is more efficient at extracting meaningful information from historical memory than ANN. High-dimensional data on Bitcoin's daily price shows that logistic regression and linear discriminant analysis may get an accuracy of 66%, according to a study [33]. While statistical methods and machine learning algorithms have the highest accuracies (66 and 65.3%, respectively), exceeding (a powerful machine learning algorithm) beats the benchmark results for daily price prediction. Neural networks (NN), support vector machines (SVM), and a random forest is all put to the test in [34]. (RF). In this study, we show that NN beats the other models and that machine learning and sentiment analysis maybe utilized to predict cryptocurrency markets (with Twitter data alone able to predict specific coins). The cryptocurrency's price history is a major factor in the investment process. The investor relies heavily on constructing Markov chains as one of their primary techniques. Using a series of decision trees, this method predicts which cryptocurrency will yield the highest return upon sale and then checks its predictions against the actual numbers [41]. This paper focuses on three models that can predict the future prices of cryptocurrencies using machine learning algorithms and artificial intelligence approaches to achieve accurate prediction models in an effort to aid investors, given the importance of prediction in the investment process upon which many people depend for income.

METHODOLOGY

The most amazing aspect of bit coin is decentralization, which may effectively remove the influence of traditional financial sectors and monetary authorities due to its block chain network features. Furthermore, Bitcoin's electronic payment system is based on cryptographic proof rather than trust between each other, as its transaction history cannot be changed without redoing all proof of work of all block chain, which plays a critical role of being a trust intermediary and can be widely used in reality, such as recording charitable contributions to avoid corruption. The developed system can forecast the value of a cryptocurrency. This rate is forecasted using machine learning and data mining. To efficientlytrain bit coin prices as time series data, LSTM, RNN, Decision tree, ANN, and Linear regression are employed. This technique can forecast the movement of a crypto currency across multiple time intervals. The time required to compile the model and its prediction accuracy vary depending on the algorithm. Although present efforts on Crypto currency priceresearch and prediction are limited, a few studies have been conducted with the goal of understanding Crypto currency time series and developing statistical models to recreate andpredict market dynamics.

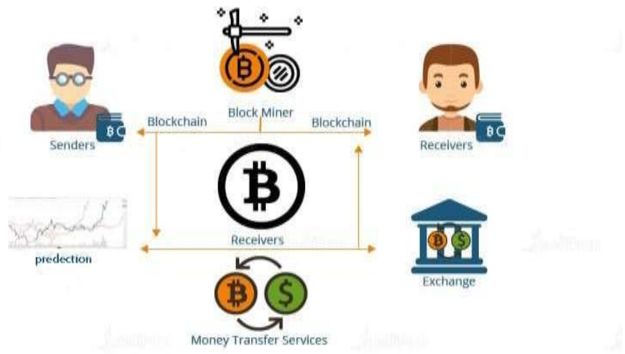

Fig.1 proposed architecture

Proposed algorithm

Inputs: Training data T1, Test data T2, LSTM and ANN as M

Output: Detection results R

1. Start
2. Add convolution layers
3. Add avg pool layers
4. Add max pool layers
5. Add con cats
6. Add dropouts
7. Add fully connected layer
8. Add soft max layer
9. Create the AI model M
10. For each epoch e in E
11. For each batch n in N
12. Update M with T1
13. End For
14. End For
15. Deploy frame work
16. R□Predict(M,T2)
17. Return R

Dataset description

The historical price data for crypto currencies were obtained fromhttps://www.blockchain.com/markets, and the total number of samples is 1030 trading days from August 7, 2015 to June 2, 2018. The price data consisted of four components: opening, high, low, and closing prices. In this study, we look at the prices of three popular crypto currencies: Bit coin, Ethereum, and Ripple. We use the four elements as input to our model, and then anticipate the next few days' opening price, which is used as the model's output. Theopening price is chosen as the output since it reflects all of the preceding memories and occurrences. To avoid overfitting during model training, the dataset was separated intotraining and testing sets in an 80%:20% ratio. The mean price of the three crypto currencies is

$ 3082.084, Ethereum is $ 194.810, and Ripple is $ 0.223, with a 95% confidence interval of [2834.034, 3330.134], [176.977, 212.642], [0.196, 0.248]. As illustrated in Figure 1, the

prices of Bitcoin and Ethereum fluctuate dramatically, with standard deviations as high as 4063, 292, and 0.43, respectively.

EXPERIMENTAL RESULTS

A prototype application is used to evaluate the proposed system. In terms of detectionoutcomes, many observations are made. The dataset is shown to assess the performance of the proposed improved Model.

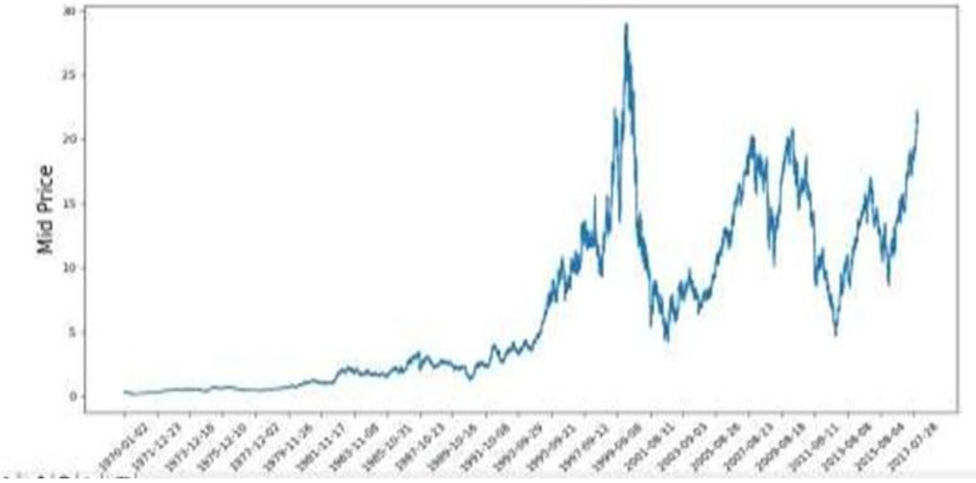

Fig.2. **Dataset analysis**

As illustrated in Figure 2, dataset analysis To avoid overfitting during model training, the dataset was separated into training and testing sets in an 80%:20% ratio. The mean price of the three cryptocurrencies is $ 3082.084, Ethereum is $ 194.810, and Ripple is $ 0.223, with a95% confidence interval of [2834.034, 3330.134], [176.977, 212.642], [0.196, 0.248]. As illustrated in Figure 1, the prices of Bitcoin and Ethereum fluctuate dramatically, withstandard deviations as high as 4063, 292, and 0.43, respectively.

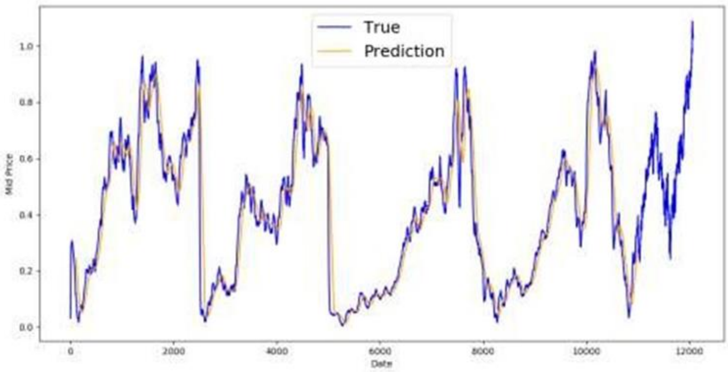

Figure 3: Results of modified LSTM and ANN with **True Predictions**

As shown in Figure 3, the observations are supplied for the date on the horizontal axis and theperformance in terms of mid-price on the vertical axis. Except for a few mid-priced models, the results demonstrated that the model's accuracy rose as the date increased.

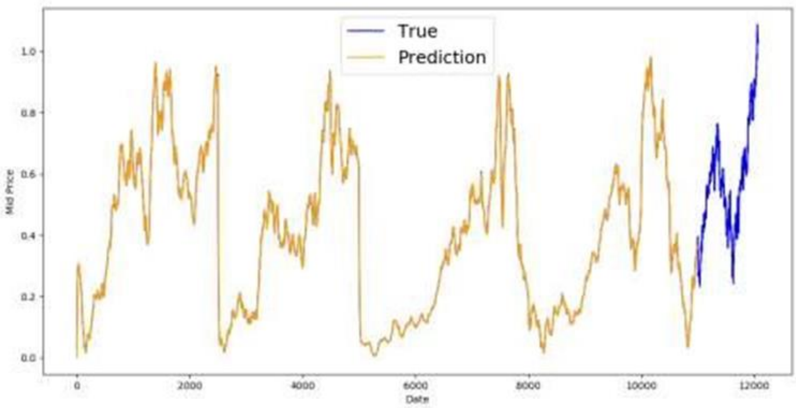

Figure 4: Results of modified LSTM and ANN with **True Predictions**

As shown in Figure 4, the observations are supplied for the date on the horizontal axis and theperformance in terms of mid-price on the vertical axis. The results demonstrated that the model's accuracy grew with the date, except in the outlier portion of mid-price.

CONCLUSION

Bitcoin and other cryptocurrencies have become the market leader in decentralization. Numerous additional cryptocurrencies, such as Ethereum and Ripple, appeared after Bitcoin. Due of the extreme ambiguity around their worth, many people view them as a type of conjecture. Therefore, it's crucial to comprehend the internal traits and predictability of different cryptocurrencies. In this study, we use two different artificial intelligence frameworks—fully-connected Artificial Neural Network (ANN) and Long-Short-Term Memory—to analyze and forecast the price patterns of Bitcoin, Etherum, and Ripple (LSTM). We showed that the performance of the ANN and LSTM models in price prediction is comparable, despite variations in their underlying architecture. The impact of historical memory on model prediction is then investigated further. We discover that ANN relies more on long-term history, whereas LSTM relies more on short-term dynamics, indicating that LSTM is more efficient than ANN in utilizing relevant information hidden in historical memory. However, given enough historical data, ANN can attain comparable accuracy to LSTM. This study is a one-of-a-kind showing that the cryptocurrency market price is predictable. However, depending on the nature of the underlying machine-learning model, theexplanation for predictability may differ.

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