Cryptocurrency Prices Prediction

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Abstract

These days, cryptocurrencies are well-established and widely accepted as a substitute for traditional trade methods. They have penetrated into the majority of financial transactions, making cryptocurrency trading one of the most well-liked and promising forms of successful investments. However, this rapidly expanding financial sector is characterized by high volatility and sharp price swings over a short period of time; as a result, the creation of a precise and trustworthy forecasting model is seen to be crucial for portfolio optimization and control. In this paper, we propose a model for predicting the price and movement of cryptocurrencies using numerous inputs of a deep neural network. In order to extract valuable information from each cryptocurrency separately, the proposed forecasting model uses various cryptocurrency data as inputs and manages them independently. Overall, this paper's prediction models provide accurate findings that are near to the current prices of cryptocurrencies. These models are crucial because they can have a big impact on the economy by assisting traders and investors in determining when to buy and sell cryptocurrencies. The proposal is made to look into additional variables like social media, tweets, and trading volume that could have an impact on the values of the cryptocurrency market in the future.

KeyWord: cryptocurrencies, blockchain, Bitcoin, Ethereum, LSTM,

1 Introduction

Cryptocurrencies go by a lot of names. The three cryptocurrencies that are most well-known are Bitcoin, Litecoin, and Ethereum. Alternatives to traditional currencies are being used for online transactions. An alternative payment system created utilizing encryption techniques is referred to as a digital currency, or cryptocurrency. Cryptocurrencies can function as a virtual accounting system and a medium of exchange by deploying encryption technology. A user could install a cryptocurrency wallet in order to use cryptocurrencies. Bitcoin, the most well-known cryptocurrency, was created in 2009 and remained the only Blockchain-based cryptocurrency for more than two years. Today, however, the cryptocurrency market has more than 5000 cryptocurrencies and 5.8 million active users.

The Internet of Things (IoT) ecosystem is one area where the blockchain (BC), the technology that powers the Bitcoin cryptocurrency system, is viewed as essential in providing the foundation for ensuring improved security and privacy. The majority of it is a digital log of transactions that is spread out across the entire blockchain network of computer systems. The blockchain is made up of two fundamental parts: blocks, which arrive after transactions in the second. The block is a collection of data that contains the transaction as well as additional details like the correct order and creation time, as well as the participant-initiated activity represented by the transaction. A signaling system named BloSS is used by each autonomous system (AS) in a multi-domain, blockchain-based cooperative DDoS defense system to join the defensive alliance.

It shows that the impact of networks on exchange rate competition in the developing cryptocurrency market over time depends on two factors:
(1) competition among different currencies, and
(2) competition among exchanges.
There are several cryptocurrencies, but Bitcoin is the most widely used one since it is a tough rival and did not win the cryptocurrency race. As a result, it has become the dominant cryptocurrency.

Although there are numerous hidden risks associated with every investment process, many people have made a lot of money through speculating in the digital markets. As a result, some investors, especially those with a high-risk tolerance, are interested in investing in cryptocurrencies. As a result, prediction is used by market analysts and speculators. The prediction capability of machine learning and artificial intelligence systems varies depending on the cryptocurrency. Subsequently, the proposed prediction model uses as inputs the transformed data from various cryptocurrencies and handles them independently, in the sense that each cryptocurrency data consist of inputs to different convolutional layers, in order for each cryptocurrency information to be exploited and processed, separately. Finally, the processed data from each cryptocurrency are merged and further processed for issuing the final prediction. The main idea behind these models is to extract valuable information from each category of mixed data, independently and then concatenate the information for issuing the final prediction.

2 Related Work

Analysis and forecasting of cryptocurrency prices is a very difficult study topic and a very demanding challenge in time-series analysis. The substantial changes and volatility in the time series of cryptocurrencies, which are strongly influenced by a vast array of events, are what give rise to its complexity and difficulty.

Using a variety of complex prediction models, Derbentsev et al. [3] attempted to model the short-term dynamics of the three most capitalized cryptocurrencies, namely Bitcoin, Etherium, and Ripple. They specifically assessed the prognostic performance of three models: a binary autoregressive tree (BART), a random forest, and an artificial neural network. From 1 August 2015 to 1 December 2019, 1583 daily bitcoin prices were collected for the data that was used. According to their experimental findings, ANN and BART models were significantly more accurate than the "naive" model at predicting directional movement, with an average accuracy of 63

For the purpose of predicting future price movements, Chowdhury et al. [4] used sophisticated machine learning prediction models to the index and individual components of cryptocurrencies. According to more analytical standards, their main goal was to help cryptocurrency traders by forecasting the closing prices of the CCI30 index and nine key cryptocurrencies. They used a range of machine learning models in their study, including robust ensemble learning models, gradient-boosted trees, ANNs, and k-nearest neighbors. They made use of information that included daily closing prices between January 1 and January 31, 2017. The best prediction performance was demonstrated by ensemble models and gradient boosted trees, which was competitive and occasionally superior to that of comparable state-of-the-art models proposed in the literature.

Exciting research was done by Pintelas et al. [5], who assessed complex deep learning models for forecasting cryptocurrency prices and movements. Their study exposed the major forecasting accuracy limitations of deep learning models. The authors emphasized the need for adopting more sophisticated algorithmic approaches for the construction of effective and trustworthy bitcoin models based on their experimental findings.

In a similar manner, Livieris et al[7] .'s proposal examined enhancing the forecasting effectiveness and consistency of deep learning models by utilizing three commonly used ensemble algorithms, namely averaging, bagging, and stacking. The hourly values of Bitcoin, Ether, and Ripple were used by the writers between 1 January 2018 and 31 August 2019. Additionally, they used a number of Conv-based and LSTM-based learners as the foundation for a thorough performance evaluation of several ensemble models. They found that deep learning and ensemble learning may be effectively applied to create robust and accurate bitcoin prediction models, but at a high computational cost.

A hybrid approach to cryptocurrency prediction that focuses on Litecoin and Monero was put forth by Patel et al. [6]. The suggested model is based on an LSTM and GRU-layered recurrent neural network architecture. The data used in their study included daily information on average price, open price, close price, high and low prices, as well as the volume of trades for Litecoin from 24 August 2016 to 23 February 2020 and Monero from 30 January 2015 to 23 February 2020. According to the described trials, the suggested hybrid model outperforms conventional LSTM networks while displaying some interesting outcomes.

Symbol	Name	Price (Intraday)	Change	% Change	Market Cap	Volume in Currency (Since 0:00 UTC)	Volume in Currency (24Hr)	Volume All Currencies (24Hr)	Circulating Supply	52 Week Range	Day Chart
BTC-USD	Bitcoin USD	21,358.20	+670.50	+3.24%	408.934B	44.156B	44.156B	44.156B	19.146M	17,708.62 68,789.63	
ETH-USD	Ethereum USD	1,718.56	+21.24	+1.25%	210.2B	17.033B	17.033B	17.033B	122.312M	896.11 4,891.70	
USDT-USD	Tether USD	1.0004	+0.0002	+0.02%	67.57B	66.555B	66.555B	66.555B	67.546B	0.95 1.03	
USDC-USD	USD Coin USD	1.0000	-0.0001	-0.01%	51.716B	6.903B	6.903B	6.903B	51.715B	1.00 2.35	
BNB-USD	BNB USD	295.25	+5.40	+1.86%	47.634B	1.015B	1.015B	1.015B	161.337M	184.54 669.35	
BUSD-USD	Binance USD USD	0.999982	-0.000030	-0.00%	20.003B	14.137B	14.137B	14.137B	20.003B	1.00 1.02	
XRP-USD	XRP USD	0.354944	+0.003743	+1.07%	17.685B	1.34B	1.34B	1.34B	49.826B	0.29 1.35	
ADA-USD	Cardano USD	0.513543	+0.019333	+3.91%	17.554B	998.107M	998.107M	998.107M	34.182B	0.41 2.80	
SOL-USD	Solana USD	34.66	-0.79	-2.24%	12.24B	979.54M	979.54M	979.54M	353.118M	26.06 260.06	
DOT-USD	Polkadot USD	7.7281	-0.0161	-0.21%	8.619B	453.332M	453.332M	453.332M	1.115B	6.09 55.00	
DOGE-USD	Dogecoin USD	0.064123	+0.000650	+1.02%	8.507B	470.987M	470.987M	470.987M	132.671B	0.05 0.34	
MATIC-USD	Polygon USD	0.889272	+0.007505	+0.85%	7.767B	417.192M	417.192M	417.192M	8.734B	0.32 2.92	
SHIB-USD	Shiba Inu USD	0.000013	-0.000000	-2.65%	7.149B	854.385M	854.385M	854.385M	549.063T	0.00 0.00	
HEX-USD	HEX USD	0.040146	-0.000061	-0.15%	6.962B	8.105M	8.105M	8.105M	173.411B	0.03 0.56	
DAI-USD	Dai USD	0.999921	-0.000294	-0.03%	6.884B	399.168M	399.168M	399.168M	6.884B	0.98 3.67	

Figure 1: Yahoo Finance Data

2.1 Data

Over the past few years, cryptocurrency investment has increased dramatically and shown that it may draw new investors to the trading sector. Since buying, trading, and holding cryptocurrencies like Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), and others is difficult for many people, trading companies are working hard to make it as easy as possible for their clients.

The data is taken from Yahoo Cryptocurrency Data API. it will take data from first January to now. I took data from yahoo finance because it's updated and precious. it is easy to train all the data. I took BTC or Bitcoin data from it. by giving ETH and DOGE it will easily take Ethereum and Dogecoin data.

Methodology

Python is simple to use, simple to understand, and adaptable. The Python library supplies base-level objects, so developers do not have to build code from scratch every time. This implies that Python, which is used to develop machine learning, can run on all systems, including Windows, Linux, Unix, and macOS. Python libraries enable you to access, handle, and transform your data, which is necessary for machine learning. Scikit-learn can handle fundamental ML techniques like classification, regression, logistic and linear regression, and clustering. For sophisticated structure and data analysis, utilize Pandas. It enables you to combine, filter, and gather information from additional outside sources (such as Excel). Using large data sets to design, train, and use artificial neural networks, TensorFlow is used to manipulate deep understanding. A state-based interface to matplotlib is matplotlib.pyplot. It offers an implicit plotting method likened to MATLAB. Additionally, it opens figurines on your screen and manages the figure GUI. Every 61 days, it will make a prediction based on previous values.

Results

This section shows the results obtained from long short-term memory (LSTM) for a popular cryptocurrency: BTC (Bitcoin). It represents a negligible difference between the predicted and the actual price along the testing set of the time series.

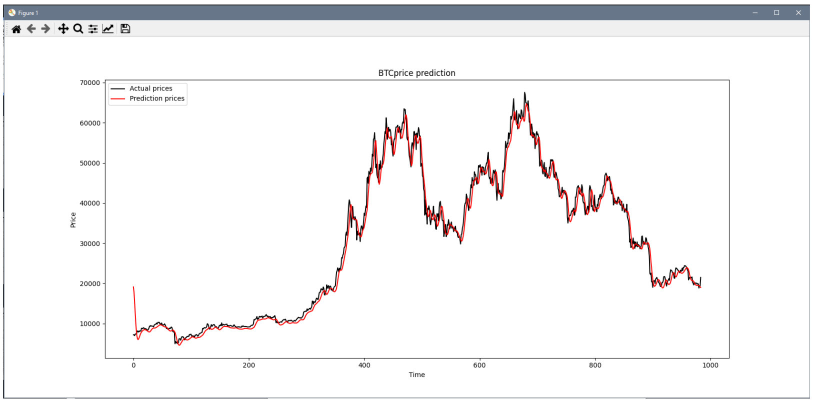

Fig2: Actual and predicted price of BTC using the LSTM model

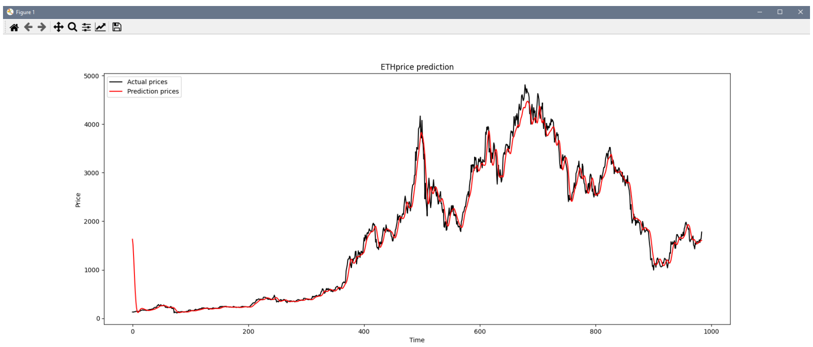

Fig3: Actual and predicted price of ETH using the LSTM model

Here black line indicates the actual prediction and the red line indicate the prediction values. in the x-axis, it shows the time period in days, and in the y-axis, it shows the price in USD. This prediction is made on Bitcoin and Ethereum.

Conclusion

In this study, we suggested a deep neural network model for predicting bitcoin price and movement based on a multi-input architecture. The suggested prediction model uses cryptocurrency data as inputs, handling each one separately so that it can be first utilized and processed independently. More particular, the inputs to several convolutional and LSTM layers used to learn each cryptocurrency's internal representation and determine its short- and long-term dependencies are included in the data for each cryptocurrency.

In this experiment, LSTM algorithms are built and utilized to forecast the prices of two different cryptocurrencies, including BTC and ETH. As shown in Tables 2-3, performance measurements were carried out to evaluate the precision of several models. Additionally, the cryptocurrencies used in this study were chosen because they represent the ones with the largest market capitalization. The proposed work should therefore be viewed as a first step toward improving forecasting performance with regard to future cryptocurrency prediction. Clearly, the addition of new cryptocurrencies could expand the proposed methodology. Thoughts are still being given to the questions of "which cryptocurrencies are more associated" and "which features have a bigger impact on price prediction." The assessment of the suggested model on high-frequency data may also be another exciting area for future research. The idea of enhancing the suggested model with advanced pre-processing methods based on moving averages and exponential smoothing is appealing given how positive our studies have been.

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