Bitcoin Price Prediction using the Hybrid Convolutional Recurrent Model Architecture

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Received: 24 July 2023 | Revised: 13 August 2023 | Accepted: 18 August 2023

 DOI: https://doi.org/10.48084/etasr.6223

ABSTRACT

The field of finance makes extensive use of real-time prediction of stock price tools, which are instruments that are put to use in the process of creating predictions. In this article, we attempt to predict the price of Bitcoin in a manner that is both accurate and reliable. Deep learning models, as opposed to more traditional methods, are used to manage enormous volumes of data and to generate predictions. The purpose of this research is to develop a method for predicting stock prices using the Hybrid Convolutional Recurrent Model (HCRM) architecture. This model architecture integrates the advantages of two separate deep learning models: The 1-Dimensional-Convolusional Neural Network (1D-CNN) and the Long-Short Term Memory (LSTM). The 1D-CNN is responsible for the feature extraction, while the LSTM is in charge of the temporal regression. The developed 1D-CNN-LSTM model has an outstanding performance in predicting stock values.

Keywords-1D-CNN; LSTM; Bitcoin; deep learning; prediction

I. INTRODUCTION

The future financial value of a company's stock, as predicted by its stock price, is important information for investors, shareholders, and organizations in order to maximize their returns and achieve their goals. The prediction of stock prices can be difficult by external elements, such as the velocity and volume of data, which make conducting and directing stock analysis and forecasting a difficult process [1]. The improvement in technology enables more precise information to be predicted, which is beneficial in the field of finance in order to grow and make decisions in accordance with that growth. Forecasting the movements of the stock market is a difficult effort due to the volatile nature of the market. When it comes to the development of significant trading techniques that may assist consumers in buying and selling stocks, the accuracy of stock prediction is a critical factor [2]. In general, the data on the stock market are plagued by two primary issues: uncertainty and noise. The volatility in stock prices may be caused by many external factors. These may include market circumstances, the value of a firm, the political status, global events, etc. All these can have an impact on the trading of stocks on the stock market. The volatility, instability, and variability of the stock market, on the other hand, makes anticipating the future difficult and contributes to noisy data.

In order to predict how markets will behave in the future using data from the past and the present, researchers have developed various different models. The pattern of the data in regard to the temporal attribute is what is used to derive the behavior of the market. Due to the random fluctuations that occur over time, these temporal patterns provide changed obstacles in the process of computing the data regarding the stock market. Statistical procedures have been developed specifically for the purpose of computing such data.

Nevertheless, as time passes, not only does the market continue to develop and improve, but so too does the amount of data [3]. As investors from different countries come with their various interests, new global trades are born. When compared to traditional stock markets, making predictions on the Bitcoin market has a number of significant advantages. Bitcoin is not reliant on events in the marketplace or on the actions of interfering governments. The limited availability of the coins serves as the primary factor in establishing its price [4].

Bitcoin is a crypto currency that is used globally for digital payments and investments. Because Bitcoins are decentralized and not affiliated with any government, it is incredibly easy and quick to use them to make financial transactions. The term "bitcoin exchanges" refers to a number of different online markets that are up for business for investors to use. Users have the ability to purchase and sell Bitcoins using a wide variety of currencies as a result of this feature. When they are not being used, Bitcoins are stored in a digital wallet, which is effectively the same thing as having an online bank account. Blockchain is the name of the location where the records of all of the transactions and the data about the timestamps are stored. Each individual entry in a blockchain is referred and stated to as a block. Each block has a pointer that refers to a data block that came before it. The information stored on blockchains is encoded. During transactions, the user's name will never be disclosed; just their wallet ID will be shared with the other parties.

In this paper, we present the Hybrid Convolutional Recurrent Model (HCRM) architecture by combining the 1-D-CNN and the LSTM for stock price prediction. The 1D-CNN is used for feature extraction and the LSTM is used for the temporal regression task.

II. RELATED WORKS

This section provides a concise summary of the previous research on the application of deep learning to the prediction of Bitcoin prices. Authors in [5] introduced two prediction models based on Recurrent Neural Networks (RNNs) and LSTM, and they compared them with the Autoregressive Integrated Moving Average (ARIMA) model, which is a commonly used time series forecasting model. They used the information on the price of Bitcoin to develop classification models, which make predictions about whether the price will increase or decrease in the future based on historical values. It was demonstrated that the RNN and LSTM models are superior to the ARIMA model. The number of Bitcoin wallets and unique addresses, the difficulty of mining blocks, the hash rate, and other aspects of the Bitcoin blockchain were examined in [6] in addition to the price data. The authors used these features, which are highly correlated with the Bitcoin price, to create prediction models. They investigated a number of different regression models, including linear regression, random forests, gradient boosting, and neural networks. In addition to the data from the blockchain, authors in [7] also took into account several macroeconomic factors, including the S&P 500, Euro STOXX 50, DOW 30, and NASDAQ, as well as the exchange rates between the major fiat currencies. They studied three different prediction models based on a Bayesian Neural Network (BNN), linear regression, and Support Vector Regression (SVR), and they found that the BNN performed better than the other two prediction models. Authors in [8] developed a rolling window LSTM model and showed that it outperformed the prediction models that were based on linear regression, SVR, neural networks, and LSTM. Authors in [9] introduced a deep learning-based random sampling model and demonstrated that it performed better than LSTM-based models. Authors in [10] looked at social data in an attempt to forecast the variations in the price of bitcoin. The proposed model in [11] overcomes the instability in prediction. The authors manually adjusted the DNN hyperparameters, such as the model's number of layers, learning rate, neurons, and number of epochs, for greater accuracy. The metrics MAE and RMSE were used for the evaluation of the hybrid stock price model and the results were satisfying. Authors in [12] created a revolutionary hybrid deep learning approach with the purpose of forecasting stock market prices. A hybrid model was created for this purpose by combining Bi-LSTM and GRU networks with three layers of dense units. They also used the same datasets to create other cutting-edge predictive deep learning networks for comparison. The suggested hybrid model outperforms previous deep learning models for ASIANPAINT business starting prices derived from NIFTY-50 stock data.

III. METHODOLOGY

CNNs and RNNs are two varieties of neural networks that can be utilized for prediction tasks. These deep learning networks are also capable of being utilized in predicting systems for the stock market. In this article, we propose a new model for predicting stock prices using convolutional recurrent hybridization as the underlying algorithm. The 1D-CNN-LSTM model structure is shown in Figure 1.

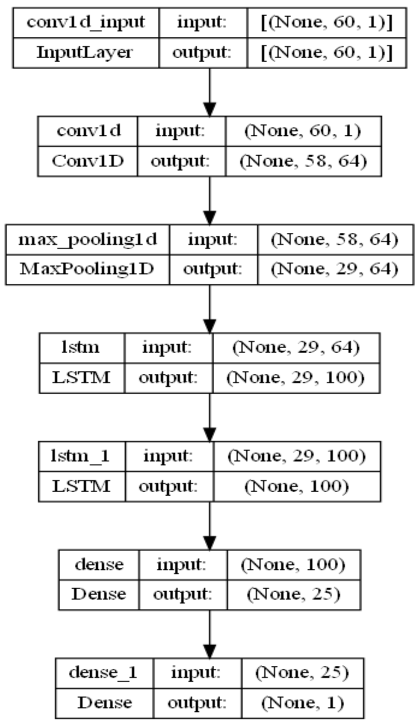

Fig. 1. The proposed 1D-CNN-LSTM model structure.

A. 1D-CNN

CNNs are among the most effective deep learning techniques and have found widespread application in a many computer vision applications. The conventional architecture of a CNN consists of a stack of convolution and pooling layers. The primary purpose of this succession of layers is to extract high-level features, which, in contrast to traditional approaches to machine learning, removes the need for a stage that involves manually engineering features. The pooling layers can reduce the size of the feature map that the convolutional layers generate. At the very end of the network, there is an attachment of several fully linked layers. The purpose of this attachment is to produce the final output and introduce nonlinearity into the network [13]. CNNs, in general, anticipate a 2D input for processing, such as images, but they can be adjusted to analyze 1D data, such as time series financial or stock data. Images are an example of a 2D input. In the current study, we used 1D-CNN to process the historical data that were read. The structure of the incoming stock data was taken into consideration when selecting the convolutional kernels as well [14].

B. LSTM

The deep RNN family includes LSTM. The LSTM algorithm was developed specifically for the analysis of sequential data. It is possible that the addition of a variety of gates to its architecture will enable it to recall more extensive data histories. It is capable of resolving the difficulties that typical RNNs face, such as gradient vanishing and gradient explosion. The gates are responsible for determining how the information will move through the network. The amount of information taken from history that will be stored is determined by the Input Gate. The amount of information that can be forgotten from previous moments is determined by the Forget Gate, while the Output Gates are responsible for controlling the internal memory unit, which is responsible for producing the required quantity of information for the subsequent cycle [15].

C. Structure and Learning

Following a series of intensive experiments, we came to the conclusion that the best potential 1D-CNN-LSTM design is one that has one 1D-convolutional layer in addition to one 1D-max pooling layer. The 1D-CNN layer's settings include a kernel size of 2, strides of 1, a rectified linear unit (ReLU) as the activation function, and a filter size set to 64. In the end, we came up with the optimum LSTM architecture, which consists of two layers of sequential LSTMs and two levels of dense layers. In the tests that we ran, we used a value of 100 for the number of units in both LSTM layers. Additionally, the "return_sequence" argument was given the value of true for the first LSTM layer and false for the second layer. This was done to ensure that each cell in the layer returned all of the outputs from the unrolled LSTM cell so that we could compare these outputs at each time step with the very next price in the sequence. At the very end, the network consists of two dense layers that follow one another for the purpose of making a final regression prediction. In the first dense layer, there are 25 neurons, and in the final dense layer, there is just one neuron. Also, we employed the Adam optimizer with a batch size of 32 and the Mean Squared Error (MSE) as our loss function.

IV. RESULTS

The data were gathered from the Yahoo Finance website, in the form of a time series. The historical data ranged from November 17, 2014, to December 31, 2022. Following the gathering of the data, a stage known as preprocessing was performed in order to rid the data of any missing values or noise and choose the features that will be utilized (feature extraction). We divided the data to 80% training and 20% testing subsets. We were unable to employ random splitting when dividing the data into training and validation sets since doing this will eliminate the time factor [16]. Therefore, we used the first 80% of the dataset to train the model, and the last 20% to test it. The outcome was evaluated with the Root Mean Square Error (RMSE). The RMSE statistic determines how well a model can forecast a continuous variable. Because the RMSE units are the same units as the dependent objective of your data, it is possible to utilize this information to determine whether or not the magnitude of the error has any significance. The RMSE should be as low as possible for the model to have the best performance [17].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (\mathrm{predicted}(t) - \mathrm{actual}(t))^2}{n}} \tag{1}$$

We selected the following number of epochs: 50, 100, 150, 200, and 250. According to Table I, the results are more conservative when using 150 epochs.

TABLE I. RMSE RESULTS VS NUMBER OF EPOCHS

No.	Epoch No.	RMSE
1	50	603.40959
2	100	443.38573
3	150	37.13838
4	200	925.09971
5	250	1179.22304

The results provided in Figure 2 were generated by making predictions using the proposed model with 150 epochs. The green line represents the result of a close prediction, while the blue and yellow lines represent the results of data training.

V. CONCLUSION

The proposed 1D-CNN-LSTM model was successful in predicting the bitcoin value in the Yahoo Finance stock market. Our model, which makes use of the time series approach, was able to construct and produce results, and those results that were able to predict the price for the upcoming days. On the other hand, the result was not satisfactory in terms of RMSE, which is a drawback. It is worth mentioning that the stock markets are affected by a variety of factors, including political and economic issues that might have an impact on either the local or global level. Therefore, the price prediction of bitcoin with the use of any model cannot be perfectly precise.

In future work, emphasis will be placed on a large number of additional deep learning layers, the addition of dropout, the modification of the number of epochs, and the utilization of a variety of unstable datasets in order to evaluate the prediction accuracy.

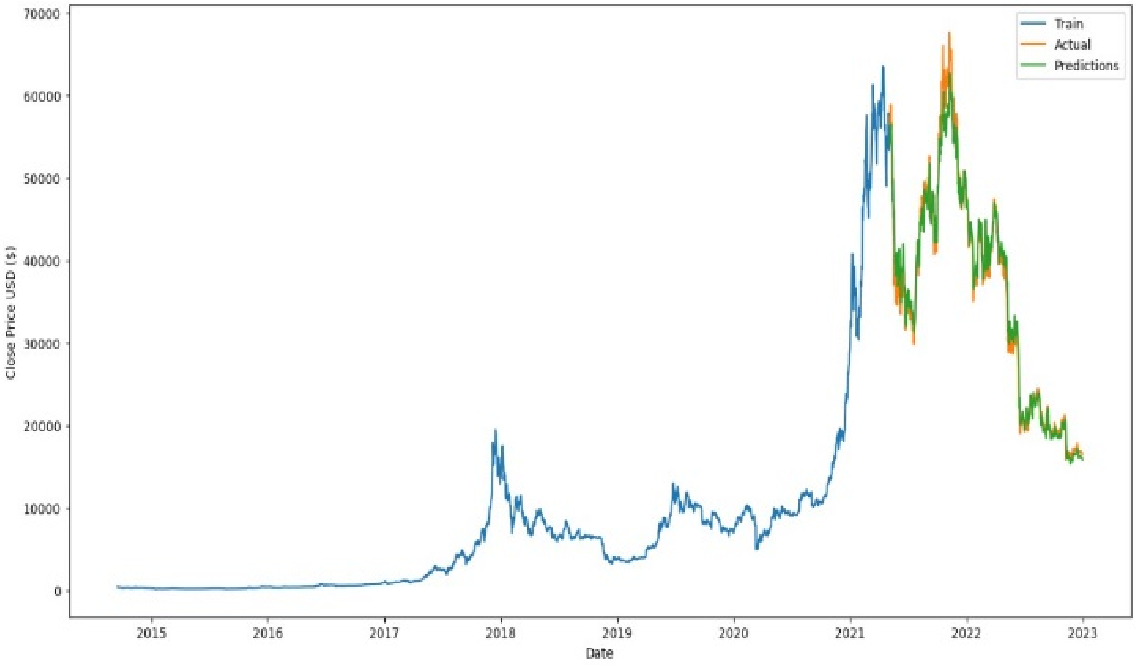

Fig. 2. Prediction result of the price of bitcoin on epoch 150.

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