ISSN 2063-5346

PREDICTING CRYPTOCURRENCY VOLATILITYUSING LSTM AND NEURAL NETWORKS

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Article History: Received: 01.02.2023 Revised: 07.03.2023 Accepted: 10.04.2023

Abstract

Cryptocurrency price predictions are the most popular way for investors to get more money in cryptocurrency investments today. Not all cryptocurrency price prediction methods reported in the existing literature are suitable for real-time the investment in price prediction in general. To find solution to above problems, a Long- Short-Term Memory (LSTM) Neural Network (NN) for cryptocurrency price prediction is proposed. This method relies on machine learning techniques, which are mainly used in financial markets to predict stock prices. Min-Max-Scaler is used for preprocessing to change the value to a common scale in the dataset.

For the purpose of determining future prices of crypto currencies, the artificial Recurrent Neural Network (RNN) model known as LSTM is utilised in the field of deep learning. LSTM-based neural networks can be implemented as a model that processes a set of sequences computed by an optimization process such as gradient descent via time propagation to compute the gradients required for optimization to change each weight. This model trains a machine learning algorithm and output layer weights calculate the LSTM network error. This proposed method protocol uses a model's output as a fresh input for the same model, endlessly.

Keywords- *Bitcoin, Machine Learning, RNN, LSTM*

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DOI:10.31838/ecb/2023.12.s1-B.373

1. INTRODUCTION

Crypto currencies are financial system virtual currency. It's cryptographically safeguarded against counterfeiting and double-spending. These are decentralised virtual currencies that may be converted via cryptographic mechanisms, unlike regular currencies. Blockchain, a complicated technology, built it to store data that is hard to manipulate, hack, or cheat.Bitcoin is carving out a niche, which may help or hurt its popularity.

Crypto currencies are young, making it hard to predict their global adoption. Bitcoin, the first blockchain-based cryptocurrency, was introduced in 2009. Now, there are approximately 5,000 coins and 5.8 million users. Bitcoin has garnered attention in economics, cryptography, and computer science due to its ability to mix crypto with monetary units.

Blockchain (BC), the technology behind Bitcoin, is thought to offer the foundation forenhanced security and privacy in other sectors, including the internet ecosystem items (IoT). A blockchain records digital transactions over a network of computers. Blockchains have transactions and blocks. A block stores transactions and other data, such as the correct command and creation time.

2. LITERATURE SURVEY

Randomness has been included into neural networks by Jay Patel and colleagues [1], and the mathematics of hierarchical random walks has been formulated by these researchers. In addition to that, stochastic forward propagation methods are brought into neural networks. It has been suggested that the prices of cryptocurrencies can be predicted using stochastic MLP and LSTM models. The random walk theory, which is commonly used in the financial markets to simulate stock values, serves as the foundation for the approach that has been suggested. For the purpose of simulating market volatility, the model that has been presented integrates stacked randomness into the observed neural network feature activations. The forecasting models also incorporate a method for learning the patterns of market reaction as an additional component. Models for Bitcoin, Ethereum, and Litecoin have been trained using the Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) algorithms. The findings demonstrate that the model that was proposed is superior than the one that was deterministic.

The researchers Hamayel, Mohammad J., et al.,[2] developed three different machine learning algorithms, which they then utilised to make price predictions for Bitcoin, Ethereum, and Litecoin. Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bi- directional LSTM (bi-LSTM) are the three algorithms that are offered and compared in this study. These algorithms are based on historical data and are used to predict the prices of three cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), and Ethereum (ETH). The accuracy of the proposed model is compared to the accuracy of existing models in a five-step process, which includes the collection of historical data on cryptocurrencies, the exploration and visualisation of that data, the formation of three different types of models, pattern testing, andthe extraction and comparison of results. Determine which of the available models is the best depending on the most recent closing price of the currency.

The architecture of DL-GuesS was suggested by Parekh Raj et al.,[3] earlier this year. The proposed DL-GuesS is comprised of two stages: the first stage is responsible for determining the sentiment of tweets, and the second stage is responsible for forecasting cryptocurrency values by utilizing price history in conjunction with the features that were extracted in thefirst stage. DL-GuesS is a hybrid model for predicting the price of cryptocurrencies that takesinto accounts both the price history as well as recent sentiment on Twitter. The authors examine the performance of DL-GuesS on two distinct cryptocurrencies and compare the results, specifically with the loss function of the current structures, in order to provide a description of the robustness of DL-GuesS. When it comes to predicting bitcoin prices, the newly proposed DL-GuesS performs far better than traditional algorithms.

3. PROPOSED SYSTEM3.1.RNN

The acronym RNN refers to a specific type of neural network called a recurrent neural network, which is designed to handle sequential input. It has widespread application in fields such as natural language processing (NLP), speech recognition, and other activities that need the examination of various types of data. The main difference between an RNN and a traditional feedforward neural network is that an RNN can maintain a state or memory of previous inputs it has processed. This memory allows the network to process sequences of arbitrary length, making it ideal for tasks such as language modeling, machine translation, and speech recognition. The basic building block of a RNN is a unit that takes an input and a previous hidden state as its input, and produces an output and a new hidden state as its output.The hidden state is passed to the next cell in sequence, allowing the network to retain memory of previous entries. The leakage gradient problem is one of the most significant obstacles that recurrent neural networks (RNNs) must overcome. This problem occurs when the gradients that are utilised to update network weights become very small as they propagateover time. Because of this, it may be challenging for the network to understand the long-term dependencies that exist in the data. To solve this problem, several variations of RNNs have been developed, including long-short-term memory networks (LSTMs) and closed recurrent units (GRUs), which use additional gates to control the flow of information in network and optionally enable remember or forget previous entries. In the process of learning long-term dependencies in sequential data, several versions have been shown to be beneficial.

3.2.LSTM

The Long Short-Term Memory (LSTM) recurrent neural network (RNN) is an attempt to solve the leaking gradient problem that plagues conventional RNNs. This issue might arise when regular RNNs are used. The leaky gradient problem happens when the gradient of the loss function becomes very small during back propagation. This problem causes delayed learning or perhaps stops the learning process entirely, depending on the severity of the situation. LSTMs solve this problem by introducing a unit of memory that can store information over time, allowing the model to learn long-term dependencies.

The LSTM architecture consists of several components, including:

Input Gate: Controls whether new inputs are allowed into the memory cell.

Forget Gate: Controls whether information should be deleted from the storage unit. Output Gate: Controls whether or not information is output from the memory unit. Memory: A component that stores time information.

Hidden state: The output of the LSTM cell has passed to the next cell in the sequence.

During training, an LSTM model takes a sequence of inputs and produces a sequence of outputs. Each entry in the sequence passes through an LSTM cell, which updates the memorycells based on the entry and the previous state.The updated memory cell is then sent to the output gate, which decides which part of the cell's contents should be output as the hidden state. Then use the hidden state as input for the next cell in the row. LSTM models are trainedusing time-based backpropagation, which involves calculating gradients at each time step in the sequence and propagating them backwards through the network to update the weight. During training, the LSTM model learns to update memory cells and gates based on the input sequence to make accurate predictions. Overall, LSTM models are powerful tools for sequence prediction tasks that require learning long-term dependencies. Because of its capability to store information across time, it is able to recognise complex patterns in sequential data. As a result, it is ideally suited for applications such as natural language processing, speech recognition, and time series forecasting.

4. WORKING OF THE MODEL

By this study the detailed description of the working of model is discussed.

4.1. DATA PREPROCESSING

Then, restrict the range of the data to between 0 and 1. As part of the process of getting data ready for machine learning, normalisation is a technique that is frequently utilised. The objective of normalisation is to transform the values of a numeric column within a dataset to conform to a standard scale while preserving the integrity of the original ranges of values. The MinMaxScaler from scikit-learn is used for this purpose. The scaler expects the data to be of (x,y) shape, so reshaping is used to add a dummy dimension before applying it. NaN's are now removed because the model does not handle NaN values well. isnan is used as a mask to filter NaN values. Again, reformat the data after deleting the NaN's.

4.2. MAKING A SEQUENCE

LSTM (Long Short Term Memory) expects data to be 3-dimensional. The data is divided intorows of a certain length. The required form of data is: [batch_size, sequence_length, n_features]. The sequencing process works by creating sequences at position 0 of the specified length. By moving one position to the right and creating another sequence. This process is repeated until all possible positions have been used.

4.3. BUILDING LSTM MODEL

It works by using special gates that allow each LSTM layer to get information from the previous and current layer. Data is passed through various gates (e.g., forget gate, enter gate, etc.) and various activation functions (e.g., tanh function, reread function) and sent via LSTMcells. The main advantage of this is that it allows each LSTM cell to memorize the pattern forsome time. Note that LSTMs can remember important information while forgetting irrelevantinformation.

The LSTM architecture looks like this:

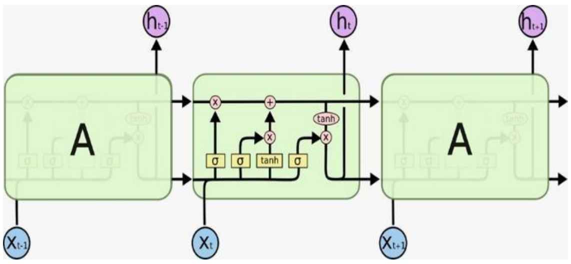


Fig.1.

4.4. DATA VISUALIZATION

When it comes to evaluating and making sense of vast volumes of data, especially in the context of predicting the price of cryptocurrencies, data visualisation is an essential component. It entails presenting information in a way that is understandable and succinct, making use of tables, graphs, and other visual aids. Data visualisation can be helpful in the process of predicting the price of cryptocurrencies since it can assist discover trends and patterns that might not be immediately obvious from the raw data. For instance, a line chart can be used to monitor the price of a cryptocurrency over a period of time, but a scatter chart can be used to demonstrate the correlation between two factors, such as volume and price. Both charts can be created using Excel.

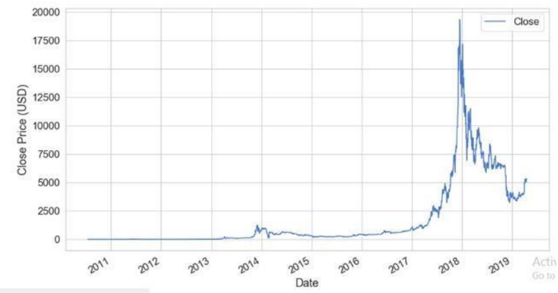


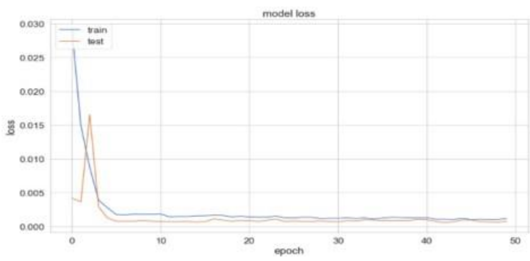
Fig.2.

4.5. CRYPTOCURRENCY PRICE PREDICTION

The use of neural networks and Long Short-Term Memory (LSTM) is becoming an increasingly popular method for predicting the future price movements of cryptocurrencies. One such method is cryptocurrency price prediction. A neural network is a type of machine learning system that may be taught to generate predictions by processing input data through a sequence of interconnected nodes, often known as "neurons." This allows the neural network to be trained to produce predictions. The weights that are assigned to the connections between the neurons are modified throughout the learning process so that the network can become more accurate in its forecasts. The LSTM neural network is a form of neural networkthat works very well when used to the task of evaluating time series data. It is able to "remember" information from past inputs and then make predictions about future valuesbased on that knowledge by using its ability to "remember." In order to use neural networks and LSTM for predicting the price of cryptocurrencies, historical price data, along with other relevant data such as trading volume, market capitalization, and sentiment data, can be usedas input to train the network. This allows the networks to learn how to make accurate predictions. After then, the network is able to recognize recurring themes and connections within the data and use this newfound information to the task of forecasting future pricing. Several other measures, such as mean squared error, mean absolute error, and root mean squared error, can be utilised in order to assess the level of performance exhibited by the network. The use of neural networks and LSTM in the prediction of cryptocurrency prices will serve as a powerful tool for generating accurate forecasts, and it has become increasingly popular in recent years as the cryptocurrency market continues to evolve and grow. Once the network has been trained and evaluated, it can be used to generate predictions for future pricechange. In general, the use of neural networks and LSTM in cryptocurrency price prediction will serve as a powerful tool for generating accurate forecasts.

5. RESULT

The outcomes of running the LSTM model are presented below. During the training period, itwas discovered that the accuracy of the prediction on the test set decreased in proportion to the size of the clusters. It should come as no surprise that this is the case, given that the morea model trains, the more likely it is that they will become overfit. Experimenting with Gated Recurrent Unit variants of RNNs is going to be part of the work that will be done in the future, along with altering the hyper parameters that are already in place. It is illustrated here how much of a loss there is for the mean absolute error function when the model is used to predict training data and test data.



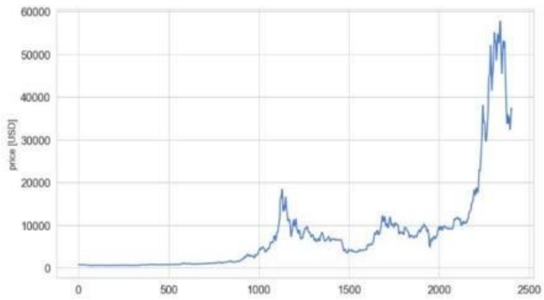


Fig.3. a. b.

The fig () represents the final graph of the predicted closing price.

6. CONCLUSION

By study, LSTM with RNN is constructed and used to predict cryptocurrency prices. The result analysis revealed that LSTM with RNN performs well. This model serves as a target for cryptocurrencies which can be considered as an efficient and reliable one. The ML algorithm is reliable and acceptable for cryptocurrency prediction. Both, LSTM and RNN can predict cryptocurrency prices better than other existing methods. In future, the factors that may affect cryptocurrency market prices has to be focused in particular the impact of social media in general and tweets on cryptocurrency prices, trading volumes, analysis and processing of natural language processing techniques.

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