Cryptocurrency Prediction Based on One Hour Change Using Recurrent Neural Networks (RNN)

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Abstract

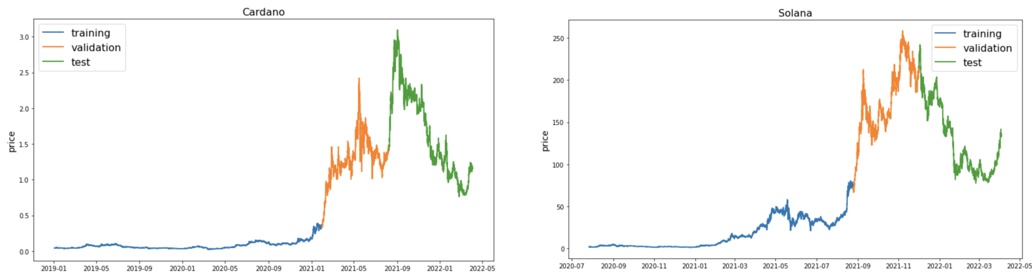
Cryptocurrency trade is gaining popularity in financial markets in recent years, however, the uncertainty and volatility in its price change has risked the investment. Thus, many intelligent forecasting models based on the price changes have been created by the previous researches to predict and analyze the factors affecting popular cryptocurrencies, such as Bitcoin (BTC), Ethereum (ETH) and Litcoin (LTC). In this paper, we build a Gated Recurrent Unit (GRU) model, a Long Short-Term Memory (LSTM) model and a Bidirectional Long-Short Term Memory (Bi-LSTM) model that focus only on two less-studied cryptocurrencies, Cardano and Solana. Our results showed that (temp) LSTM model was able to predict the cryptocurrency prices more accurately.

1 Introduction

Over the past few decades, a great deal of machine learning research has been conducted on financial trading, and various methods have been successfully applied to real-world stock forecasting. With the increasing importance of cryptocurrency trading in the international financial markets, cryptocurrency price prediction has become a hot research topic around the world. However, most of the current approaches only focus on the popular cryptocurrencies of the moment and cannot be applied to other cryptocurrencies. In addition, although these current models can theoretically predict prices, they cannot be adopted in real-time practice. To solve these problems, we have used the GRU model, the LSTM model and the Bi-LSTM model to make predictions for Cardano and Solana. In our model, we make two major improvements: On the one hand, our model can predict prices more accurately by changing the time interval from a week or a day to an hour; on the other hand, in addition to basic information, we also consider technical analysis indicators and social media indicators.

2 Related Work

In this section, we will briefly review the development of modern techniques applied to cryptocurrency price prediction including both statistical models and machine learning techniques. The traditional statistical methods will use mathematical equations combined with the economic theories to integrate different features and estimate the price [3]. However, it is difficult for us to use this approach in real life because it requires us to make a large number of unrealistic linear assumptions [7]. The next stage of development in cryptocurrency price prediction is the use of state-of-the-art machine learning algorithms. In [6], the authors generate three recurrent neural network (RNN) models, LSTM, GRU, bi-LSTM to predict the price change of BTC, LTC, ETH, and use the mean absolute percentage error (MAPE) to measure the accuracy of these models, where they found the limitations of using singe-price feature and suggested exploring the influence of other social or media factors on the cryptocurrency markets. Moreover, since most recent RNN models are only proposed for the currently



(a) Dataset Split for Cardano (b) Dataset Split for Solana

Figure 1: Dataset Split

popular cryptocurrencies [2] [1], there are fewer models making predictions for Cardano and Solana, which may have the best chance of dominating the future cryptocurrency trading market [5].

3 Methodology

In this section, we will explain how we preprocess and analyze our data, how we propose and improve our model mathematically/algorithmically, and how we evaluate our models and visualize our results.

3.1 Data Description and Preprocessing

The source of our data is obtained from TradingView, containing two separate price history datasets of Cardano (ADAUSD) and Solana (SOLUSD) collected on a hourly basis [8]. Then, we will use Cardano's data from 17:00 UTC, 2 January 2019 to 12:00 UTC, 3 April 2022 (28423 timestamps in total) and solana's data from 08:00 UTC, 27 July 2020 to 12:00 UTC, 3 April 2022 (14765 timestamps in total) to train our RNN models. The two datasets contain the same features consisting of some basic information about the cryptocurrency price change, trend and momentum indicators, and sentiment related indicators [4], which can help us comprehensively analyze the data. The 13 detailed features and associated descriptions are explained in Appendix A.

In our study, we split our dataset 1 into 80% sub dataset containing both training data and validation data for generating the model and 20% test data for tuning the hyperparameters. Then, we split the sub dataset into 80% training data and 20% validation data. Since models with features of similar scale generally tend to converge faster, either a zero-based scalar (scaling all the data between -1 and 1) or a min-max scalar (scaling all the data between 0 and 1) will be chosen to perform the scaling. To change our data format to fit the RNN model better, we convert the continuous time series data to discrete time intervals. Specifically, we have grouped the data into sequences of length T, where T is a hyperparameter waiting for tuning. When we want to make a prediction for the cryptocurrency price at time T_i, we will use cryptocurrency prices from times T_1, T_2, ..., T_{i-1} as predictors. Mathematically, let $x_t \in \mathbb{R}^{13}$ be the value of the features at time t, and f be the model. The input χ to the model therefore have the shape $\chi \in \mathbb{R}^{T\times 13}$. To predict the close price for the cryptocurrency $y_t = f(\chi)$, then we have $\chi = transpose(x_{t-T}x_{t-T+1}\cdots x_{t-1}) = (x_{t-T}x_{t-T+1}\cdots x_{t-1})^T$, where T is the length of each time sequence.

3.2 Algorithms

3.2.1 Long Short-Term Memory (LSTM)

Given an input $\chi \in \mathbb{R}^{T\times 13}$, and number of neurons L, the forward training process of the LSTM model is formulated as follows:

$$h_1 = LSTM(\chi) \in \mathbb{R}^L \quad (1)$$
$$h_2 = DropOut(h_1) \quad (2)$$
$$y_t = Dense(h_2) \in \mathbb{R} \quad (3)$$

3.2.2 Bidirectional LSTM (bi-LSTM)

Given an input $\chi \in \mathbb{R}^{T \times 13}$, and latent dimension L, the forward training process of the bi-LSTM model is formulated as follows:

$$h_1 = bi\text{-}LSTM(\chi) \in \mathbb{R}^L \quad (4)$$
$$h_2 = DropOut(h_1) \quad (5)$$
$$y_t = Dense(h_2) \in \mathbb{R} \quad (6)$$

3.2.3 Gated Recurrent Unit (GRU)

Given an input $\chi \in \mathbb{R}^{T \times 13}$, and latent dimension L, the forward training process of the GRU model is formulated as follows:

$$h_1 = GRU(\chi) \in \mathbb{R}^L \quad (7)$$
$$h_2 = tanh(h_1) \quad (8)$$
$$h_3 = DropOut(h_2) \quad (9)$$
$$h_4 = Dense(h_3) \in \mathbb{R} \quad (10)$$
$$y_t = ReLU(h_4) \quad (11)$$

3.2.4 Optimization: Optimizer, Loss Function, Hyperparameters

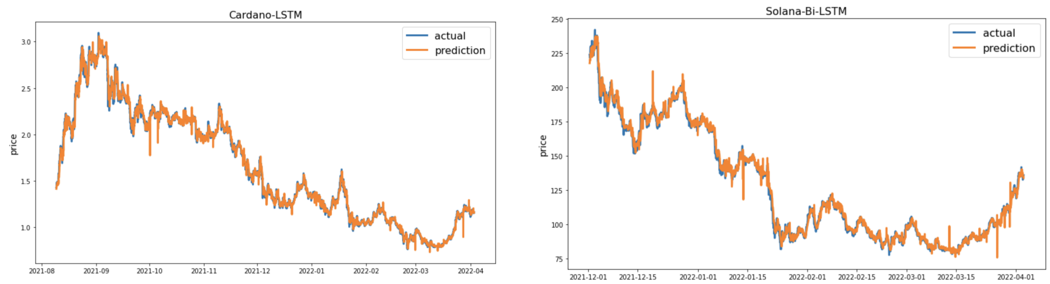
To reduce the overall loss and improve the final accuracy while training the model, we finally choose Adam as our optimizer after several trials. Since our data has been reformatted to sequences of length T, we used Mean Absolute Error (MAE) as the loss function to train the model. The hyperparameters we used to tune the model are the sequence length of T, number of neurons, number of epochs, batch size, drop out rate, and learning rate.

3.2.5 Evaluation: Matrix

To evaluate the trained model, we used the following 4 perspectives to measure. We used the Root Mean Squared Error (RMSE) to measure how concentrate the predicted result is. We used the Mean Absolute Percentage Error (MAPE) to measure how accurate the predicted result is. We used the Symmetric Mean Absolute Percentage Error (sMAPE) to measure the accuracy based on percentage errors. We also used the trend prediction accuracy, which is the accuracy of predicting whether the close price goes up or down at time t the close price at time $t - 1$.

4 Experiments

The section shows the results obtained from the three different RNN architectures: LSTM, bidirectional LSTM, and GRU for price prediction of the two cryptos. Table 1 shows the result for Cardano and we observe that LSTM is the best model by our criteria. While the models are able to make predictions close to the true price since the values of RMSE, MAPE, and sMAPE are low, the models to not perform well on predicting the trend of the price, since the trend prediction accuracy are all close to 50%. Table 2 shows the result for Solana, and we observe that bi-LSTM is the best model by our criteria. We observe that the models fitted for Solana generally performs worse than Cardano, this



(a) Cardano LSTM Result

(b) Solana bi-LSTM Prediction Result

Figure 2: Prediction Result

is potentially due to the fact that Solana has less training data, and has higher fluctuations because it has a smaller market cap.

Figure 2 displays the comparisons between the actual close price of the cryptos on the test set and the predicted price from the best models. Overall, the predicted price matches the actual price.

Nevertheless, from Figure 2, we observe that the there are a few spike predictions that are off from the actual value. We suspect that there are some outliers from the training set, or the model is overfitted for some instances. Regularization techniques can potentially prevent the spike predictions.

Based on our experiments, LSTM is the best predictive algorithm for Cardano, and bi-LSTM is the best model for Solana, despite [6] shows that GRU performs that best for other crypto currencies such as Bitcoin, Ethereum, and Lite Coin. Moreoever, the result showcases that technical analysis indicators and social media indicators improves the price predictions of the cryptos.

Model	RMSE	MAPE	sMAPE	Trend Prediction Accuracy
LSTM	0.0369	1.3533%	1.35%	0.5313
bi-LSTM	0.0518	2.0675%	2.06%	0.5206
GRU	0.0635	1.9397%	1.9%	0.5251

Table 1: Cardano Modelling Result

Model	RMSE	MAPE	sMAPE	Trend Prediction Accuracy
LSTM	3.7627	2.0128%	1.99%	0.5153
bi-LSTM	3.2399	1.7260%	1.72%	0.5029
GRU	3.5351	1.9816 %	1.98%	0.5215

Table 2: Solana Modelling Result

5 Conclusion

In this paper, we present three types of machine learning algorithms to predict the prices of two of the less studied cryptocurrencies in the market, Cardano and Solana. We measure the performance of the different models by their RMSE, MAPE, sMAPE and accuracy. The results show that LSTM outperforms the other models on the Cardano data and Bi-LSTM obtains the best results on the Solana data. The experimental results also show that technical analysis metrics and social media metrics improve the price prediction of cryptocurrencies.

The current algorithms predict the future prices of cryptocurrencies deterministically. However, the future is uncertain, so we can improve the model, i.e., be able to produce probabilistic outputs for future price prediction.

References

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A Appendix

Here is the detailed descriptions for three main parts of the dataset.

For Basic Information, we have 5 features in total:

Open: Price at which the crypto began in the time period;
High: Max price in the time period;
Low: Min price in the time period;
Close: Price at which the crypto ended in the time period;
Volume: Sum total of actual trades taking place in the time period.

For Trend and Momentum Related Indicators, we have 2 parts and 6 features in total:

Moving Average Convergence Divergence (MACD), built by 3 features:

Histogram, **MACD**, and **Signal**;

(Notice that the "MACD" is calculated as the 26-period exponential moving average (EMA) of the closing stock price minus the 12-period EMA, where the "Signal" is a nine-day EMA of the "MACD", and the "Histogram" is equal to "MACD" subtract by "Signal".)

Relative Strength Index (RSI), built by 3 features:

RSI, **RSI-based MA**, and **Bollinger Bands Width**.

(Notice that RSI and the Bollinger Bands Width are considered to be a momentum indicator that measures whether the crypto is overbought or oversold on a scale of 0 to 100 based on recent price changes.)

For Sentiment Indicators, we have 2 features in total:

Crypto FOMO Indicator and **The Fear and Greed Index**.

(Notice that the sentiment indicators indicates both the sentiment of the crypto market on a scale of 0 to 100, where a value of 0 mean "Extreme Fear" and 100 means "Extreme Greed".)