ANALYZING AND PREDICT CRYPTO CURRENCY PRICES USING LSTM

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I. Introduction

Cryptocurrency has emerged as a revolutionary asset class in the financial world, characterized by its decentralized nature and volatile market behavior. Unlike traditional currencies, cryptocurrencies operate on blockchain technology, providing transparency and security but also posing significant challenges for price prediction. Accurate forecasting of cryptocurrency prices is essential for investors, traders, and financial analysts aiming to navigate the complexities of this dynamic market.

In recent years, machine learning techniques, particularly deep learning models, have shown promise in tackling the intricacies of financial data analysis. Among these, Long Short-Term Memory (LSTM) networks have garnered attention due to their ability to capture temporal dependencies and patterns in sequential data. LSTM, a specialized form of recurrent neural network (RNN), is adept at handling long-term dependencies and mitigating issues like vanishing gradients, which are prevalent in traditional RNNs.

This study aims to leverage LSTM networks for the prediction of cryptocurrency prices, exploring their efficacy and accuracy in forecasting future trends. By analyzing historical price data, trading volumes, and other relevant features, the LSTM model can identify underlying patterns and make informed predictions. The research focuses on key cryptocurrencies, such as Bitcoin (BTC), Ethereum (ETH), and others, given their significant market capitalization and influence on the broader cryptocurrency market.

The introduction of LSTM for cryptocurrency price prediction not only highlights the advancements in deep learning applications but also emphasizes the need for robust and reliable forecasting models in the financial domain. As the cryptocurrency market continues to grow and evolve, accurate prediction models will play a crucial role in strategic decision-making, risk management, and maximizing returns for stakeholders.

In summary, this paper explores the potential of LSTM networks in predicting cryptocurrency prices, providing a comprehensive analysis of model performance, challenges, and implications for the future of financial forecasting in the cryptocurrency domain.

II. Related Works

A. Long short-term memory [1]

Recurrent networks can in principle use their feedback connections to store representations of recent input events in form of activations (short-term memory", as opposed to long-term memory" embodied by slowly changing weights). This is potentially significant for many applications, including speech processing, non-Markovian control, and music composition (e.g., Mozer 1992). The most widely used algorithms for learning what to put in short-term memory, however, take too much time or do not work well at all, especially when minimal time lags between inputs and corresponding teacher signals are long. Although theoretically fascinating, existing methods do not provide clear practical advantages over, say, backprop in feedforward nets with limited time windows. This paper will review an analysis of the problem and suggest a remedy

B. Savitzky-Golay Smoothing and Differentiation Filter [2]

The Savitzky-Golay (savgol) Filter: For a given signal measured at N points and a filter of width, w, savgol calculates a polynomial fit of order o in each filter window as the filter is moved across the signal. This is shown for three filter windows in the left of Figure 1 for w = 7. In this case, the signal is a spectrum measured at discrete points (blue line with measurements at the filled dots). The filter estimate at the center of each window is given by the polynomial fit at the center point (to make the calculation easy w is typically an odd integer). An example fit for the window [22,28] is shown in the subplot in the top right of Figure 1. The filtered signal at the center point, point 25, is given by the “X” in the subplot. The filter calculation is complete when the filter window moves the signal one-at-a-time.

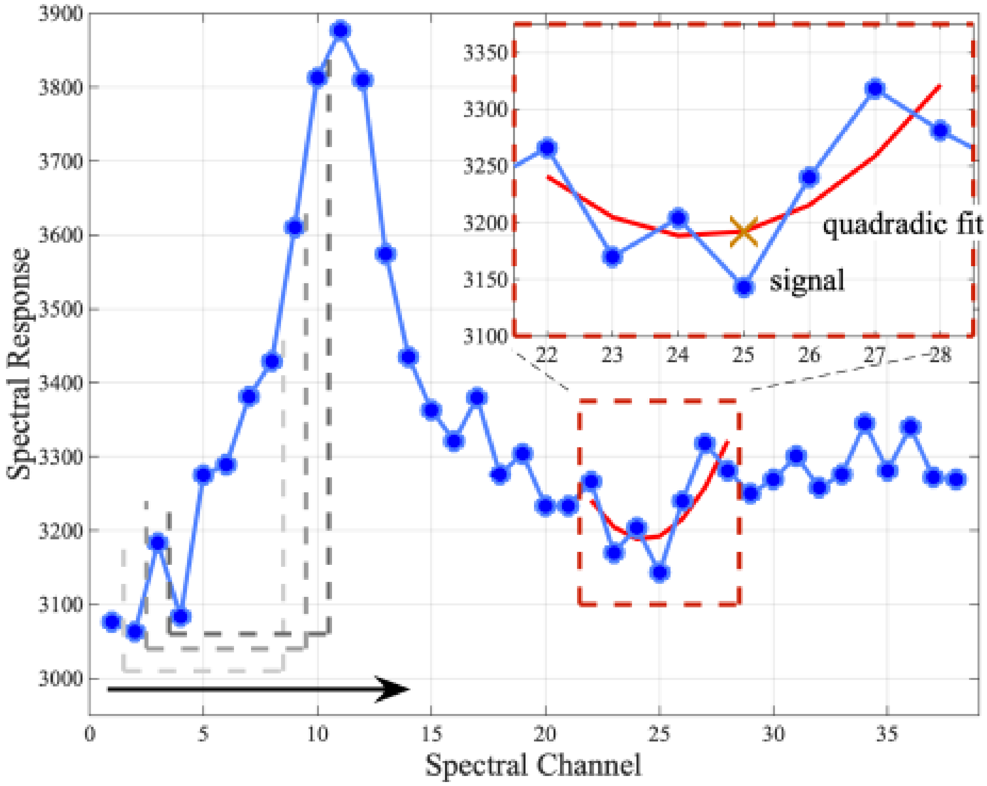

Fig. 1. Spectrum measured at discrete points (blue line with dots). Filter windows, w = 7, are shown in the bottom left. A quadradic fit is shown in the top right for window [22,28] with corresponding filter value at point 25 given as X.

C. *Moving average convergence divergence (MACD) histogram [3]*

The MACD is a trend momentum indicator and was created by Gerald Appel in the late 1970s. It consists of MACD line, which is the difference between fast EMA line and slow EMA line, the signal line, which is the EMA line of MACD and Histogram, which is the difference between MACD line and Signal Line. In general, the parameter of MACD can be adjusted case by case. 12, 26, 9 days combination is the most popular usage in realistic trade. Before you calculate the MACD indicator, you should understand the EMA formula. The mathematical formula is defined as follow:

$$EMA_t = \alpha * closingprice + (1-\alpha) * EMA_{t-1} \tag{1}$$

MACD Line: The difference between the fast EMA and the slow EMA.

$$MACD = EMA_{12} - EMA_{26} \tag{2}$$

Signal Line: It is the EMA result of MACD Line:

$$Signal = EMA_9 \tag{3}$$

Histogram: A bar to represent the difference between MACD line and Signal line

$$Hist = MACD - Signal \tag{4}$$

D. *The Stochastic RSI [4]*

The Stochastic RSI (StochRSI) is an indicator used in technical analysis that ranges between zero and one (or zero and 100 on some charting platforms) and is created by applying the Stochastic oscillator formula to a set of relative strength index (RSI) values rather than to standard price data. Using RSI values within the Stochastic formula gives traders an idea of whether the current RSI value is overbought or oversold. The StochRSI oscillator was developed to take advantage of both momentum indicators in order to create a more sensitive indicator that is attuned to a specific security's historical performance rather than a generalized analysis of price change.

$$StochRSI = \frac{CurrentRSI - LowestRSI}{HighestRSI - LowestRSI} \tag{5}$$

E. Detrended Price Oscillator (DPO) [5]

A detrended price oscillator, used in technical analysis, strips out price trends in an effort to estimate the length of price cycles from peak to peak or trough to trough.

$$DPO = price from \frac{X}{2} + 1 periods ago - X periods SMA \tag{6}$$

where: X : numer of periods used in look-back period
SMA : Simple moving average

F. The Coppock Curve

The Coppock Curve is a long-term price momentum indicator used primarily to recognize major downturns and upturns in a stock market index. It is calculated as a 10-month weighted moving average of the sum of the 14-month rate of change and the 11-month rate of change for the index. The Coppock formula was introduced in Barron's in 1962 by Edwin Coppock.

$$\text{Coppock Curve} = WMA_{10} \text{ of } (ROC_{14} + ROC_{11}) \tag{7}$$

where: WMA_{10} : 10-period weighted moving average
ROC_{14} : 14-period rate of change
ROC_{11} : 11-period rate of change

III. Project Management Plan

TABLE I
Project plan

Task name	Priority	Owner	Start date	End date	Status
Find documents	High	All	13/05/2024	15/05/2024	Done
Review papers	High	All	16/05/2024	18/05/2024	Done
Review and analyze public dataset	High	All	19/02/2024	26/05/2024	Done
Collect data and data engineering	High	Trai	27/05/2024	04/06/2024	Done
Experiment	Medium	Trang	05/06/2024	12/06/2024	Done
Writing appendix	Medium	Thong	13/06/2024	19/06/2024	Done

IV. Materials And Methods

A. Materials

Data: We started by crawling data from the Alpha Vantage API Documentation — TIME-SERIES-DAILY and performed the following data engineering tasks:

- Cleaned the data
- Pre-processed the data

Model: We chose LSTM as a predict model for the following reasons:

- The LSTM model was chosen because of its ability to handle time series data and derive long-term patterns.
- This fits well with Bitcoin price data, where the current price depends on previous price history.
- In particular, LSTM can capture complex nonlinear relationships and flexibly adapt to the high volatility of the cryptocurrency market.
- The model also enables real-time predictions, continuously updated with the latest data.

Training and Inference Platform: We utilized Kaggle and Google Colab for training and inference as they provide free GPUs and are user-friendly.

B. Methods

LSTM [1] is an updated version of RNN. They are specifically designed to avoid long-term dependence problems, whilst solving the vanishing gradient problem with an added mechanism, for regulating information, allowing it to be retained for long periods of time [24]. In short, the LSTM architecture is made up of a number of memory blocks that are recurrently connected sub networks. The network's memory blocks serve the dual functions of maintaining the network's state over time and regulating the flow of information between the cells. Figure 2 shows the LSTM block architecture, with input signal x_t, output h_t, and the activation function. The input gate step is responsible for determining the information which should be kept in the cell state while the output is responsible for computation of the information that should be sent out from the cell state. The forward training process of an LSTM network can be described using the following equations:

$$\begin{aligned}
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
c_t &= f_t * c_{t-1} + i_t * \tanh(W_c[h_{t-1}, x_t] + b_c) \\
o_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
h_t &= o_t * \tanh(c_t)
\end{aligned}$$

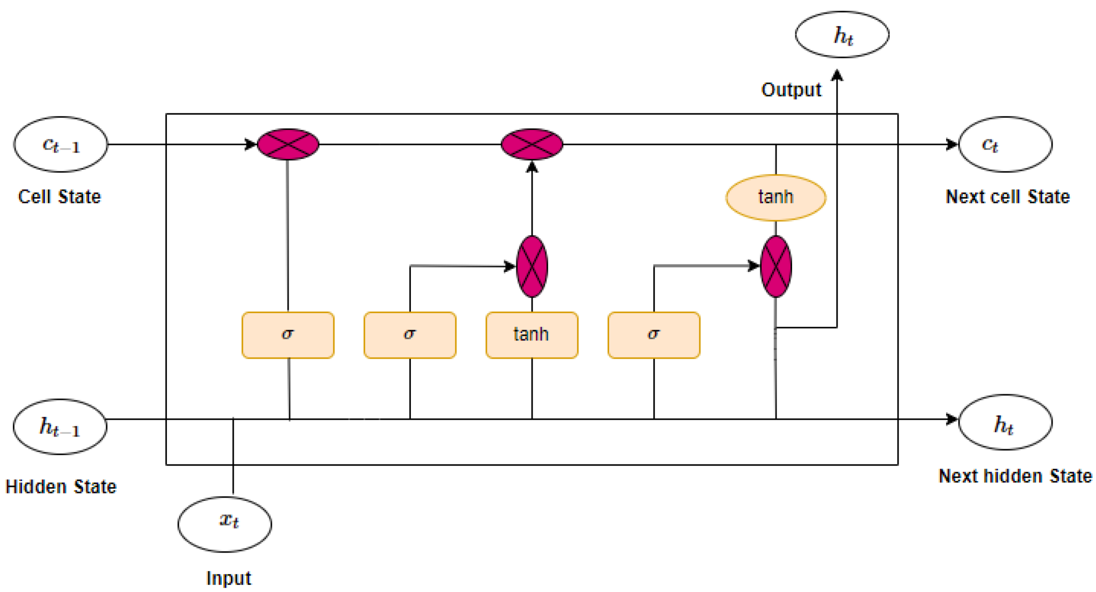

Fig. 2. The structure of a long short-term memory (LSTM) algorithm.

V. Discussion

The application of Long Short-Term Memory (LSTM) networks in cryptocurrency price prediction demonstrates notable potential, but also presents several challenges. Our findings indicate that LSTM models can effectively capture temporal dependencies and patterns in cryptocurrency price data, resulting in higher predictive accuracy compared to traditional methods. The inclusion of multiple features, such as trading volumes and market sentiment, further enhances prediction reliability.

However, the inherent volatility of the cryptocurrency market poses a significant challenge. Rapid and unpredictable price swings, influenced by factors like regulatory changes and market sentiment, can reduce the model's predictive performance. Additionally, the relatively limited historical data available for cryptocurrencies, coupled with data noise and anomalies, complicates model training and accuracy.

Future research should focus on developing hybrid models that combine LSTM with other machine learning techniques to improve robustness. Implementing real-time data integration and online learning algorithms will help models adapt to sudden market changes. Extending analysis to a broader range of cryptocurrencies and incorporating external factors such as regulatory and geopolitical events can further enhance model comprehensiveness and accuracy. Finally, developing risk assessment models to quantify prediction uncertainty will aid in better risk management.

In summary, while LSTM networks offer promising capabilities for cryptocurrency price prediction, addressing market volatility and data limitations is crucial for improving model effectiveness and reliability.

VI. Conclusions and Perspectives

In conclusion, the application of LSTM networks in cryptocurrency price prediction represents a significant advancement in financial forecasting. While challenges remain, the ongoing development of more sophisticated models and the integration of diverse data sources hold the promise of achieving more reliable and actionable predictions. This will ultimately contribute to the stability and efficiency of cryptocurrency markets and provide valuable insights for all market participants.

References

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