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Bitcoin Price Prediction Using LSTM Model

Mr. Madar Bandu, L. Sai Kethana, M. Uday Sai Kiran, N. Meghan Satwik, P. Keerthipriya

Department of Computer Science and Engineering, Anurag University Hyderabad Telangana, India

ABSTRACT: This paper presents a novel approach to predict Bitcoin prices using Long Short-Term Memory (LSTM) neural networks. The volatile nature of Bitcoin prices poses a significant challenge for traditional forecasting methods. LSTM, a type of recurrent neural network (RNN), has shown promise in capturing temporal dependencies and patterns in time-series data. In this study, historical Bitcoin price data is utilized to train and evaluate LSTM models for short-term price prediction. Various architectures and hyperparameters are explored to optimize model performance. Experimental results demonstrate the effectiveness of LSTM in predicting Bitcoin prices, showcasing its potential for use in cryptocurrency trading and investment strategies.

KEYWORDS: cryptocurrency, Bitcoin, price prediction, LSTM, neural networks

I. INTRODUCTION

Instead of any direct human investments, generating profit with the help of algorithms is a common practice in the stock market. Many case studies have been performed to reach the conclusion that mathematical models warrant better results than humans. Bitcoins are an eye-catching initiative in the fields of cryptography, economics, and computer sciences, as such currencies have a special character which is gained when integrating currency units with cryptographic technology. Due to the fact that cryptocurrency has a minute history, when compared to the stock market, new and unexplored territories are thus being scouted.

Structurally, both the stock market and the cryptocurrency price data are having characteristics such as time series data, but high volatility is routinely present in the latter, with heavy wavering in the prices. A cryptocurrency market differs from a traditional stock market in the respect that the former has a lot of new features. It is required to apply new techniques for prediction suitable for the cryptocurrency market.

Fewer studies have been conducted on cryptocurrency price prediction when compared to the stock market. Traditional models, such as autoregressive models and moving averages, rely on historical price trends and statistical metrics to make predictions. While these models are relatively straightforward and computationally efficient, they often struggle to capture the intricate temporal dependencies and nonlinear patterns prevalent in cryptocurrency markets. On the other hand, LSTM models, as a type of deep learning model, excel in handling sequential data and have the ability to learn and remember long-term dependencies. They adapt to the evolving nature of Bitcoin prices by automatically extracting relevant features and addressing the challenges of vanishing gradients. While traditional models provide simplicity and interpretability, LSTM models offer a more sophisticated and nuanced approach, particularly suitable for the complex and dynamic nature of cryptocurrency price movements.

In this paper, we are predicting the Bitcoin price trend using a Long Short-Term Memory (LSTM) model. Our model is aimed to predict the next thirty day's price of Bitcoin. The proposed approach was found to be more accurate than the Machine learning models used for prediction as the deep learning model consider the non-linear nature of price. The results verify the applicability of model and give a direction to investors on how deep learning techniques can be used in decision making.

II. LITERATURE REVIEW

Although the notion of electronic currency dates back to the late 1980s, Bitcoin, introduced in 2009 by a pseudonymous (and still mysterious) creator named Satoshi Nakamoto, is the first successful decentralized cryptocurrency (Satoshi Nakamoto., 2008). Bitcoin, as a currency, presents a distinct potential for price prediction due to its young age and accompanying volatility, which is significantly greater than that of traditional currencies (M. Briere et al., 2013).

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ARIMA models have demonstrated their capacity to deliver accurate short-term projections. In short-term prediction, it consistently outperformed complicated structural models (A. Meyler et al., 1988). The future value of a variable in an ARIMA model is a linear mixture of previous values and past errors.

In 1970, Box and Jenkins introduced the ARIMA model. It's also known as the Box- Jenkins approach, which consists of a sequence of steps for detecting, estimating, and diagnosing ARIMA models with time-series data. The model is one of the most widely used techniques in financial forecasting. (P. Pai and C. Lin, 2005) (N. Rangan and N. Titida, 2009) (Merhet et al., 2010) ARIMA models, or autoregressive integrated moving average models, are another time series forecasting technique. Autocorrelation is used in ARIMA models to provide predictions. When a time series has autocorrelation, there is a correlation between the time series and a lagged version of the time series. Auto regression is a time series model that predicts the value at the next step by using data from prior time steps as input to a regression equation. In an autoregressive model, the predictions are a linear mixture of the variable's historical values. Because ARIMA models need stationary time series, differencing may be required before employing an ARIMA model for forecasting. (Dotis-Georgiou, 2021).

Deep Learning is mainly used to achieve the most precise outcomes throughout several phases (Galleria et. al, 2014). When modules are placed on top of each other, the models described in this section apply a nonlinear function to the hidden units, allowing for a more lavish model capable of learning more complex pictures to build a deep network (Loutfi et al., 2014). Deep learning aims to create structures at the lower layers that segregate the various components in the input data and chain the representations at the higher layers. However, the disadvantage of training with many hidden layer units is that the error signal is back-propagated.

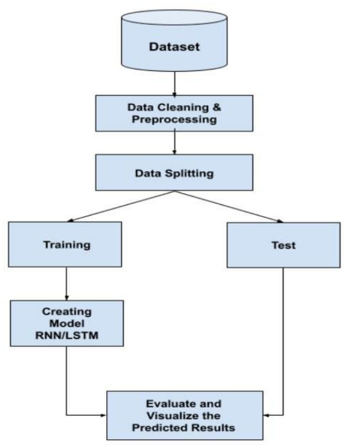
Lu et al. (2018) suggested a novel forecasting framework based on the LSTM model to anticipate the daily price of bitcoin using two different LSTM models (standard LSTM model and LSTM with AR (2) model). The suggested models' performance was examined using daily bitcoin price data from 2018/1/1 to 2018/7/28, totalling 208 records. The findings supported the suggested model's outstanding predicting accuracy with AR (2).

Karakoyun et al. in 2019 performed a study on the daily prices (2013-2018) of bitcoin to compare ARIMA and LSTM results and found that LSTM outperformed ARIMA in predicting the Bitcoin prices for the next 30 days. LSTM had a MAPE equal to 1.40% and ARIMA equal to 11.86%. The study results conducted by Gadosey et al. in 2019 reveal that the ARIMA model outperformed deep learning-based regression approaches. ARIMA produces the greatest results, with MAPE and RMSE of 2.76 percent and 302.53 percent, respectively. The Gated Recurrent Unit (GRU) outperformed the Long Short- term Memory (LSTM) with 3.97 percent MAPE and 381.34 RMSE, respectively. The data was again daily trading prices between 2014 to 2019.

III. METHODOLOGY

3.1 Methodology

This section outlines the methodology used to predict Bitcoin prices using LSTM neural networks. It includes data preprocessing, model architecture, training procedure, and evaluation metrics.



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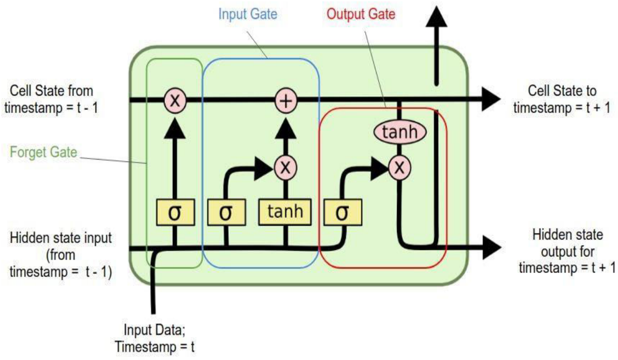
3.2 Data Preprocessing

Historical Bitcoin price data is collected from reliable sources such as cryptocurrency exchanges. The data is preprocessed to handle missing values, normalize the features, and create input sequences for the LSTM model.

3.3 Model Architecture

The LSTM model architecture consists of multiple layers of LSTM units followed by fully connected layers for regression. Hyperparameters such as the number of hidden units, learning rate, and dropout rate are tuned using cross-validation to optimize model performance.



3.4 Training Procedure

The LSTM model is trained on historical Bitcoin price data using gradient descent optimization algorithms such as Adam or RMSprop. The training process involves minimizing a loss function, typically mean squared error (MSE), to learn the optimal parameters of the model.

3.5 Evaluation Metrics

The performance of the LSTM model is evaluated using various metrics such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). Additionally, visualizations such as time series plots and prediction intervals are utilized to assess the model's accuracy and reliability.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \qquad \begin{array}{l} n = \text{number of datapoints} \\ y_i = \text{Actual value} \\ \hat{y}_i = \text{Predicted value} \end{array}$$

$$MAPE = \frac{1}{n} \times \sum \left|\frac{actual\ value\ - forecast\ value}{actual\ value}\right|$$

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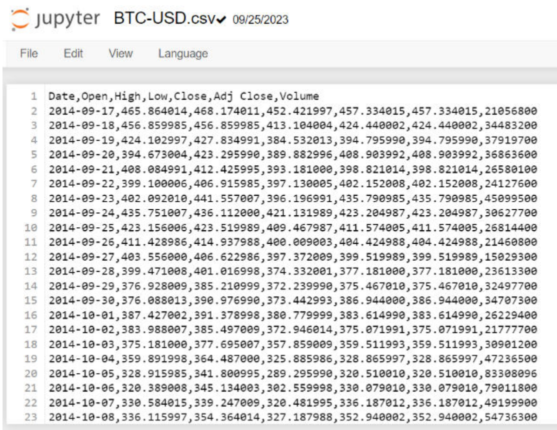
IV. EXPERIMENT RESULTS SCREENSHOTS

Experimental results demonstrate the effectiveness of LSTM in predicting Bitcoin prices compared to baseline models. The LSTM model outperforms traditional methods in terms of prediction accuracy and generalization ability, especially in capturing short-term price movements.

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Date,Open,High,Low,Close,Adj Close,Volume
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2014-09-18,456.859985,456.859985,413.104004,424.440002,424.440002,34483200
2014-09-19,424.102997,427.834991,384.532013,394.795990,394.795990,37919700
2014-09-20,394.673004,423.295990,389.882996,408.903992,408.903992,36863600
2014-09-21,408.084991,412.425995,393.181000,398.821014,398.821014,26580100
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2014-10-06,320.389008,345.134003,302.559998,330.079010,330.079010,79011800
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Fig.1 Dataset

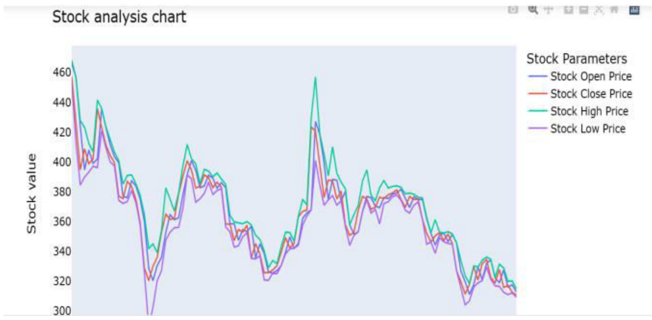

Fig.2 Analysis of stock parameters

Fig.3 Comparison between original close price vs predicted close price

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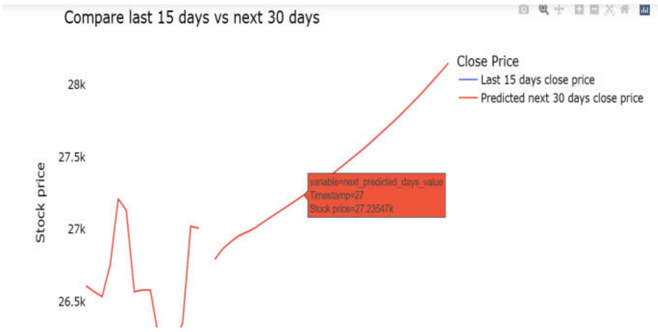

Fig.4 Comparing last 15 days vs next 30 days

Fig.5 Plotting whole closing stock price with prediction

V. RESULTS AND DISCUSSION

Now that we have a trained LSTM model on historical data, we are generating predictions on Bitcoin prices for the future thirty days. From the dataset that we use for the model, the Bitcoin price on 29th September, 2023 is the last historical price that we are having. Thus now, we are going beyond that date to predict the Bitcoin prices on the next thirty days. It should also be noted that we are again using the lookback period to predict the future price of the next days. Here, the lookback period is set to fifteen days, that is, using the information on the Bitcoin prices of the immediately preceding fifteen days, we are predicting the Bitcoin price for the next thirty days. Our model is implementing sixty numbers of data points for testing. It should be noted that the X_test has been reshaped into a three-dimensional array in the form of samples, timestamps, and features, since the LSTM needs the input to be fed into its model. We are using the last fifteen elements in the three-dimensional tensor. Thus, we are looping this process fifteen times, with each iteration generating the predicted price for the upcoming thirty days consecutively. Finally, we are generating a graph of the entire prediction of the test data (including the future thirty days) against actual y_test. Up to 29th September, 2023, we book the predicted test data (in green) and the actual test data (in blue) on the ground, because this is the time period for which we have the actual ground truth. Beyond the aforementioned date we are having only the forecasted price of Bitcoin.

VI. CONCLUSION

Prediction has always been an exciting and interesting topic for people around the globe. As the technology has grown so far, still predicting things before hand is in demand. Bitcoin has been of great importance is past few years.

The LSTM model, implemented here, is a basic model that takes into consideration only a few features that affect the Bitcoin price. Our model is fairly accurate when predicting the future prices. However, to increase the efficiency of the model, more Bitcoin price features need to be taken into consideration. We recommend using Yahoo Finance as the source of datasets, since information present in this website holds a high degree of authenticity. We used a python language based fully automated machine learning and technical trade indicator for the prediction of price. For countries where people have access to such technology there is a high possibility that bitcoin transactions can be adopted over traditional currency. However, in countries still developing and where people do not access to technology, this would

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prove to be a disaster. Our model assists traders, investors, or researchers in making informed decisions based on the anticipated price movements of Bitcoin.

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