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Deep Learning-Based Bitcoin Price Forecasting Using Neural Prophet

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Abstract

This study focuses on using the Neural Prophet framework to forecast Bitcoin prices accurately. By analyzing historical Bitcoin price data, the study aims to capture patterns and dependencies to provide valuable insights and predictive models for investors, traders, and analysts in the volatile cryptocurrency market. The Neural Prophet framework, based on neural network principles, incorporates features such as automatic differencing, trend, seasonality considerations, and external variables to enhance forecasting accuracy. The model was trained and evaluated using performance metrics such as RMSE, MAE, and MAPE. The results demonstrate the model's effectiveness in capturing trends and predicting Bitcoin prices while acknowledging the challenges posed by the inherent volatility of the cryptocurrency market.

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1. Introduction

Bitcoin is a well-known digital payment system and a widely-used cryptocurrency worldwide. It came into existence in the early 2010s and was made available as open-source software. Unlike traditional currencies, Bitcoin doesn't rely on a single person or organization to oversee its operations. Instead, it functions through a network of participants connected by the Bitcoin blockchain, often referred to as a peer-to-peer network. Bitcoin introduced the concept of blockchain technology and became the pioneering example of a decentralized digital currency, with its transaction records securely stored on the blockchain [1].

The price of Bitcoin is known for its volatility, which means it can experience significant and rapid fluctuations in a short period [2]. This volatility is characteristic of many cryptocurrencies and is influenced by various factors, such as market demand, regulatory developments, global economic conditions, and investor sentiment [3]. The value of Bitcoin can increase or decrease dramatically within hours or even minutes, making it a very unpredictable asset. While this volatility provides an opportunity to earn profits, it also carries risks, as sudden price movements can result in large profits or significant losses for individuals involved in Bitcoin trading and investing [4].

Having accurate and reliable Bitcoin price predictions is extremely important in the fast-paced cryptocurrency market we have today [5, 6]. Investors, traders, and analysts depend on these forecasts to make smart choices, improve their trading strategies, and reduce financial risks. Being able to predict Bitcoin prices accurately gives people the power to take advantage of good opportunities, prevent losses, and make the most of their investments [7, 8].

Traditionally, statistical techniques such as Auto-Regressive Integrated Moving Average (ARIMA) [9–11] and Exponential Smoothing (ETS) [12, 13] dominated the field of forecasting. However, their performance in real-world applications is limited due to their restrictive assumptions and parametric nature [14]. To achieve better forecasting performance, a skilled expert must possess deep domain knowledge in the specific application as well as classical time series modeling.

In recent years, there has been a growing trend of using deep learning methods for forecasting [15–17]. Compared to traditional statistical techniques, deep learning has the advantage of automatically extracting meaningful features without requiring extensive domain knowledge or manual effort [18, 19]. However, these methods have been criticized due to their black-box nature. The explainability of these models remains an ongoing research challenge in the field of forecasting [20]. Additionally, these models often require significant engineering efforts for data preprocessing and hyperparameter tuning [21, 22]. As a result, many non-expert forecasters in different industries preferred to use simpler statistical techniques that may not be as accurate but were easier to understand, scalable and required less tweaking. This created a gap between traditional forecasting methods and deep learning-based approaches.

To address this issue, a method that can be used is the Neural Prophet. This method is a deep learning-based approach that combines its strengths with the interpretability and user-friendliness of traditional techniques. Neural Prophet is built on PyTorch [23] and incorporates innovative techniques such as automatic model selection, feature engineering, and uncertainty estimation, making it a powerful tool for accurate and reliable predictions [24]. With its flexibility and ability to handle complex temporal patterns, Neural Prophet has gained attention as a promising framework for forecasting time series data [25–27].

This study aims to use Neural Prophet to forecast Bitcoin prices accurately. We analyzed historical Bitcoin price data to capture complex patterns and relationship. This study contributes to the field of cryptocurrency analysis by providing investors, traders, and analysts with valuable insights and predictive models that can help them make informed decisions in the volatile Bitcoin market.

The paper is structured as follows: Section 2 presents the materials and methods used in this study, including how the data was collected, processed, and used to train and evaluate the Neural Prophet model. Section 3 explains the results obtained from the Neural Prophet model, discussing its performance and any insights gained. Finally, Section 4 provides a conclusion that summarizes the findings of this study and highlights their significance.

2. Materials and Methods

2.1. Data Acquisition

We downloaded the historical closing price of Bitcoin in USD for each trading day from September 17, 2014, to May 25, 2023, from Yahoo Finance [28]. The data collected used a comma-separated values (CSV) format and consisted of two columns: the date and the closing price. The date was used as the index, and the closing price as the target variable.

2.2. Neural Prophet

Neural Prophet is a time series forecasting tool based on neural network principles. It was inspired by Facebook's Prophet [29] but added more features like automatic differencing using PyTorch. Neural Prophet uses a modular structure, so it can handle large amounts of data and future updates. Neural Prophet considers different factors like trends and seasonality by using mathematical terms. It can also take into account external variables and their future values to improve the accuracy of the forecasts [24].

2.3. Model Training

In this study, we trained Neural Prophet to forecast Bitcoin prices. Prior to training, the data is normalized using min-max scaling, and the Neural Prophet is automatically restoring the original scale of the data during the forecasting process. The model was trained for 100 epochs, and the learning rate was dynamically adjusted to enhance convergence and improve the overall training performance.

Table 1. Performance of the model

Metrics	Score
RMSE	6117.16
MAE	4008.28
MAPE	1.77

2.4. Loss Function

A loss function is a mathematical measure used to evaluate how well the Neural Prophet model performs to forecast Bitcoin prices during training. We used Huber loss as a loss function, which combines the benefits of Mean Absolute Error (MAE) and Mean Squared Error (MSE). Huber loss is less sensitive to outliers and provides a robust measure of the model's performance. Equation 1 shows the formula for Huber loss.

$$\begin{aligned} Huber &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}(y_i - \hat{y}_i)^2 \qquad |y_i - \hat{y}_i| \le \delta \\ Huber &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}\delta(|y_i - \hat{y}_i| - \frac{1}{2}\delta) \qquad |y_i - \hat{y}_i| > \delta \end{aligned} \tag{1}$$

where n represents the total of data points, y is the actual value of the data point, $\hat{y}$ is the predicted value of the data point, and δ defines the specific thresholds at which the Huber loss function transitions from a quadratic to linear form [30].

2.5. Optimizer

An optimizer is an algorithm to optimize the performance of the Neural Prophet model during the training process. We employed the AdamW optimizer, which integrates weight decay regularization with the optimization process to prevent overfitting [31]. The formula for the AdamW optimizer is presented in Equation 2.

$$\Delta w_t = -\frac{\eta}{\sqrt{\hat{v}_t + \epsilon}}\left(\frac{m_t}{\sqrt{\hat{u}_t + \epsilon}} + \lambda w_t\right) \tag{2}$$

where Δw_t represents the update to the weights at time step t, η denotes the learning rate, m_t represents the first-order moment estimate of the gradients at time step t, $\hat{u}_t$ represents the exponentially decaying average of squared gradients at time step t, $\hat{v}_t$ represents the exponentially decaying average of squared weights at time step t, λ denotes the weight decay coefficient, and ϵ is a small value added for numerical stability.

2.6. Model Evaluation

We used scikit-learn to evaluated the performance of the forecasting models using three evaluation metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). RMSE calculates the square root of the average of the squared differences between the predicted and actual values, providing an assessment of forecast accuracy. Similarly, MAE calculates the average absolute difference between predicted and actual values, whereas MAPE measures the average percentage difference. Lower values for RMSE, MAE, and MAPE indicate better performance and accuracy in forecasting. The equations for RMSE, MAE, and MAPE are given in Equation 3, 4, and 5, respectively [32, 33].

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n_{samples}}\sum_{i=0}^{n_{samples}-1}(y_i - \hat{y}_i)^2} \tag{3}$$

$$MAE(y, \hat{y}) = \frac{1}{n_{samples}}\sum_{i=0}^{n_{samples}-1}|y_i - \hat{y}_i| \tag{4}$$

$$MAPE(y, \hat{y}) = \frac{1}{n_{samples}}\sum_{i=0}^{n_{samples}-1}\frac{|y_i - \hat{y}_i|}{\max(\epsilon, |y_i|)} \tag{5}$$

3. Results and Discussion

3.1. Neural Prophet Forecasting Model

We trained our Neural Prophet model for 100 epochs and evaluated its performance. Table 1 presents the results obtained from the model. The model achieved an RMSE value of 6117.16, indicating that the average differences between the predicted Bitcoin and actual prices is approximately $6117.16. In terms of MAE, the model obtained a value of 4008.28, which indicates that the predicted prices deviate from the actual prices by average of $4008.28. Although both metrics assess the forecasting error, they provide different perspectives. MAE measures the average absolute difference between predicted and actual values without considering the error direction. RMSE, on the other hand, incorporates squared differences, takes the average, and then calculates the square root, giving more weight to larger errors. For MAPE, the model achieved a value of 1.77, which represents the average deviation difference between the predicted and actual values.

To see the differences between actual and predicted Bitcoin prices, we visualize the actual vs. predicted plot in Figure 1. There is a close alignment between the predicted prices and the actual prices, indicating that our model is performing well in capturing the patterns and trends of Bitcoin price movements. The minimal deviations between the actual and predicted values in the plot highlight the effectiveness of our forecasting approach in accurately estimating Bitcoin prices.

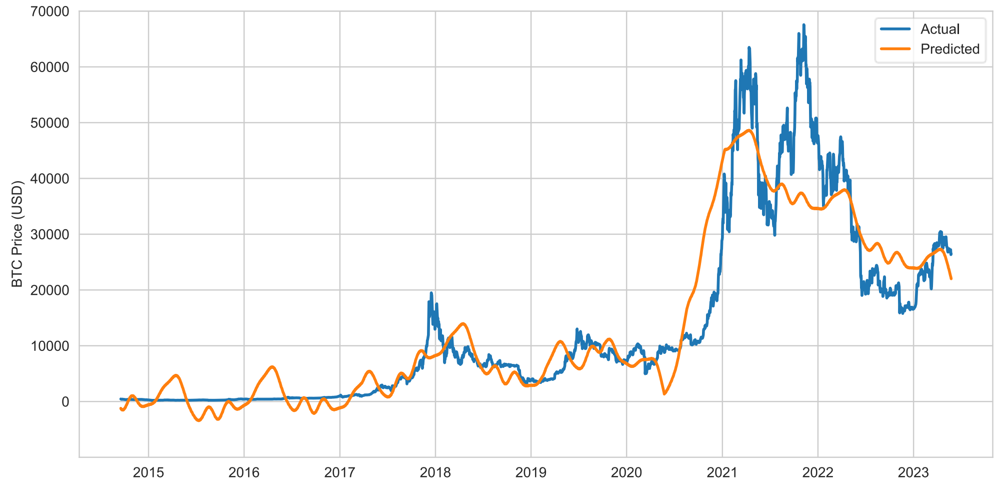
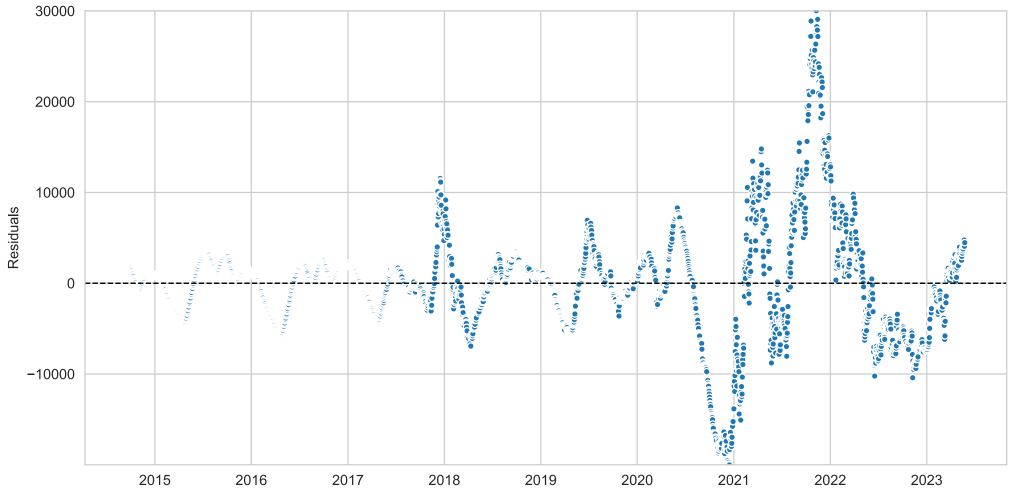


Figure 1. Actual vs predicted plot of Bitcoin prices.



Figures 2. Residual plot of predicted Bitcoin prices.

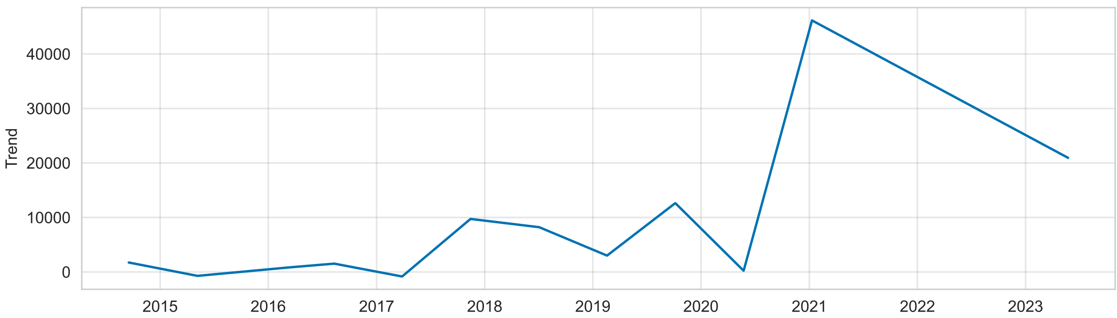
To provide information about the prediction error made by the model, we visualize the residual plot in Figure 2. It can be observed that starting from the middle of 2020 until 2023, the residuals get a noticeable increase. This indicates that the model's predictions deviate more from the actual values during this period. However, it is worth noting that despite the higher residuals, the overall trend captured by the model remains accurate. The model successfully captures the major fluctuations and movements in Bitcoin prices, even though there are some instances where the predictions have large errors.

Overall, our model demonstrates promising performance in forecasting Bitcoin prices. The combination of accurate predictions, as demonstrated by the actual vs. predicted plot, and the model's ability to capture significant price fluctuations, as observed in the residual plot, indicates its potential as a valuable tool for analyzing and predicting Bitcoin price movements. However, it should be noted that during certain periods with higher prediction errors, such as the one highlighted in the residual plot, the model's performance may need to be stronger. Therefore, further research and refinement are required to enhance the model's accuracy, particularly during these challenging periods.

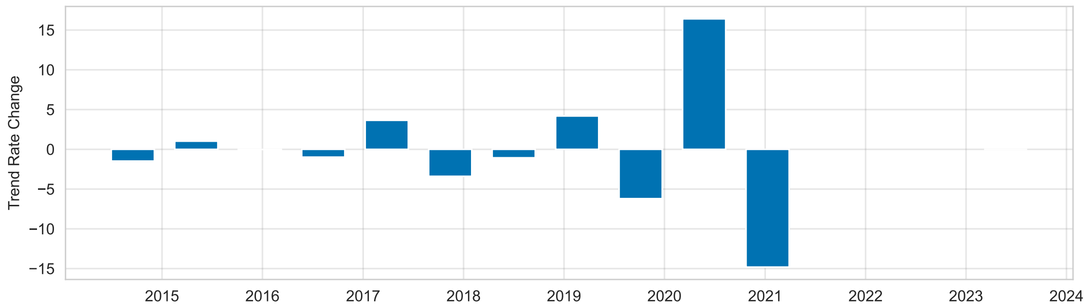
3.2. Trend Analysis

The trend plot in Figure 3a and the trend change rate plot in Figure 3b illustrate the overall trend of Bitcoin's price. To model the trend in Bitcoin prices, Neural Prophet implements a classic approach depicted by Equation 6 by combining an offset (m) and a growth rate (k). The trend effect at a specific time point ($t1$) is determined by multiplying the growth rate (k) by the difference in time ($t1 - t0$) since the starting point ($t0$), in addition to the offset (m). This methodology enables us to capture and visualize the underlying trend in Bitcoin prices, considering both the offset and growth rate components.

$$T(t1) = m + k \cdot (t1 - t0) = T(t0) + k \cdot (\Delta t) \qquad (6)$$



(a)



(b)

Figure 3. (a) Trend plot; (b) Trend rate change plot.

Based on our analysis of Bitcoin price trends, it is known that since 2014, the increase in Bitcoin prices has been relatively linear with gradual growth. This was a time when the scale of Bitcoin use was not significant, and public awareness of cryptocurrencies was still low. However, a significant increase occurred in 2017, when the Bitcoin price reached $19,783. Nevertheless, this did not last long because, in 2018, the price of Bitcoin experienced a sharp decline. Bitcoin was down about 80% from its peak, creating negative sentiment in the market and resulting in a long adjustment period for this cryptocurrency. The new Bitcoin price started to recover gradually in the second half of 2019.

It is interesting to note that a significant and sharp increase in the price trend for Bitcoin was observed starting from mid-2020. Furthermore, on November 8, 2021, the price of Bitcoin reached its all-time high, which was $67,567. The sharp rise is coincided with several factors, including the economic impact of the COVID-19 pandemic and increased institutional adoption of Bitcoin as a hedge against inflation. Market uncertainty caused by the pandemic and fiscal stimulus measures implemented by central banks has increased interest in alternative investment assets, including cryptocurrencies such as bitcoin [34]. After reaching its peak, the price of Bitcoin continued to decline, with a nearly 30% decrease from its highest price by the end of 2021. The downward trend in Bitcoin's price has persisted until 2023. Several factors have contributed to this decline, including the ongoing war in Ukraine has harmed the global economy and affected the cryptocurrency market. Another factor is the increasing market share of other cryptocurrencies, such as Ethereum, Cardano, and Solana. This decreased the dominance and demand for Bitcoin, as some investors invested in alternative cryptocurrencies. sentiment can all contribute to a downward trend. Additionally, the overall maturity of the Bitcoin market and increased regulatory scrutiny have also played a role in stabilizing prices and cushioning extreme price fluctuations.

3.3. Limitation of This Study

In this study, we trained our Neural Prophet model using historical Bitcoin price data. While this data provides valuable insights into past price movements, it does not guarantee accurate predictions of future prices. The price of Bitcoin is highly volatile, characterized by rapid and significant fluctuations. The dynamic and ever-changing nature of the cryptocurrency market, coupled with external factors and investor sentiment, can significantly impact Bitcoin's price trajectory. Therefore, it is crucial to acknowledge the inherent volatility of Bitcoin prices when interpreting our forecasts and recognizing the limitations of our study.

It is also essential to understand that, like any forecasting model, Neural Prophet is not immune to inherent uncertainty. Despite its ability to capture patterns and trends, unforeseen events or sudden shifts in market conditions can lead to inaccuracies in the model's predictions. It is necessary to interpret the forecasts generated by Neural Prophet with caution, understanding that they are probabilistic estimates rather than deterministic outcomes.

4. Conclusions

In this study, we have succeeded in developing a model capable of predicting the price of Bitcoin using Neural Prophet. The model performs well in capturing the overall trend and pattern of Bitcoin price movement, and can be used to assist traders in identifying potential buying or selling opportunities. However, it is important to understand is that the price of Bitcoin is very volatile, so it becomes a challenge to produce accurate forecasts. In future work, exploring additional techniques to reduce the impact of volatility and improve the model's predictability will be helpful. Additionally, incorporating external factors such as market sentiment, regulatory changes, and macroeconomic indicators can improve the accuracy of Bitcoin price forecasts. Continuous research and improvement of forecasting models will contribute to a deeper understanding of the cryptocurrency market and facilitate decision-making processes.

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