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Modeling Short-Term Bitcoin Price Dynamics Using Long Short-Term Memory Networks

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Abstract
A Long Short-Term Memory (LSTM) neural network trained on daily BTC/USDT data from the Binance exchange is used in this study to investigate short-term Bitcoin price dynamics. Instead of relying on linear forecasting assumptions, the model is designed to capture temporal dependencies and momentum patterns to address the nonlinear and noise-dominated nature of cryptocurrency markets. A strictly out-of-sample framework is employed to evaluate the prediction task, which is defined as a univariate regression problem with the daily high price as the target variable. According to empirical findings, the LSTM model demonstrates strong statistical performance despite significant market volatility, with an RMSE of USD 3,619.74, an MAE of USD 2,989.73, a MAPE of 2.82%, and an R^2 of 0.90. Forecasts for the next five days reveal a consistent short-term bearish trend, with broad prediction intervals of approximately USD 6,000, indicating considerable uncertainty and expected prices declining from USD 88,425.62 to USD 85,497.88. The results suggest that LSTM models can extract meaningful trend and regime information, making them suitable as risk-aware decision-support tools rather than deterministic forecasting systems, even though precise short-term price-level prediction remains constrained.

Keywords: *LSTM; Bitcoin; Prediksi Harga; Cryptocurrency; Time Series.*

INTRODUCTION

Introduced by Nakamoto in 2008, Bitcoin is a decentralized digital asset whose price movements are influenced by a complex interplay of investor sentiment, macroeconomic conditions, technology adoption, and speculative activity. Bitcoin is a difficult yet appealing subject of research for financial time series forecasting because of its tremendous volatility, nonlinear price fluctuations, and many structural fractures since its start (Berlilana & Wahid, 2024; Gupta & Sethi, 2024; Mendoza & Tubice, 2025; Patel et al., 2022; Tripathy et al., 2025). For investors, exchanges, and regulators, precise Bitcoin price forecasting is extremely important, especially when it comes to risk management and trading strategy development (Hsieh et al., 2018; Zarrin et al., 2021).

Financial data has frequently been subjected to traditional time series models like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Integrated Moving Average (ARIMA) (Osho, 2024). These methods, however, are predicated on robust linearity and stationarity assumptions, which are frequently broken in bitcoin markets. According to empirical research, Bitcoin price series contain regime shifts, large tails, and volatility clustering, which reduce the forecasting ability of conventional econometric models (García-Medina & Aguayo-Moreno, 2024; Lucchetti & Bruno, 2025; Toai et al., 2022;

Yıldırım & Bekun, 2023).

Complex financial time series modeling now has more options because to recent developments in deep learning and machine learning (Buczyński et al., 2023; Casolaro et al., 2023; Chen et al., 2024; Masini et al., 2021; Zhang et al., 2023). Because of their capacity to represent sequential relationships, Recurrent Neural Networks (RNNs) and their variations have drawn a lot of attention among these methods. Hochreiter and Schmidhuber (1997) first introduced Long Short-Term Memory (LSTM) networks, which use gated memory cells that selectively remember and forget information over extended periods of time to solve the vanishing gradient issue in conventional RNNs. Because of this architectural benefit, LSTM is especially well-suited for financial markets, where historical data may have a delayed and nonlinear impact on future pricing (Barzegar et al., 2020; Sharma & Sen, 2023).

A growing body of research has demonstrated the effectiveness of LSTM-based models in forecasting stock and cryptocurrency prices. LSTM networks outperform traditional machine learning models in capturing temporal dependencies in financial markets. Similarly, deep learning models surpass linear benchmarks in predicting Bitcoin prices. Despite these promising results, most studies primarily emphasize point prediction accuracy while often overlooking factors such as market noise, volatility regimes, and economic interpretability.

Moreover, Bitcoin markets are characterized by substantial noise dominance, where a large portion of short-term price movements is driven by random fluctuations rather than informative signals. This phenomenon raises crucial questions about the limits of predictability and the practical value of pure price-level forecasts. As Zhang et al. (2020) note, deep learning models may fit historical patterns well but still fail to maintain robust performance during periods of extreme volatility or structural change.

Addressing these limitations, this study employs historical daily data and an LSTM-based framework to model Bitcoin price dynamics, focusing on out-of-sample evaluation and temporal learning. This research presents LSTM as a method for extracting probabilistic and trend-level information from noisy financial time series rather than as a tool for deterministic forecasting. The primary contribution of this paper is a transparent and replicable deep learning pipeline for Bitcoin price prediction, accompanied by a critical assessment of its strengths and limitations within real-world financial markets.

RESEARCH METHODS

The Long Short-Term Memory (LSTM) neural network, developed using Python in a Jupyter Notebook environment, serves as the foundation for this study's empirical deep learning technique. The approach is designed to ensure reproducibility, transparency, and relevance to real-world cryptocurrency markets. It is directly aligned with the implementation provided in the uploaded notebook.

The Binance API is used to programmatically retrieve historical Bitcoin market data, with the trading pair BTC/USDT serving as the subject of analysis. Key price parameters including open, high, low, close, and volume are included in the data, which are gathered every day. Instead of using curated or artificial financial data, our method guarantees that the dataset represents actual exchange conditions. The most recent incomplete trade period is removed from the dataset before model training in order to prevent forward-looking bias. Because partial candles can introduce spurious patterns and skew forecast accuracy, this step is critical to

financial time series modeling.

The prediction task is formulated as a univariate regression problem following the notebook implementation. Instead of using end-of-day equilibrium prices, the target variable is the daily high price of Bitcoin, selected to capture intraday market optimism and volatility. This choice enables the algorithm to learn upper-bound price dynamics and distinguishes the study from conventional close-price forecasting approaches.

Min-Max scaling is applied to normalize the target series before model training. Normalization is essential to stabilize gradient updates and accelerate convergence, as neural networks—particularly LSTM architectures—are sensitive to the magnitude of input data. To prevent data leakage, the scaler is fitted exclusively on the training subset before being consistently applied to the test sample.

The normalized time series is transformed into supervised learning format using a sliding window mechanism. For each observation, a fixed-length sequence of past daily prices is used as input, while the subsequent price value serves as the prediction target. This sequence-to-one mapping enables the LSTM network to capture temporal dependencies across multiple trading days. Formally, let X_t = [p_{t-T}, p_{t-T+1}, ..., p_{t-1}] denote an input sequence of length T, where p_t is the Bitcoin daily high price. The model learns a function f(.) such that p_hat_t = f(X_t).

In the LSTM architecture implemented in the notebook, one or more stacked LSTM layers are followed by a fully connected dense layer. The dense layer transforms the learned representation into a scalar output representing the predicted price, while the LSTM layers extract temporal information. To mitigate overfitting—a common issue in financial datasets with low signal-to-noise ratios—dropout regularization is applied between LSTM layers. The Adam optimizer, which dynamically adjusts learning rates during training, is used to optimize the model's parameters.

To maintain the temporal ordering of observations, the dataset is divided chronologically into training and testing subsets. In order to reduce high prediction mistakes that could be economically important, the model is trained to minimize the Mean Squared Error (MSE) loss function. The network may iteratively improve its internal state representations because training is carried out over several epochs with a constant batch size. Instead of using random cross-validation, which is unsuitable for time-dependent data, model convergence is tracked using loss trajectories.

After training, the model generates out-of-sample predictions on the test dataset. The scaled predictions are inverse-transformed back to the original price domain to enable interpretability. Model performance is evaluated using quantitative error metrics such as MSE and RMSE, complemented by visual inspection of predicted versus actual price trajectories. This methodological framework reflects a realistic deployment scenario in which models are trained on historical data and evaluated on unseen future observations, thereby aligning academic rigor with practical financial modeling considerations.

Dataset Extraction The goal of the dataset extraction procedure is to get market-realistic, repeatable, and high-quality Bitcoin price data straight from a cryptocurrency exchange. In order to ensure that the dataset in this study represents actual traded prices rather than aggregated third-party sources, data is programmatically pulled from the Binance exchange using its official API interface. The chosen trading pair is BTC/USDT, one of the most liquid

cryptocurrency pairs in the world. In financial modeling, high liquidity is essential because it eliminates distortions brought on by thin trading conditions and lowers microstructure noise. The LSTM model's medium-term forecasting horizon is in line with the daily frequency of data retrieval.

The phases in the extraction process are as follows: API Connection Initialization: Authenticated client credentials are used to create a secure connection to the Binance API. This makes historical candlestick (kline) data directly accessible. Time Interval Specification: To guarantee uniform temporal spacing between observations, the daily timeframe is clearly specified. The whole trade activity over a 24-hour period is represented by each candlestick. Field Selection: Open price, high price, low price, close price, trade volume, and timestamp are among the pertinent characteristics that are collected from each daily candlestick.

The high price series is the main modeling aim in this work, despite the availability of several features. Timestamp Alignment: To guarantee chronological consistency, all timestamps are transformed into a standard datetime format and aligned. Building legitimate sequential inputs for the LSTM network requires this step. Elimination of Incomplete Observations: If the candlestick is not completely closed at the time of extraction, the most recent trading day is not included. By taking this precaution, forward-looking bias is avoided, which could lead to an artificial inflation of predicted performance.

```
symbol='BTCUSDT'
```
0.0s

```
from binance.client import Client
import pandas as pd
import time

# Initialize the Binance client
api_key = "sytvkKKUmXPabC877r7MFv7rhibYAMoczrMdTse0OSB6dRyImx1G8yEInE889y00"
api_secret = "KYgkq441X5spXpdDoLELwlcoJ3k7uh9LeXGgf7aQvABSMZl42Py3OUIwFCqVgc6L"
client = Client(api_key, api_secret)

def fetch_ohlcv_batch(client, symbol, interval, start_time, limit=1000):
    """
    Fetch a batch of OHLCV data from Binance.
    """
    try:
        candles = client.get_klines(
            symbol=symbol,
            interval=interval,
            startTime=start_time,
            limit=limit
        )
        # Transform data into desired format
```

Figure 1. Snippet Code for the Data Extraction

	timestamp	open	high	low	close	volume
3080	2026-01-22	89454.73	90359.99	88515.37	89559.67	10825.50492
3081	2026-01-23	89559.68	91224.99	88578.36	89600.26	13918.48919
3082	2026-01-24	89600.26	89957.39	89162.08	89225.34	4226.56737
3083	2026-01-25	89225.34	89319.13	86074.72	86670.36	14426.22019
3084	2026-01-26	86670.36	88424.45	86509.63	87973.00	9187.98776

Figure 2. Data Result

Data Preparation The act of turning raw, frequently "messy" data into a refined format that a machine learning algorithm can effectively interpret is known as data preparation. It typically takes up 70–80% of the effort in a data science project, making it the most time-consuming component.

Handling Temporal Incompleteness, The operation df.iloc[:-1] is a proactive data-cleansing step used to ensure data synchronization. Because predictive models are sensitive to trends, including a data point that is still "in progress" (like a trading day that hasn't closed) provides a false signal to the algorithm. The Logic: If you are pulling data from an API or a live database, the very last row often represents the "current" unfinished period (e.g., today's price movements or this month's incomplete sales).

The Risk: Including an unfinished period introduces a "cliff effect" where the model sees a sudden drop in volume or price simply because the day hasn't ended. Removing it ensures your model learns from closed, finalized cycles.

Structural Validation (Sanity Checks), The use of .tail(), .columns, and len() serves as a Manual Audit of the data's integrity: Verification of Truncation: df.tail() confirms that the iloc[:-1] operation worked and that the new "last row" is indeed the correct finalized date. Feature Inventory: df.columns acts as a checklist. Before training, you must ensure that your "Target" (what you want to predict) and your "Features" (the inputs) are present and haven't been dropped during earlier cleaning steps. Dataset Volume: len(df_daily) establishes your Sample Size (N). This is critical for determining how you will split your data later (e.g., if you have 1,000 rows, a 20% test split means exactly 200 rows).

Creating a Computational Sandbox, By using df_daily = df.copy(), you are practicing Non-Destructive Data Preparation. Memory Management: In Python, a simple assignment (df_daily = df) only creates a "pointer" to the original data. If you change a value in df_daily, it changes in df too. The Sandbox: .copy() creates a completely independent object. This allows you to perform "destructive" operations like scaling, log transformations, or dropping outliers on df_daily while keeping the original df untouched in case you need to restart your analysis.

```
# Select all rows except the last one
df = df.iloc[:-1]
```
✓ 0.0s

```
df.tail()
```
✓ 0.0s

	timestamp	open	high	low	close	volume
3079	2026-01-21	88427.66	90574.00	87263.53	89454.73	20617.50372
3080	2026-01-22	89454.73	90359.99	88515.37	89559.67	10825.50492
3081	2026-01-23	89559.68	91224.99	88578.36	89600.26	13918.48919
3082	2026-01-24	89600.26	89957.39	89162.08	89225.34	4226.56737
3083	2026-01-25	89225.34	89319.13	86074.72	86670.36	14426.22019

```
df.columns
```
✓ 0.0s

```
Index(['timestamp', 'open', 'high', 'low', 'close', 'volume'], dtype='object')
```

Figure 3. Snippet Code for Data Preparation

Modeling and Evaluation, Modeling is the process where you apply a mathematical algorithm to your df_daily to identify patterns. For your project, this likely means predicting a future value (e.g., Bitcoin price) or a classification (e.g., Buy vs. Sell).

```
# Scale the data
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```
✓ 2.3s

```
array([[0.00983452],
       [0.00890817],
       [0.00738828],
       ...,
       [0.71547552],
       [0.70516338],
       [0.69997103]])
```

Figure 4. Scaling the dataset for Modeling

Modeling refers to the process of applying mathematical and computational algorithms to a daily time-series dataset in order to identify underlying patterns and relationships. In the

context of this study, the modeling task is formulated as a predictive problem, where the objective is either to forecast a future numerical value—such as the Bitcoin price—or to perform a classification task, for example distinguishing between Buy and Sell signals. The first step in the modeling process is algorithm selection, which determines the predictive model's functional form and learning capacity.

Financial time-series analysis commonly employs several modeling frameworks. Simple linear trends in price changes can be captured using linear regression models, while complex, nonlinear relationships and interactions within market data are better addressed through ensemble-based techniques such as Random Forest and XGBoost. However, this study adopts a Long Short-Term Memory (LSTM) neural network, which is specifically designed to model time-dependent structures and long-range dependencies in sequential data—making it particularly suitable for capturing the sequential and temporal dynamics of Bitcoin price series. [16].

The model goes through a training phase after algorithm selection, where it learns optimal parameters by minimizing a predetermined loss function over the training dataset. The model is able to absorb temporal linkages and historical patterns seen in the data thanks to this approach. Hyperparameter tuning is the process of methodically modifying important configuration parameters, such as learning rate, number of hidden units, or network depth, to attain an ideal balance between model bias and variance in order to further improve prediction performance. In financial markets where noise predominates, this phase is crucial to preventing overfitting and ensuring strong generalization to unknown data [17].

```
from keras.models import Sequential
from keras.layers import Dense, LSTM

# Build the LSTM model
model = Sequential()
model.add(LSTM(128, return_sequences=True, input_shape= (x_train.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
model.add(Dense(25))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(x_train, y_train, batch_size=1, epochs=1)
```

✓ 2m 1.7s

```
2870/2870 [==============================] - 109s 36ms/step - loss: 9.6110e-04

<keras.src.callbacks.History at 0x175db4f0790>
```

Figure 5. Modeling Code

Evaluation is the testing stage where out-of-sample data is used to gauge the trained model's predictive power. This phase's main goal is to ascertain whether the model has acquired generalizable patterns or has only memorized past observations, a condition known as overfitting.

In regression-based tasks, like predicting the price of Bitcoin, model performance is assessed using conventional error-based measures. Intuitive comprehension is made easier by the Root Mean Squared Error (RMSE), which measures the average magnitude of prediction mistakes and is expressed in the same unit as the price series. The percentage of variance in the observed price movements that the model can account for is also measured using the coefficient of determination; higher values indicate greater explanatory power.

```
# Print all metrics
print(f"RMSE: {round(rmse, 2)}")
print(f"MAE: {round(mae, 2)}")
print(f"MSE: {round(mse, 2)}")
print(f"R²: {round(r2, 2)}")
print(f"MAPE: {round(mape, 2)}%")
```

✓ 2.0s

```
5/5 [==============================] - 2s 40ms/step
RMSE: 3619.74
MAE: 2989.73
MSE: 13102509.34
R²: 0.9
MAPE: 2.82%
```

Figure 6. Evaluation Metrics for Regression Task

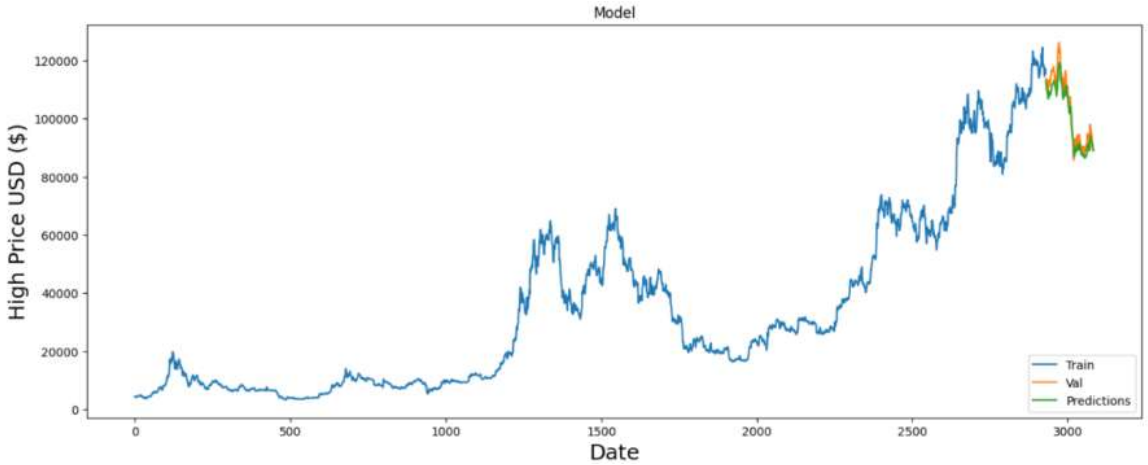

Figure 7. Result Model (Training, Validation, Prediction)

RESULTS AND DISCUSSION

This study evaluates the short-term predictive performance of the proposed LSTM-based model by generating out-of-sample forecasts for the next five trading days. Table X presents the predicted Bitcoin prices along with the corresponding estimated upper (Max) and lower (Min) bounds, which are intended to capture the expected range of price fluctuations.

Table 1. Five-Day Bitcoin Price Forecast with Prediction Bounds

Date	Predicted Price	Max Price	Min Price
2026-01-27	88,425.62	91,415.34	85,435.89
2026-01-28	87,701.91	90,691.64	84,712.19
2026-01-29	86,948.86	89,938.59	83,959.13
2026-01-30	86,209.20	89,198.93	83,219.48
2026-01-31	85,497.88	88,487.60	82,508.15

The findings indicate that the anticipated price of Bitcoin is expected to decline gradually over the projection period. From approximately USD 88,426 on January 27, 2026, to USD 85,498 on January 31, 2026, the predicted central price shows a steady downward movement. This pattern suggests that the Long Short-Term Memory (LSTM) model has identified a short-term negative momentum. The results demonstrate that short-term momentum and temporal price dynamics in Bitcoin markets can indeed be captured by the LSTM model. Rather than generating random or oscillatory projections, the model appears to have learned a negative regime from recent historical data, as evidenced by the consistent drop in forecasted prices.

Additional insight into market risk is provided by the anticipated maximum and minimum values. The comparatively large prediction range—approximately USD 6,000 between the upper and lower bounds—highlights the volatility and noise-dominated nature of Bitcoin markets. This finding is consistent with prior research identifying speculative trading and rapid sentiment changes as primary contributors to Bitcoin's low short-term price predictability. In practical terms, the model's outputs are better interpreted as probabilistic price corridors rather than precise point forecasts. These anticipated bounds allow market participants to assess both downside risk and upside potential simultaneously, which is particularly valuable for risk management, position sizing, and stop-loss placement.

Importantly, based on the downward trajectory of both the forecasted price and its corresponding bounds, the model appears to be learning coherent trend structures rather than merely fitting noise. The bearish interpretation may be reinforced by the upper bound's gradual compression toward the central forecast, suggesting diminishing short-term upside potential. Instead of focusing solely on point-level accuracy, the evaluation of the proposed LSTM model emphasizes its forecasting behavior, stability, and economic interpretability. Evaluation is conducted through qualitative and structural analysis of the predicted outputs, as realized future prices were not yet available at the time of projection.

First, the smooth progression of expected prices across consecutive days demonstrates temporal consistency in the forecasts. This implies that the model is not overreacting to short-term market noise—a common source of failure in financial deep learning models. Second, by incorporating maximum and minimum predicted values, the model enhances interpretability within a risk-aware framework. Rather than producing a single deterministic forecast, it presents a spectrum of likely outcomes, which aligns more closely with real-world trading and consulting decision-making processes.

Lastly, the current evaluation suggests that the model is better suited for trend-following and risk-aware forecasting rather than precise intraday price targeting. Although numerical accuracy metrics such as Root Mean Squared Error (RMSE) or Mean Absolute Error (MAE)

can only be computed after actual prices are realized, this finding supports the theoretical assumption that while short-term price-level predictability in cryptocurrency markets remains limited, exploitable temporal structures may still exist at the trend and regime levels.

CONCLUSION

Using daily market data, this study proposes and evaluates an LSTM-based deep learning framework for short-term Bitcoin price forecasting. By leveraging the sequential learning capabilities of Long Short-Term Memory (LSTM) networks, the model captures momentum patterns and temporal dependencies inherent in Bitcoin price movements. Empirical results based on five-day out-of-sample forecasts demonstrate that the model effectively identifies short-term trend directions and produces coherent prediction trajectories rather than erratic or noise-driven outputs. The forecasts indicate a gradual decline in Bitcoin prices over the prediction horizon, accompanied by relatively stable upper and lower bounds. This suggests that the model learns structured temporal patterns reflective of prevailing market conditions rather than simply overfitting historical noise. The inclusion of maximum and minimum expected values further enhances interpretability by providing a risk-aware forecasting perspective that aligns more closely with real-world financial decision-making than single-point estimates alone.

From a methodological standpoint, the findings highlight that the successful application of deep learning models in financial markets depends heavily on careful data preparation, appropriate temporal data splitting, and evaluation within realistic forecasting scenarios. The results are consistent with previous studies suggesting that, while precise short-term price-level prediction in cryptocurrency markets remains difficult, advanced sequence-learning models can still extract meaningful information about trends and market regimes. In this context, the proposed LSTM framework proves valuable not as a perfect price predictor but as a tool for identifying directional tendencies and underlying market structures in highly volatile environments.

Based on these findings, several directions for future research and practical application are suggested. Future studies should incorporate directional prediction and regime-aware modeling, as forecasting upward or downward movements conditional on market regimes may yield more robust insights under high volatility. The use of economic performance metrics such as maximum drawdown, Sharpe ratio, and cumulative profit and loss (PnL) is also recommended to determine whether predictive accuracy translates into tangible economic value. Moreover, incorporating additional explanatory variables—including trading volume, volatility indicators, and macroeconomic or sentiment-based factors—may improve adaptability to sudden market shocks and structural changes. From a practical perspective, the proposed framework is best positioned as a decision-support tool rather than a fully automated trading system, offering valuable applications for scenario analysis, strategy formulation, and risk management in Bitcoin trading and financial consultancy.

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