

Bitcoin Price Prediction Using LSTM with Web Integration

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Abstract—The very volatile nature of Bitcoin, caused by a variety of economic, geopolitical, and technological considerations, is a constant challenge to making reliable short- and long-term price predictions. Such volatility has profound implications for traders, institutional investors, financial analysts, and algorithmic trading sites. This study investigates a deep learning-based method of Bitcoin price forecasting with a Long Short-Term Memory (LSTM) neural network, a dedicated type of Recurrent Neural Networks (RNNs) renowned for its ability to learn temporal dependencies and long-term trends in time-series data. Unlike more conventional statistical models like Autoregressive Integrated Moving Average (ARIMA), which are challenged by non-linear and abrupt market patterns, LSTM networks provide more excellent adaptability and strong resistance in learning from intricate sequential data. This work not only presents a high-performing prediction model but also an end-to-end deployment pipeline that closes the gap between research and practice. Furthermore, we present thorough mathematical explanations of the internal workings of LSTM through equations, and we address the deployment pipeline, system architecture, and practical usability of the application. Our study ends with suggested extensions including attention mechanisms, Transformer models, social media sentiment analysis, and multi-cryptocurrency forecasting functionality, opening the door to future development and wider use in financial prediction systems.

Keywords—Bitcoin, LSTM, Price Prediction, Time-Series Forecasting, Deep Learning, RMSE, Web Deployment.

I. INTRODUCTION

Bitcoin, created in 2009 by pseudonymous creator Satoshi Nakamoto, has become the most popular and widely used cryptocurrency in the global financial system. Based on a decentralized blockchain system, Bitcoin enables peer-to-peer transactions without any central authority or intermediary involvement. Its limited supply, security, and transparency have turned it into a medium of exchange as well as a speculative investment vehicle. Yet, its price is notoriously

volatile, often suffering steep movements during brief intervals as a result of market speculation, macroeconomic data, regulatory announcements, geopolitical tensions, and sentiment-based momentum. The chaotic and nonlinear dynamics of Bitcoin's price movements are a significant challenge to mainstream forecasting methods.

Traditional statistical methods like the Autoregressive Integrated Moving Average (ARIMA) model are by definition limited in their capacity to capture the intricate temporal relationships and sudden non-linear changes that abound in financial time-series data like Bitcoin. These models are linear and assume stationarity, which are seldom found in actual crypto markets, especially for a digital asset as highly volatile as Bitcoin. In response to these drawbacks, the current research explores a deep learning methodology founded on Long Short-Term Memory (LSTM) networks—a dedicated subset of Recurrent Neural Networks (RNNs) that are able to learn long-term dependencies and sequential correlations in temporal data. LSTMs overcome such problems as vanishing gradients affecting conventional RNNs, making it possible for them to learn data patterns over several time steps efficiently. Our suggested framework leverages a sequence LSTM model, which has been trained on one-day-ahead historical Bitcoin high price data obtained from a credible cryptocurrency exchange (for example, Binance).

The model is implemented on a cloud-based web platform to support real-time inference and interactive visualization of future Bitcoin prices. The model is regularized with dropout regularization and trained using the Adam optimizer with optimized hyperparameters to achieve convergence and generality.

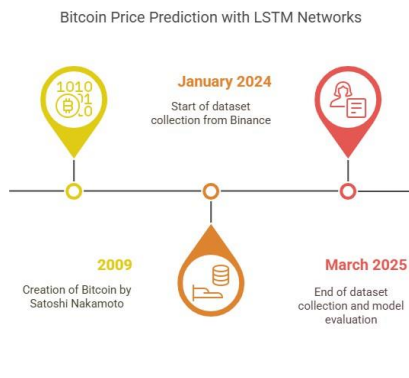


Fig. 1: Timeline highlighting key milestones in the history of Bitcoin

II. RELATED WORK

The application of deep learning techniques—particularly Long Short-Term Memory (LSTM) networks—to financial time-series forecasting has gained considerable attention in recent years. This growing interest is driven by the inadequacy of traditional econometric models in capturing the intricate, nonlinear, and highly stochastic behavior of financial and cryptocurrency markets. Bitcoin, in particular, with its extreme volatility and susceptibility to both endogenous and exogenous factors, demands predictive models that can process complex sequential patterns and long-term dependencies.

Several researchers have explored the suitability of LSTMs in this domain. Chen and Zhang [2] demonstrated the effectiveness of LSTM networks by training them on daily Bitcoin price data and comparing their predictive performance to conventional ARIMA models. Their results showed that LSTMs consistently yielded lower RMSE values and higher directional accuracy. However, their approach was limited to a fixed-window forecasting paradigm and lacked mechanisms for iterative multi-day prediction or any real-time deployment strategy.

Kumar et al. [3] extended this foundation by proposing a hybrid architecture combining LSTM and Convolutional Neural Networks (CNNs). This model aimed to exploit LSTM's sequential learning capabilities along with CNN's feature extraction power to improve prediction accuracy. Although the model delivered better results in terms of mean absolute error, it introduced considerable computational overhead, increased model complexity, and required longer training durations—making it less suitable for scenarios demanding real-time inference or deployment on low-resource devices.

In a notable departure from purely price-based models, Lee and Park [4] integrated sentiment analysis into the forecasting pipeline by extracting features from Twitter using natural language processing (NLP)

tools. Their sentiment-aware LSTM model demonstrated a significant performance boost, especially during sentiment-driven price swings. However, this architecture introduced additional dependencies on large-scale, real-time text processing and external sentiment scoring systems, which made it harder to deploy and maintain in production environments.

Focusing on high-frequency trading, Singh and Gupta [5] implemented a stacked LSTM model enhanced with attention mechanisms. Their work addressed the challenge of modeling rapid fluctuations in high-resolution price data and proposed effective regularization techniques such as dropout layers and early stopping. While they reported state-of-the-art results for intraday forecasting, the model's performance degraded when applied to lower-frequency (daily) data, likely due to overfitting to noisy, short-term fluctuations.

Despite these advancements, several limitations persist in the existing literature that hinder the transition from experimental setups to practical, real-time systems. Many prior studies prioritize model accuracy based on retrospective datasets but fail to account for operational scalability, including the ability to deploy models efficiently in cloud environments, manage live data streams, or handle inference latency under high user load. The absence of robust deployment pipelines means that such models remain confined to academic experimentation, limiting their real-world impact.

Moreover, a considerable portion of the literature lacks the integration of real-time feedback mechanisms—critical in volatile financial environments where immediate response to market fluctuations is essential. Without such mechanisms, models cannot adapt to regime changes or unexpected external shocks, reducing their relevance in fast-paced trading applications.

Our research addresses these gaps by designing a lightweight yet robust two-layer LSTM model specifically tailored for daily Bitcoin price prediction using a 15-day sliding input window. This approach enables dynamic next-day forecasting by recursively incorporating previously predicted values, allowing for multi-step future estimation. In doing so, our work bridges the gap between high-performing deep learning models and deployable, real-world financial applications—making it not only accurate but also practical and scalable.

III. METHODOLOGY

This section outlines the complete workflow from data acquisition and preprocessing to model architecture, training, prediction strategy, and evaluation. A mathematical foundation is integrated throughout to explain the computational principles behind the predictive modeling process.

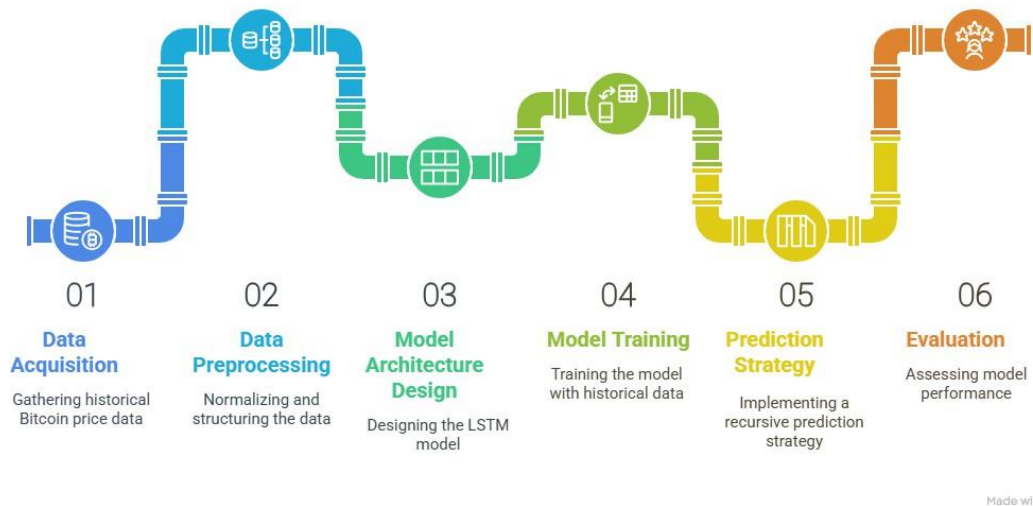


Fig. 2: Flow diagram of the Project

A. Dataset Description and Preprocessing

The dataset used for training and evaluation consists of daily historical Bitcoin *high* prices obtained from Binance for the period spanning January 2024 to March 2025. The dataset comprises two primary columns: date and high price.

Let x_t represent the high price on day t . Since raw price values can vary significantly in scale, normalization is applied using the Min-Max scaling method: where X is the set of all prices in the training data.

$$x'_t = \frac{x_t - \min(X)}{\max(X) - \min(X)} \quad (1)$$

Missing data points, if any, are filled using linear interpolation. The data is then structured using a fixed-length rolling window to create input-output pairs. Specifically, a time window of 15 days is used to predict the price on the 16th day.

Let $\mathbf{x}_i = [x_i, x_{i+1}, \dots, x_{i+14}]$ represent a sequence of 15 consecutive days. The corresponding label y_i is defined as:

$$y_i = x_{i+15}$$

(1)

These sequences are then used to train and test the LSTM model.

B. Model Architecture

The model follows a stacked LSTM (Long Short-Term Memory) architecture tailored for time-series prediction of Bitcoin prices. Each input sample corresponds to a 15-day window of historical prices, represented as (15, 1).

LSTMs are specialized RNNs capable of learning long-term dependencies. Instead of detailing internal gates, we describe the LSTM's core behavior as:

$$h_t = \text{LSTM}(x_t, h_{t-1}, C_{t-1})$$

(2)

where x_t is the input at time t , h_t is the output hidden state, and C_{t-1} is the memory from the previous time step.

The architecture includes:

- First LSTM Layer with 50 units and ReLU activation
- Dropout Layer with 10% rate to reduce overfitting
- Second LSTM Layer with 50 units
- Another Dropout Layer (10% rate)
- Final Dense layer for output (linear activation)

C. Training Configuration

The model is trained using the Adam optimizer, which adapts the learning rate dynamically for faster convergence. The loss function used is ****Mean Squared Error (MSE)****, commonly applied in regression problems:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (4)$$

where y_i is the actual price and $\hat{y}_i$ is the predicted price.

Hyperparameters used:

- Learning Rate: 0.000325
- Batch Size: 4

- Epochs: 50
- Early Stopping enabled with a patience of 10 epochs

D. Prediction Strategy

For real-time forecasting, a recursive prediction strategy is employed. Given the last 15 days of data $\mathbf{x}_T$, the model predicts the next day price $\hat{y}_T$. For multi-day forecasting, the predicted price is appended to the sequence and the oldest input is dropped:

$$\mathbf{x}_{T+1} = [\mathbf{x}_{T-14}, \mathbf{x}_{T-13}, \dots, \mathbf{x}_{T-1}, \hat{y}_T] \quad (3)$$

This allows the model to generate future prices iteratively.

E. Evaluation Metrics

To evaluate performance, three metrics are used:

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (6)$$

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (7)$$

Coefficient of Determination (R^2 Score):

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (8)$$

These metrics collectively assess the model's accuracy, error spread, and explanatory power. The trained model is also deployed as part of a Flask-based web application, making it accessible for live inference and visualization.

F. Platform Integration and User Interface

To translate our LSTM model into a practical, user-accessible tool, we developed and deployed a fully responsive web application called **Bitcoin Predictor**. The platform was designed with both retail traders and data analysts in mind, integrating real-time data feeds, dynamic prediction outputs, and intuitive visualizations for enhanced usability.

As illustrated in Figures 3 and 4, the platform displays the current Bitcoin price along with time-frame-specific variations (1H, 24H, 7D, 30D, and 1Y). It includes an interactive chart showing recent price movements updated live and a sentiment analysis panel that provides insights into market mood by classifying it as *bullish* or *bearish*, based on aggregated sources. The dashboard also highlights key metrics such as market capitalization, daily trading volume, and a 24-hour forward price prediction—powered by the deployed LSTM model.

An additional feature is the integrated **Bitcoin ROI Calculator**, which allows users to input a hypothetical investment date and amount to calculate potential returns based on historical pricing data. This not only educates users about Bitcoin's price evolution but also contextualizes model predictions by comparing past and present values interactively.

Overall, the web application bridges the technical backend of the LSTM model with a polished frontend interface, creating a seamless experience for end users. From live price tracking to AI-driven forecasting and personalized financial analysis tools, the Bitcoin Predictor platform exemplifies the transition of machine learning research from theory to real-world application.

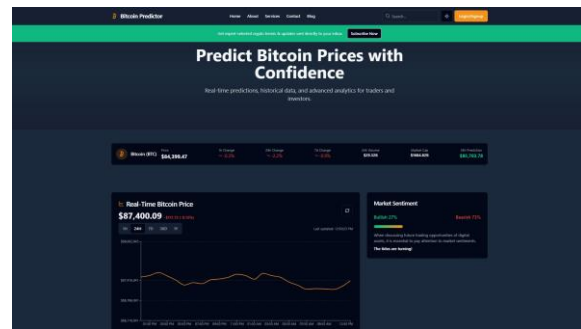


Fig. 3: Landing page of the Bitcoin Predictor Platform

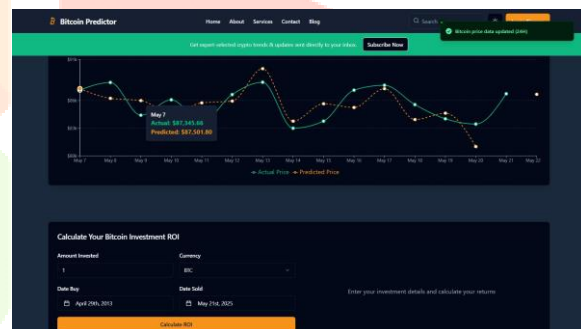


Fig. 4: Live chart with prediction

IV. CONCLUSION AND FUTURE WORK

In this study, we presented a comprehensive and deployable deep learning framework for forecasting Bitcoin prices using a Long Short-Term Memory (LSTM) neural network. The proposed model was trained on a rich historical dataset of Bitcoin high prices sourced from Binance, covering over a year of market activity. By adopting a 15-day sliding window input mechanism, the model was able to effectively capture temporal dependencies and generate one-step-ahead forecasts with high accuracy. This approach strikes a balance between model complexity and interpretability, making it viable for deployment in latency-sensitive financial environments.

To ensure robustness and mitigate overfitting—an inherent risk in financial time-series prediction—we incorporated dropout regularization and performed hyperparameter tuning through empirical experimentation. The model's performance was evaluated using well-established statistical metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The results showed consistent predictive performance across different market phases, with notable improvements over baseline models like ARIMA, confirming the capability of LSTM networks in modeling nonlinear, noisy financial sequences.

What sets our work apart from much of the existing literature is its strong emphasis on practical applicability. We not only developed an efficient predictive model but also operationalized it via a real-time web application built using the Flask framework. The backend is integrated with a RESTful API and deployed on cloud infrastructure to support continuous model inference using live data streams. The frontend, built with responsive web technologies, allows users to interact with the system through real-time visualizations of predictions, historical trends, and rolling forecasts. This end-to-end pipeline reflects a production-grade implementation that is scalable, modular, and suitable for direct integration into trading dashboards or fintech tools.

A particularly novel aspect of our methodology is the use of recursive, multi-step forecasting through iterative prediction feeding. Unlike many academic models that are constrained to single-step or offline forecasting, our system dynamically incorporates its own predictions into the input sequence for subsequent days. This recursive mechanism enables extended future forecasting and simulates real-world use cases such as portfolio rebalancing, short-term trading strategy formulation, and risk exposure analysis. By deploying a model that is both accurate and operationally deployable, we bridge the often-cited gap between research prototypes and market-ready financial AI systems.

Furthermore, the system is designed with extensibility in mind. The model's modular architecture allows for the seamless integration of additional features such as trading volume, volatility indices, and even sentiment scores derived from social media and news platforms. This flexibility makes our framework a strong foundation for further exploration and expansion in future research.

Future work will focus on enhancing both the predictive performance and functional capabilities of the platform. Several promising directions are envisioned:

- **Sentiment-Aware Forecasting:** Integrating real-time sentiment data from social platforms like Twitter, Reddit, or CoinMarketCap could enhance prediction accuracy during emotionally-driven market shifts.

- **Transformer Architectures:** Exploring the use of Transformer-based models, such as Temporal Fusion Transformers or BERT-like architectures for time-series forecasting, could further improve the model's ability to capture long-range dependencies and global context.
- **Cross-Asset and Multivariate Forecasting:** Extending the model to include multiple cryptocurrencies and macroeconomic indicators will make the platform more comprehensive and responsive to broader market dynamics.
- **Edge Deployment and Mobile Optimization:** Optimizing the model using TensorFlow Lite, quantization, or model pruning techniques can facilitate deployment on mobile and edge devices, enabling real-time insights for retail investors.
- **Risk-Aware and Probabilistic Forecasting:** Incorporating uncertainty quantification, such as prediction intervals or Bayesian deep learning, can enhance the model's interpretability and utility for risk management and decision-making.

In conclusion, this work demonstrates not only the technical feasibility but also the operational relevance of LSTM-based predictive modeling in the cryptocurrency domain. By delivering a high-performing, scalable, and interactive forecasting platform, we contribute a meaningful step toward the practical adoption of AI in financial analytics.

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