“Enhancing cryptocurrency price forecasting: Performance evaluation of baseline versus Bayesian-optimized LSTM models”

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ENHANCING CRYPTOCURRENCY PRICE FORECASTING: PERFORMANCE EVALUATION OF BASELINE VERSUS BAYESIAN-OPTIMIZED LSTM MODELS

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Abstract

Cryptocurrency markets are highly volatile, making price prediction a complex yet essential task for investors, financial engineers, and institutions. The purpose of this study is to evaluate whether Bayesian optimization of technical indicator parameters significantly improves the forecasting performance of Long Short-Term Memory (LSTM) models compared to baseline configurations. The study used daily Bitcoin and Ethereum price data from January 2016 to September 2025. Six technical indicators representing trend, momentum, volatility, and volume-based technical indicators are constructed and dynamically optimized through Bayesian optimization. The optimized indicators are then used as inputs to an LSTM forecasting framework. The study found that the baseline LSTM model achieved moderate predictive accuracy, where Ethereum outperformed Bitcoin. After optimization, both models exhibited improved performance, reducing the forecasting error for Bitcoin by 36.4% and for Ethereum by 12.2%. LSTM model with Bayesian optimized indicators showed a higher forecasting accuracy as compared to the baseline model, with 32% and 18.6% improvements for Bitcoin and Ethereum, respectively. These findings suggest that combining optimized technical indicators with LSTM models enhances predictive power in cryptocurrency markets. The approach offers a robust forecasting framework for traders, analysts, and algorithmic systems in high-volatility environments.

Keywords cryptocurrency, forecasting, optimization, technical indicators, Bayesian, accuracy

JEL Classification C53, C45, G17

Conflict of interest statement:
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INTRODUCTION

The accuracy of predicting future cryptocurrency prices has gained significant interest in the recent past. This is because of the inherent volatility and speculative nature of digital currencies. The evolving nature of cryptocurrency markets raises unresolved challenges in forecasting price movements accurately and reliably. There are also high volumes of data generated in the crypto market, which is mainly attributed to the current digital revolution. Effective handling of this huge crypto data in the volatile market to generate insights is a challenging adventure (Alghamdi et al., 2025). Cryptocurrencies have unique features of volatility, decentralized character, and increasing economic significance. These properties have led to considerable research interest in global financial markets (Bouri et al., 2021). Assets like Bitcoin and Ethereum are traded globally in high volumes (CoinMarketCap, 2024). They exhibit extreme price fluctuations, making them both attractive and challenging for investors and analysts. This unpredictability is driven not only by market forces but also by news cycles, public sentiment, and the absence of centralized regulation (Kristoufek, 2015).

Despite this growing interest from investors, researchers, and financial engineers in cryptocurrency forecasting, accurately modeling and forecasting these markets' behaviors remains an unsolved scientific problem. The decentralized and highly reactive nature of digital assets means that traditional financial models such as GARCH and ARIMA frameworks often fail to capture the non-linear and regime-shifting behaviors of these markets (Baur & Dimpfl, 2018; Corbet et al., 2019). Moreover, the influence of externalities, speculative bubbles, and irrational trading behaviors introduces substantial noise into the data, further complicating predictive efforts. Even advanced models such as LSTM networks, while capable of learning time-based patterns, often underperform without proper feature selection or tuning, especially in environments with rapid regime shifts and unpredictable volatility.

Despite ongoing research, forecasting cryptocurrency prices remains an open scientific problem due to the difficulty in extracting stable and meaningful predictive patterns from complex and unstable environments. While there are huge amounts of data available, its volatility and sensitivity to unstructured factors such as social media trends make it difficult to model using standard techniques. As such, there remains a critical need for models that can dynamically adapt to shifting market conditions, while maintaining accuracy, interpretability, and robustness in the face of noise and speculation.

1. LITERATURE REVIEW

The rapid growth and volatility of cryptocurrency markets are challenging both traditional and modern financial forecasting models, prompting increasing academic interest in advanced prediction frameworks. Understanding how forecasting techniques have evolved, especially in crypto contexts, is key to addressing ongoing gaps in predictive accuracy. Cryptocurrency markets differ fundamentally from traditional financial markets due to their extreme volatility, decentralized structure, and rapid information diffusion. These characteristics create unique challenges for price forecasting, as cryptocurrency returns often exhibit nonlinear dynamics, volatility clustering, and frequent regime shifts (Katsiampa, 2019). Still, these markets are highly volatile and feature a lack of liquidity in certain tokens as well as a response to market sentiment and regulatory news (Kristoufek, 2015; Corbet et al., 2019). Compared to traditional financial markets, cryptocurrencies lack an underlying earnings report or economic indicator to drive them. Rather, price trends are usually mirrored by social media tendencies, network, and behavioral indicators (Baur & Dimpfl, 2018). Also, there are no definite regulatory controls and price checks in this market, which, as shown in Amirzadeh et al. (2023), predisposes to price manipulation and speculative bubbles. These aspects bring about special difficulties for researchers and traders working to formulate proper forecasting models. Consequently, more advanced, information-intensive solutions like machine learning and deep learning are also being considered in the case of learning and forecasting price behavior in this field.

One widely adopted strategy in financial engineering forecasting is the use of technical indicators, which summarize historical price and volume data into interpretable patterns of market behavior. In financial forecasting research, these indicators serve as feature-engineering tools that translate raw market data into structured inputs for predictive models. The major assumption of the technical analysis is that all the relevant information is already taken into consideration in the price movements (Achelis, 2001), and the past patterns have a high chance of happening again. Due to their assumptions and inherent strengths, technical indicators are widely adopted in financial forecasting. In empirical research, technical indicators often serve as feature-engineering tools rather than standalone trading rules. Several studies show that incorporating technical indicators as inputs to statistical and machine learning models improves predictive accuracy by enhancing the representation of nonlinear market dynamics (Atsalakis & Valavanis, 2009; Patel et al., 2015a).

In the context of cryptocurrencies, momentum and volatility indicators have shown particular value due to the markets' speculative and reactive nature. There are various inefficiencies in the Bitcoin market in the short term, which could suitably be addressed by technical strategies (Urquhart, 2016). Katsiampa (2019) further observed that the co-movement of the volatility of Bitcoin and Ether implies that conventional volatility models may still be useful in crypto-related situations. According to Amirzadeh et al. (2023), the effectiveness of technical indicators depends critically on the choice of parameter settings. Research shows that default or heuristic parameter values borrowed from traditional financial markets may not be optimal for rapidly evolving cryptocurrency environments (Guo, 2025). This limitation highlights the importance of adaptive approaches that optimize technical indicator parameters in response to market conditions, especially when indicators are integrated into deep learning-based forecasting frameworks.

The limitations of traditional statistical models have driven researchers toward deep learning approaches. The emergence of deep learning has led to significant improvements in time-series modeling, particularly through Recurrent Neural Networks (RNNs) and their advanced variants such as LSTM networks. These models can capture long-range dependencies and nonlinear dynamics. These features make them suitable for complex financial data forecasting (Patel et al., 2015a). In cryptocurrency forecasting, LSTM has shown great potential, but its success is often contingent on the choice and structure of input features (Hochreiter & Schmidhuber, 1997). LSTM-based models are better than random forests and logistic regression predictors of the returns of S&P 500 constituents. While LSTM models outperform methods like logistic regression or random forests (Fischer & Krauss, 2018), their performance still hinges on the quality of input features and architecture design.

Recent studies have explored combining LSTM models with technical indicators to leverage both sequential learning and engineered market features. The resultant hybrid model is considered to have a high prediction accuracy because technical indicators give an alternate perspective of market data encompassing price movement, momentum, market strength, and volatility. Studies show that machine learning (ML) models trained on these indicators (Ballings et al., 2015; Amirzadeh et al., 2023) outperform models using only raw price and volume data. The strategic use of optimal indicators in ML models can enhance forecasting accuracy by up to 15% (Patel et al., 2015b). When combined with algorithms like LSTM, these features enable the identification of non-linear correlations and trends, leading to better results than standard neural networks (Nelson et al., 2017). However, a key limitation in current deep learning-based systems is the lack of optimization for both features (technical indicators) and hyperparameters, as most rely on default or manually selected values. This inspires the need for incorporating sophisticated optimization schemes, such as Bayesian optimization, to achieve optimal performance.

To further enhance forecasting accuracy, researchers have explored hyperparameter optimization techniques for deep learning models. Hyperparameter optimization is a critical factor determining the predictive accuracy of deep learning models like the LSTM network, where parameters such as the learning rate, neuron count, and batch size significantly influence performance. Recent literature has explored the use of optimization techniques such as Grid Search, Random Search, and, more recently, Bayesian Optimization to improve predictive accuracy (Shah & Zhang, 2014; Snoek et al., 2012). Bayesian optimization has emerged as a powerful approach for tuning model parameters and feature configurations in complex machine learning systems. By combining probabilistic modeling with sequential learning, Bayesian optimization efficiently explores the parameter space and balances exploration with exploitation (Xu et al., 2025; Pandya & Jaliya, 2022). A study by Guo (2025) showed that the forecasting accuracy of stock markets using technical indicators is greatly improved when the optimization of technical indicators is done using Bayesian optimization. Bayesian optimization is considered powerful due to its adaptiveness in learning assets and market regimes, efficiency in fast convergence, and generalizability (Snoek et al., 2012).

Although prior studies demonstrate the effectiveness of LSTM models and technical indicators in financial forecasting, most existing research relies on static indicator parameters and manually tuned configurations. This limits the adaptability of forecasting models in rapidly evolving markets

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such as cryptocurrencies. The limited integration of adaptive optimization techniques with deep learning frameworks represents a critical gap that motivates the present study. Therefore, the purpose of this study is to develop and empirically evaluate a forecasting framework that integrates Bayesian optimization of technical indicator parameters with LSTM neural networks, and to compare its predictive performance against baseline and benchmark models in cryptocurrency markets.

2. METHODS

2.1. Research design

This section discusses the processes and techniques adopted in the analytical process. It discusses the step-by-step process used to forecast cryptocurrency prices using an LSTM-based model with Bayesian Optimization of technical indicator parameters. The study was quantitative and experimental in nature (Creswell & Creswell, 2017). Training, refining, and evaluation of predictive models were done using past cryptocurrency price data. The study tested the effectiveness of optimized technical indicators when used in an LSTM neural network to predict cryptocurrency prices. The study was carried out in four steps: data collection and preprocessing; calculation of technical indicators using feature engineering; Bayesian optimization of indicator parameters; and lastly, training and evaluation of the LSTM model.

2.2. Data collection

The analysis was based on secondary daily cryptocurrency data of both Bitcoin and Ethereum. The data was obtained from Yahoo Finance, which is considered a reliable database. Variables used were OHLCV: Open, High, Low, Close, and Volume. Two main factors were considered in selecting the two-crypto series of Bitcoin and Ethereum: (1) Bitcoin has a huge market capitalization and a long history of operation; and (2) Ethereum has a substantial market share and strong smart-contract infrastructure. The data were collected between 1 April 2016 and 23 September 2025, which included various market regimes. The dataset has been deposited in Zenodo under DOI (10.5281/zenodo.18360564). This dataset was not used in any prior publications. They included the bull markets of late 2017 and 2021, the bear market of early 2018, and the high-volatility regime of the COVID-19 pandemic in 2020. This wide time frame was used to make sure that the study had generalizable market trends.

2.3. Feature engineering

Raw OHLCV data were transformed into optimized technical indicators using Bayesian Optimization (BO) to improve model input quality. The final feature vector for the LSTM comprises 6 selected, parametric indicators across trend, momentum, volatility, and volume categories.

(a) (Simple Moving Average (SMA) – *Trend Indicator*

$$SMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} Close_{t-i}. \quad (1)$$

For the parameter to optimize, the model used a window size $n \in [5, 100]$.

(b) Exponential Moving Average (EMA) – *Trend Indicator*

$$EMA_t(n) = \alpha \cdot Close_t + (1-\alpha) SMA_{t-1}, \quad (2)$$

where $\alpha = \dfrac{2}{n+1}$.

The parameter optimization window size was $n \in [5, 100]$.

(c) Relative Strength Index (RSI) – *Momentum Indicator*

RSI measures the magnitude of recent gains to losses over a specified window n, identifying overbought and oversold conditions.

$$RSI_t(n) = 100 - \left(\frac{100}{1+RS_t}\right), \quad (3)$$

where $RS_t = \bar{U}_t / \bar{D}_t$, $\bar{U}_t$ and $\bar{D}_t$ refer to the smoothed average gains and losses over n days. The parameter optimization range is $n \in [5, 30]$.

(d) Bollinger Bands (BB) – *Volatility Indicator*

$$BB_{upper,t} = SMA_t(n) + k \cdot \sigma_t(n), \tag{4}$$

$$BB_{lower,t} = SMA_t(n) + k \cdot \sigma_t(n), \tag{5}$$

where $\sigma_t(n)$ is the standard deviation of price over n, while k is the number of standard deviations to be optimized. The optimization ranges were $n \in [10,\ 50]$, $k \in [1,\ 3]$. *BB* was considered suitable because it captures market volatility; in crypto, extreme expansions/contractions often precede major breakouts.

(e) Average True Range (ATR) – *Volatility Indicator*

$$TR_t = max\begin{pmatrix} P_{high,t} - P_{low,t}, \\ \left|P_{high,t} - P_{close,t-1}\right|, \\ \left|P_{low,t} - P_{close,t-1}\right| \end{pmatrix}, \tag{6}$$

$$SMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} TR_{t-1}. \tag{7}$$

The *ART* is a volatility indicator used to measure market volatility, where a higher ATR means higher risk or uncertainty. The optimization range is $n \in [5,\ 30]$. ATR provides insights into market risk and helps account for extreme volatility events.

(f) On-Balance Volume (OBV) – *Volume Indicator*

$$OBV_t = \begin{cases} OBV_{t-1} + V_t \ \ if\ Close_t > Close_{t-1} \\ OBV_{t-1} - V_t \ \ if\ Close_t < Close_{t-1} \\ OBV_{t-1}\ other\ wise \end{cases}. \tag{8}$$

The On-Balance Volume (OBV) is a cumulative volume tool that incorporates price direction, showing if rising prices have strong trading activity. Lagged indicators (1, 3, 7 days) were used as features. The target was the next day's closing price $(Close_{t-1})$, with a binary price movement check (classification).

2.4. Bayesian optimization

This study adopted Bayesian Optimization as the parameter optimization strategy. The optimization problem is specified as follows.

$$\theta^* = \arg\min_{\theta \in \Theta} L\left(y, \hat{y}(\theta)\right), \tag{9}$$

where θ is the set of indicator parameters, such as RSI period, Bollinger Band width, $\hat{y}(\theta)$ is the LSTM predictions using indicators with parameters θ, while $L(\cdot)$ is the loss function. The objective is to minimize prediction error (*RMSE*) on validation data by choosing the best combination of indicator parameters.

The *BO* framework was carried out in two stages – surrogate modelling and acquisition function optimization. For the surrogate model used to estimate the true objective function, Gaussian Process (*GP*) prior was used. The model approximates the unknown objective function $f(\theta)$ as follows.

$$f(\theta) \sim GP\left(\mu(\theta),\ k(\theta, \theta')\right) \tag{10}$$

where the $\mu(\theta)$ is the mean function (prior belief of function value), while $k(\theta, \theta')$ is the kernel function such as Radial Basis Function or Matérn kernel) defining covariance between parameters.

For the acquisition function optimization, the next hyperparameter set θ_{t+1} was chosen by maximizing an acquisition function $a\left(\theta \middle| D_{1:t}\right)$, which balances exploration and exploitation. The acquisition function adopted was the Expected Improvement (EI) specified as follows

$$EI(\theta) = E\left[max\left(0, f_{best} - f(\theta)\right)\right], \tag{11}$$

where f_{best} represents the best observed value so far, while $f(\theta)$ is modeled as a normal distribution: $N\left(\mu(\theta),\ \sigma^2(\theta)\right)$. The closed form of the expected improvement was specified as follows

$$\begin{aligned} EI(\theta) &= \left(\mu(\theta) - f_{best}\right)\Phi(Z) \\ &+ \sigma(\theta)\phi(Z), \end{aligned} \tag{12}$$

where $Z = \left(\sigma(\theta) - f_{best}\right) / \mu(\theta)$, Φ and ϕ refers to the CDF and PDF of the standard normal distribution, respectively.

The search space θ was defined over the tunable parameters of the selected indicators. Each indicator configuration defines a unique feature set,

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which is fed into the LSTM model. The LSTM hyperparameters were as follows. The units per layer [50-100], the dropout rate [0.1-0.5], the learning rate of 0.0001-0.01, the batch size of 32-128, and the epochs of up to 200 with early stopping.

For the stopping criteria, the BO loop stopped when a fixed number of iterations is reached such as 50-100), or improvement in the objective falls below a threshold ε for k consecutive iterations. This helped balance the computational cost with diminishing returns.

2.5. LSTM Model

The LSTM model forecasts next-day cryptocurrency prices using optimized technical indicators and historical data. The model uses a 3D tensor input (samples, time steps, features) and stacked LSTM layers to extract temporal dependencies, where each unit's cell state (C_t) and hidden state $\left(h_t^{**}\right)$ are updated via gates.

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, xt\right] + b_f\right), \tag{13}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1},\ xt\right] + b_i\right), \tag{14}$$

$$\tilde{C}_t = tahn\left(W_C \cdot \left[h_{t-1},\ xt\right] + b_C\right), \tag{15}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \tag{16}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1},\ xt\right] + b_0\right), \tag{17}$$

$$h_t = o_t \odot tahn\left(C_t\right), \tag{18}$$

where σ is the sigmoid activation, $\odot$ is the element-wise multiplication, and W, b is the learnable weights and biases. The units were made up of 50–100 LSTM cells per layer, while the activation used was $tahn$ for hidden layers, and $linear$ or $sigmoid$ for output.

The model added a dropout layer with a rate between 0.2–0.5 to prevent overfitting.

$$Dropout(x) = \begin{cases} 0 \ with\ probability\ p \\ \dfrac{x}{1-p} \ with\ probability 1-p \end{cases}. \tag{19}$$

The objective was a loss function optimization problem, aimed at minimizing the mean squared error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2, \tag{20}$$

where y_i is the actual price and $\hat{y}_i$ is the predicted price. The Adam optimizer was adopted to update model weights, with a learning rate of $10^{-4} - 10^{-2}$ that was BO-tuned. To prevent overfitting, early stopping was used. Monitoring was done through validation loss, and training was done up to 200 epochs, with patience of 20 on validation loss, then the model automatically reverts to the weights with the lowest validation loss.

2.6. Model evaluation

The Bayesian-optimized LSTM forecasting model was evaluated to ensure reliability, generalizability, and comparative validity. Root Mean Square Error (RMSE) was the first to be used for measuring the average error.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2}. \tag{21}$$

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

Mean Squared Error (*MSE*) was also used to evaluate the average of the squares of errors.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2. \tag{22}$$

The last metric used was Mean Absolute Error (MAE) to measure the average of the absolute errors.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - \hat{y}_i\right|. \tag{23}$$

3. ANALYSIS AND RESULT INTERPRETATIONS

This chapter presents the data preprocessing steps, the results from the Bayesian Optimization of the technical indicators, the performance evaluation of the proposed LSTM forecasting model, and a comparative analysis against benchmark models. The descriptive results are summarized in Table 1. The statistics show differing volatility between the two, with Bitcoin recording the highest mean price of $29,033 for the period covered.

Table 1. Descriptive statistics of the data

	Open	High	Low	Close	Volume
Bitcoin					
count	3463	3463	3463	3463	3463
mean	29000	29613	28356	29032	17.83
std	30205.5	30719.8	29677.3	30235.6	185.8
min	415.6	416.9	412.4	415.6	0.0
max	123313.6	124436.8	118959.9	123323.4	4470.0
Ethereum					
count	3463	3463	3463	3463	3455
mean	1361.7	1400.5	1319.8	1362.9	8.8
std	1291.3	1325.3	1254.5	1292.0	83.9
min	6.7	7.3	5.9	6.7	0.0
max	4831.2	4955.9	4717.6	4831.2	1790.0

Note: Annualized volatility (approximate). Bitcoin = 21.27%; Ethereum = 44.45%.

Ether has a greater return variability (std = 0.445) than Bitcoin (std = 0.213), and this is consistent with its greater annualized volatility of 44.45 percent relative to Bitcoin at 21.27 percent. Both have returns that are concentrated around zero with heavy tails, but Ethereum has more extreme outliers (maximum return 10, minimum 0.98), reflecting more speculative dynamics.

The boxplots (Figure 1) indicate that both the Bitcoin and Ethereum prices have a large number of outliers, which indicates extreme spikes in the bullish periods. The median in both assets is closer to the lower quartile, which is a sign of right-skewed distributions that are motivated by upward surges. Bitcoin is more widely dispersed in price, whereas Ethereum is more compressed but volatile. Both are very irregular in terms of trading volumes and have numerous extreme outliers, which show sudden bursts of activity.

To train deep learning LSTM models, all features were first normalized using MinMaxScaler on numerical columns (Open, High, Low, Close, Volume) to the [0, 1] range for equal scaling and faster convergence. Due to high right-skewness, Volume was log-transformed (log1p) before scaling to reduce outlier impact and stabilize variance. The time-series data was then restructured into a supervised format using a 60-day sliding window. The model learns from the previous 60 timesteps to predict the next day's closing price $\left(Close t_{t+1}\right)$. This generated 3-D input tensors (samples, timesteps, features) for efficient loading.

The technical indicators for both coins captured different dimensions of market behavior. Trend following indicators include the 20-day SMA and EMA. The momentum was represented by the 14-day RSI and the Stochastic Oscillator %K. For volatility assessment, Bollinger Bands (20-day window with 2 standard deviations) and ATR were calculated. OBV was computed using the transformed log of volume and closing price data to capture price-volume alignment. All indicators were visualized alongside price data to verify correctness and temporal consistency. The enhanced datasets were saved for downstream use in model training and feature optimization. The figures for SMA, EMA, Bollinger Bands, and ATR are shown in Figures 2, 3, and 4.

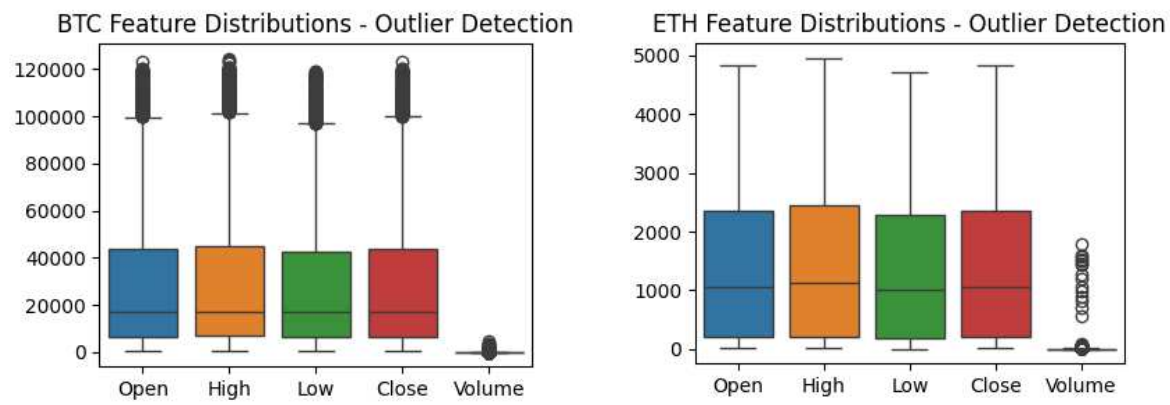

Figure 1. Boxplots for detecting outliers in key numeric features

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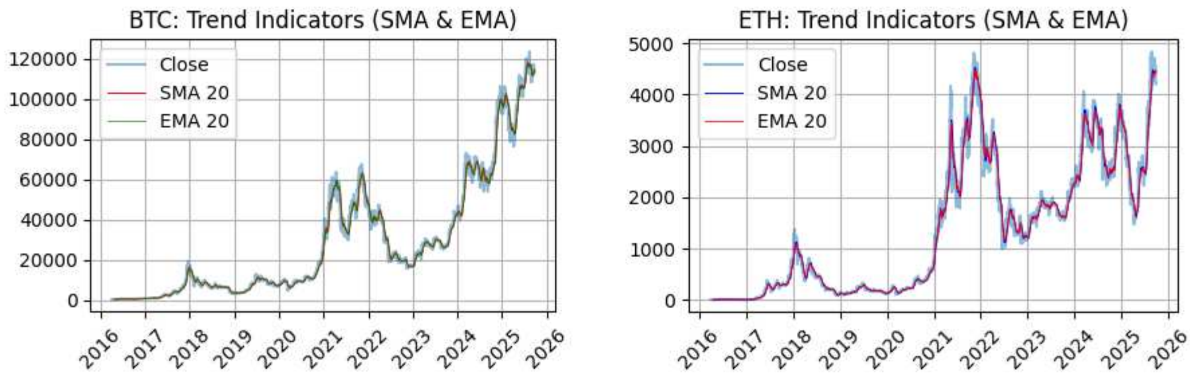

Figure 2. Technical indicators trends for SMA and EMA for BTC and ETH

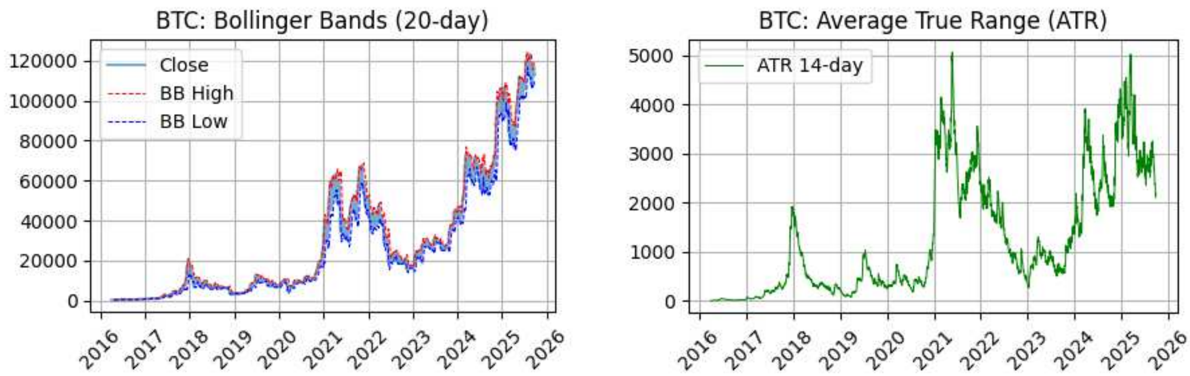

Figure 3. Technical indicators trends for Bollinger bBands and ATR for BTC

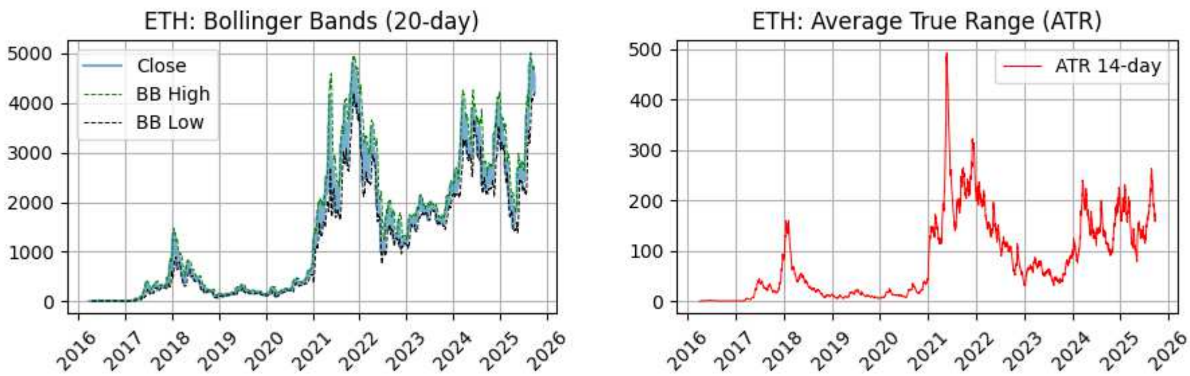

Figure 4. Technical indicators trends for Bollinger Bands and ATR for BTC

The target variable was constructed in two formats; first was the primary regression to predict the next-day closing price of each asset $(Close_{t+1})$, and secondly, a binary classification label to predict price movement direction. The label was set to 1 if the next day's price increases compared to the current day, and 0 otherwise. This binary label facilitates directional forecasting and the use of classification metrics like accuracy and F1-score.

Before Bayesian optimization, a baseline LSTM model was established as a benchmark. It used an input layer, an LSTM layer (64 units), Dropout (0.2), Adam optimizer, and MSE loss. Data was split 80% train, 10% validation, 10% test, with features scaled by MinMaxScaler. The model showed strong performance on Ethereum (MAPE = 6.21%) but weaker performance on Bitcoin (RMSE = 0.2154, MAPE = 25.18%),

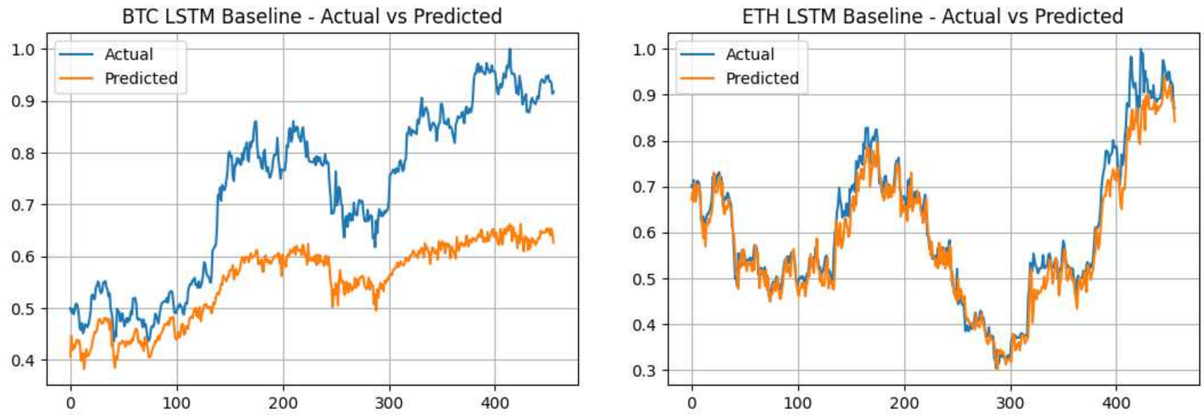

Figure 5. Baseline LSTM model predictions

showing a larger deviation for Bitcoin predictions (Table 2, Figure 5).

Table 2. Baseline LSTM model performance

Asset	RMSE	MAE	MAPE (%)
Bitcoin	0.2154	0.1944	25.18
Ethereum	0.0506	0.0398	6.21

Bayesian Optimization was used to optimize the LSTM model on Bitcoin and Ethereum individually. Technical indicators included in the hyperparameter space were trend (SMA, EMA), momentum (RSI, Stochastic Oscillator), volatility (Bollinger Bands, ATR), and volume (OBV) (Table 3).

The optimization objective was to minimize the RMSE of a simplified ensemble forecast against the next day's closing price. Using a Gaussian Process surrogate model and Expected Improvement acquisition function, optimal parameters were selected after 50 iterations. Bayesian Optimization successfully tuned both models, continuously decreasing RMSE. Ethereum converged quickly, with RMSE dropping from 0.034 to 0.0255. Bitcoin improved more slowly, reaching 0.022 RMSE after 50 iterations (Figure 6). This suggests the technique effectively enhanced the models by finding the best indicator settings.

The above Bayesian Optimization effectively identified well-tuned indicator parameters for both Bitcoin and Ethereum datasets. The chosen configurations demonstrated significantly reduced forecasting error when compared to default parameter settings. It showed that Bayesian optimization improves forecasting accuracy by allowing indicator parameters to adapt to changing market conditions, reflecting the non-stationary nature of cryptocurrency markets.

The optimization resulted in a significant increase in the accuracy of forecasting. The common practice parameters used were default parameters, 14-period RSI, 20-day SMA/EMA, and the optimized parameters were obtained using Bayesian Optimization. Table 4 contrasts the technical indicator parameters at the baseline and optimization. In the case of Bitcoin, the RMSE decreased by 36.4 percent, going down to 0.0222. The RMSE of Ethereum reduced by 12.2% to 0.0253. These profits indicate that it is important to fine-tune the parameters of indicators as opposed to the application of standard defaults.

Table 3. Hyperparameter space definition

Indicator	Parameter	Range
Simple Moving Average (SMA)	Window Size	10–50
Exponential Moving Average (EMA)	Window Size	10–50
Relative Strength Index (RSI)	Period	5–30
Stochastic Oscillator (%K)	Period	5–30
Bollinger Bands	Window + Std. Deviation	10–50, 1–3
Average True Range (ATR)	Period	5–30

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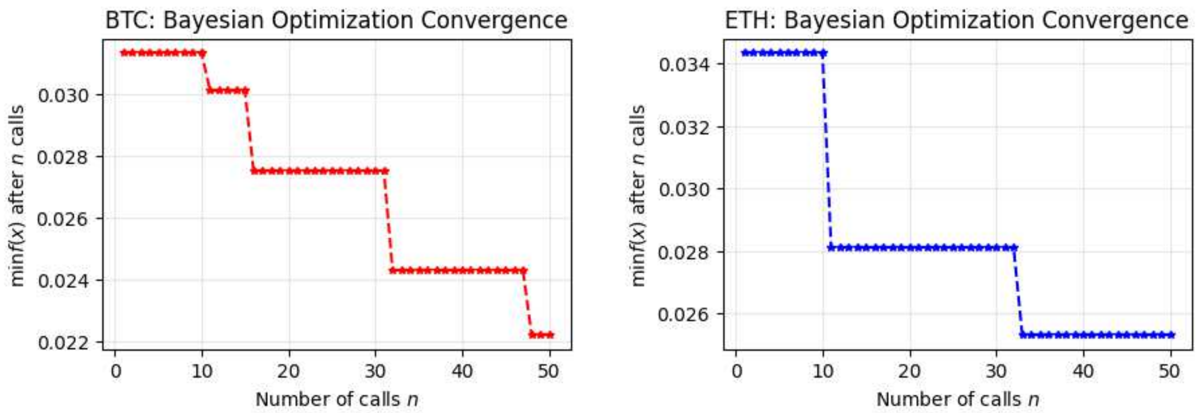


Figure 6. Bayesian optimization convergence

Table 4. Best parameter configurations

Optimal Parameters	BTC		ETH	
	Baseline	Optimized	Baseline	Optimized
Best RMSE	0.0642	0.0222	0.0288	0.0253
SMA	34	30	24	23
EMA	15	10	45	50
RSI Period	40	34	30	35
Stochastic Period	30	25	12	20
Bollinger Band Window	5	1	2	2
Bollinger Std Deviation	20	18	22	27
ATR Period:	28	23	18	21

The bar chart in Figure 7 demonstrates RMSE reduction for both assets. These improvements validate the integration of Bayesian Optimization into the forecasting workflow and justify its computational cost. These optimized indicator configurations were used as inputs for the LSTM model in the analysis. The results imply that optimized technical indicators extract more informative price and volatility signals than fixed-parameter indicators, enhancing short-term predictability in sentiment-driven markets.

The third objective of this study was to compare the LSTM models' performance before and after Bayesian optimization of technical indicators using standard evaluation metrics (MAE, RMSE, MAPE). The LSTM model was retrained using

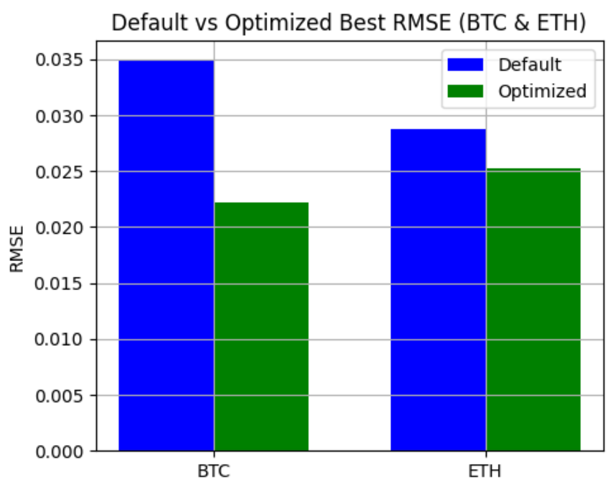
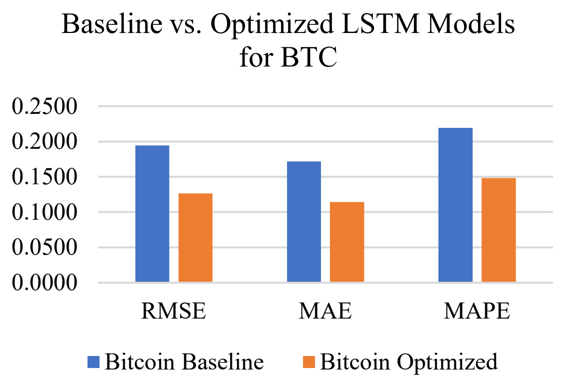


Figure 7. Default vs. optimized parameters



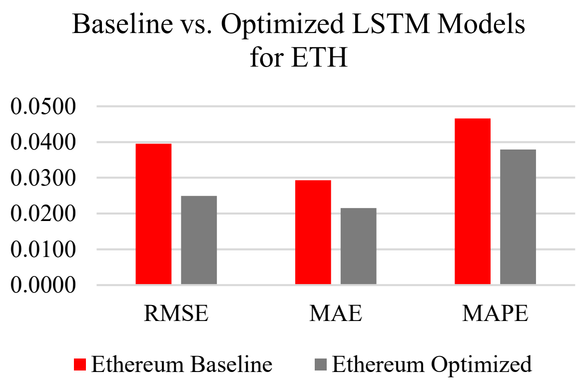


Figure 8. Forecasting accuracy – Baseline vs. optimized LSTM models

Table 5. Forecasting accuracy – Baseline vs. optimized LSTM models

	Bitcoin		Ethereum	
	Baseline	**Optimized**	**Baseline**	**Optimized**
RMSE	0.1942	0.1266	0.0395	0.0349
MAE	0.1718	0.1143	0.0293	0.0215
MAPE (%)	21.9249	14.8409	4.6586	3.7931

the same architecture but with optimized indicator parameters. Lag features were introduced to capture short-term temporal dependencies, with 1-day and 3-day lags. To prepare the data for LSTM input, all feature columns were normalized using Min-Max Scaling to ensure stability during training. This yielded a feature matrix X and corresponds to the next day's closing price vector y for both Bitcoin and Ethereum datasets. The architecture of the LSTM models remained consistent with the baseline, and the same preprocessing and train-validation-test splitting procedures were followed to ensure a fair comparison with the baseline models.

Table 5 and Figure 8 demonstrate that the accuracy of forecasting with optimized indicators is significantly higher than with normal indicators. The two assets had a significant drop in both RMSE and MAE, validating that LSTM models trained using optimized technical indicators are more effective in capturing underlying price dynamics. Relative forecasting error, as indicated by MAPE, decreased by 32 per cent in BTC and 18.6 per cent in ETH, highlighting a significant improvement in relative accuracy. The results show that there was a greater improvement in the case of Bitcoin as compared to Ethereum in forecasting. The consistent outperformance of the Bayesian-optimized LSTM over benchmark models suggests that conventional econometric and machine learning approaches are insufficient for capturing the complexity of cryptocurrency markets. Also, models relying on fixed assumptions or linear dynamics are less capable of adapting to rapidly changing market environments, leading to higher forecasting errors and reduced decision-making efficiency.

4. DISCUSSION OF RESULTS

This study evaluated whether Bayesian optimization of technical indicator parameters improves LSTM-based cryptocurrency price forecasting relative to a baseline configuration. This purpose was addressed through three objectives: (i) testing the predictive ability of technical indicators, (ii) developing and tuning an LSTM forecasting model, and (iii) comparing performance before and after Bayesian optimization. In analyzing the predictive ability of technical indicators, the results indicated that technical indicators are valuable predictive assets in cryptocurrency forecasting. Even with default parameters, the baseline LSTM models exhibited meaningful forecasting ability, particularly for Ethereum (MAPE = 6.21%). It suggests that even though the crypto market is highly efficient, volatile, and noisy, it contains structured signals in price and volume statistics that can be used to make predictive modeling. This finding aligns with previous research, such

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as Kim and Kim (2019), who found improved accuracy with trend and momentum indicators, and Mallqui and Fernandes (2019), who noted performance improvement with indicators like RSI and Bollinger Bands.

There was a difference in the accuracy of prediction between BTC and ETH in the LSTM-based model. The ETH model reflects a high correspondence between actual and forecasted prices (MAPE = 6.21%). However, the BTC model showed relatively lower performance in terms of accuracy and considerable deviation, with an MAPE of 25.18%. This divergence is attributed to market characteristics, where ETH price patterns are more consistent or cyclic, hence easier for the LSTM model to learn. On the other hand, Bitcoin is a more established and actively traded asset, hence vulnerable to macroeconomic shocks, regulatory shifts, and sentiment-driven trends (Galeshchuk & Mukherjee, 2017). Additionally, while BTC's historical volatility may be numerically lower, it likely contains more irregular, nonlinear shocks poorly captured by an LSTM relying on simple indicators. These results align with Fischer and Krauss (2018), who noted that deep learning models can fail to perform well on irregularly volatile assets unless they are well-regularized and tuned. In addition, Jang and Lee (2017) found that predictability varies across cryptocurrencies, with ETH reacting more to momentum-related cues compared to BTC.

In applying Bayesian Optimization to automatically tune hyperparameters of technical indicators, the convergence plots showed a significant reduction in forecasting error after optimization. The improvements for both Bitcoin (36.4%) and Ethereum (12.2%) could be attributed to the optimization process, which enabled better learning of more valuable patterns, decreased overfitting, and better generalization. These findings align with Shen et al. (2019) and Zhang et al. (2018)'s arguments that while traditional indicators are relevant, their forecasting value is fully realized if they are effectively optimized through techniques such as Bayesian optimization. Altogether, these findings demonstrate that optimized indicators enhance the model's ability to learn market patterns, hence offering more accurate and reliable results.

In forecasting performance, the Bayesian optimized LSTM model performed better, with 32% and 18.6% improvements in prediction accuracy for BTC and ETH, respectively. It implied that an optimized LSTM model is more efficient in forecasting future crypto prices as compared to an unoptimized model (Guo, 2025). The improvement is attributed to the model learning more significant temporal representations from fine-tuned inputs, which reduced redundancy, lowered noisy inputs, and enhanced the signal-to-noise ratio. These findings align with Shen et al. (2019), who reported improved stock market forecasting accuracy with optimized technical indicators parameters. The significant forecasting accuracy improvements, particularly in Bitcoin, suggest that even noisy markets are predictable when features are optimized. Additionally, the results imply that the indicator optimization process should be tailored to market behavior (Fischer & Krauss, 2018) as effective deep learning models in financial markets need high-quality feature engineering. Without optimized features, the deep network's complexity may not be fully utilized.

From the study, several implications were developed; first, optimized technical indicators have a higher predictive value when applied and combined with advanced deep learning systems like LSTM. This implies that trading strategies constructed based on default indicator settings underperform compared to optimized settings. Additionally, asset-specific tuning has significant benefits in enhancing predictive accuracy and the resulting financial decision making. The findings strongly advocate for incorporating dynamic feature engineering and machine-learning optimization into quantitative trading and asset management pipelines. Specifically, the study demonstrates that LSTM models combined with optimized technical indicators significantly enhance forecasting accuracy. Furthermore, the use of walk-forward validation confirms the model's robustness across varied market conditions. This implies that institutional investors and hedge funds can leverage this robust prediction framework to improve alpha generation in crypto funds and minimize overfitting in backtesting. Organizations can achieve this by integrating optimized LSTM forecasts with existing quantitative trading strategies or cross-asset signals and using walk-forward validation to more realistically simulate live fund performance, hence reducing hindsight bias. The developed framework, combining an optimized LSTM with tailored indicators, is deemed suitable for highly volatile markets like Bitcoin and Ethereum. Borrowing from these models, crypto exchanges can offer value-added forecasting dashboards or alerts using optimized models as part of their analytics services to traders and institutional users. Data vendors can build API endpoints for optimized indicator outputs or forecast signals as premium products. Researchers can use this study as a benchmark for future model validation standards, emphasizing realistic and robust testing frameworks. On the other hand, policymakers and central banks studying digital assets can rely on such models for understanding volatility patterns, especially during systemic shocks or speculative cycles.

CONCLUSIONS

The purpose of this study was to explore the enhancement of cryptocurrency price forecasting accuracy by integrating Bayesian optimized technical indicator parameters with LSTM neural networks. Using Bitcoin and Ethereum as representative assets, the study evaluated a forecasting framework that integrates Bayesian optimization with deep learning techniques. The empirical results showed that Bayesian optimized technical indicators increase the forecasting accuracy of LSTM models compared to unoptimized indicator configurations and benchmark forecasting approaches. The findings also demonstrated that the forecasting improvement differs among assets, with better performance for Bitcoin than Ethereum, which reflected varying market structure and trading dynamics. From these findings, it was concluded that using optimized technical indicators in deep learning models, such as LSTM, is essential for effective forecasting accuracy in highly volatile and non-stationary financial markets, such as cryptocurrency markets. The proposed framework offers valuable insights for investors, traders, and risk managers seeking more robust forecasting tools in cryptocurrency markets. The study highlights the importance of financial engineering approaches that combine optimization techniques with advanced learning models to improve decision-making under uncertainty.

AUTHOR CONTRIBUTIONS

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Formal analysis: Abdulilah I. Mubarak.
Funding acquisition: Abdulilah I. Mubarak.
Investigation: Abdulilah I. Mubarak.
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Validation: Abdulilah I. Mubarak.
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Writing – original draft: Abdulilah I. Mubarak.
Writing – review & editing: Abdulilah I. Mubarak.

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