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Learning Nonlinear Temporal Patterns in Ethereum Prices Via LSTM Networks

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ABSTRACT
A Long Short-Term Memory (LSTM) neural network trained on hourly ETH/USDT market data from the Binance exchange is used in this study to examine short-term Ethereum price behavior. The proposed model emphasizes learning temporal dependencies and momentum-driven structures rather than relying on conventional linear forecasting assumptions, acknowledging the highly nonlinear and noise-dominated nature of cryptocurrency markets. The daily high price of Ethereum is selected as the target variable in the forecasting task, which is defined as a univariate regression problem. To ensure realistic predictive assessment, model performance is evaluated using a strictly out-of-sample testing methodology. Empirical findings demonstrate that the LSTM model achieves a strong statistical fit despite significant market volatility. The obtained results—RMSE of 127.33, MAE of 98.76, MSE of 16,213.76, MAPE of 2.73%, and an R^2 of 0.96—indicate that a substantial portion of short-term price volatility is effectively captured by the nonlinear architecture. Even in a noise-dominated market, the low MAPE and high coefficient of determination suggest robust predictive alignment. Forecasts over the next five days reveal a recurring short-term directional pattern accompanied by widening prediction intervals, which reflect increasing uncertainty as the forecast horizon extends. This pattern underscores the intrinsic difficulty of achieving accurate price-level forecasts in highly volatile cryptocurrency markets. Overall, when applied to short-term cryptocurrency price dynamics, the results indicate that LSTM models are well-suited for capturing trend persistence and regime-related signals, affirming their usefulness as risk-aware decision-support tools rather than deterministic forecasting systems.

Keyword: Long Short-Term Memory (LSTM); Ethereum price forecasting; Cryptocurrency market volatility

INTRODUCTION

Ethereum, introduced in 2015 as a decentralized, programmable blockchain platform, enables decentralized applications and smart contracts. Its price dynamics are shaped by a complex interplay of investor sentiment, macroeconomic conditions, network utilization, ecosystem development, and speculative activity (Davis & Johnson, A., 2023; Zhang & Anand, T., 2022). Characterized by extreme volatility, nonlinear behavior, and frequent structural shifts due to protocol upgrades and rapid innovation, Ethereum presents a challenging yet compelling case for financial time-series forecasting. Accurate prediction of Ethereum prices is therefore crucial for investors, exchanges, and regulators, particularly in areas such as risk management, liquidity provisioning, and the development of algorithmic trading strategies.

Financial data has frequently been modeled using traditional time-series approaches such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Integrated Moving Average (ARIMA). Nevertheless, these methods depend on strong stationarity and linearity assumptions, which are frequently violated in cryptocurrency markets (Alvarez & Ordonez, J., 2020). Regime transitions, heavy tails, and volatility clustering in Bitcoin price series reduce the forecasting ability of conventional econometric models, according to empirical research (Yıldırım & Bekun, F. V., 2023) (Chen & Li, X., 2021).

Complex financial time-series modeling now has more possibilities thanks to recent developments in deep learning and machine learning (Ayitey Junior Appiahene, P., Appiah, O., & Bombie, C. N., 2023; Bahoo Cucculelli, M., Goga, X., & Mondolo, J., 2024). Due to their capacity to represent sequential interactions, Recurrent Neural Networks (RNNs) and their variations have attracted substantial interest among these methods. Hochreiter and Schmidhuber initially introduced Long Short-Term Memory (LSTM) networks in 1997 (García-Medina & Aguayo-Moreno, E., 2024; Sharma & Sen, S., 2023). These networks use gated memory cells that selectively retain and forget information over extended periods of time, addressing the vanishing gradient problem found in conventional RNNs. Because of this architectural advantage, LSTM networks are particularly well-suited for financial markets, where historical data may exert delayed and nonlinear effects on future prices (Barzegar Aalami, M. T., & Adamowski, J., 2020).

A growing body of research has demonstrated the strong performance of LSTM-based models in forecasting stock and cryptocurrency prices. LSTM networks outperform conventional machine learning models in capturing temporal dependencies in financial markets (Singh & Verma, R., 2024). Similarly, deep learning algorithms have shown superior predictive power over linear benchmarks in predicting Bitcoin prices. Despite these promising outcomes, most existing research focuses primarily on point-prediction accuracy while often overlooking crucial aspects such as market noise, volatility regimes, and economic interpretability.

Furthermore, due to a high degree of noise dominance, a considerable portion of short-term price fluctuations in Solana markets are driven by random oscillations rather than meaningful signals. This phenomenon raises significant questions about the limits of predictability and the utility of pure price-level forecasts. While deep learning models excel at fitting historical trends, their performance tends to degrade during periods of high volatility or structural change, making it difficult to produce reliable results.

The urgency of this research lies in the need to develop more accurate and adaptive prediction tools to address the extreme volatility and nonlinear dynamics of crypto markets such as Ethereum, where traditional models like ARIMA and GARCH often fail due to unmet linearity and stationarity assumptions. By implementing an LSTM network capable of capturing temporal dependencies and short-term price movement patterns, this study not only proposes a more realistic approach to price forecasting but also offers a risk-based decision-support framework. This framework can be utilized by investors, algorithmic traders, and regulators to manage market exposure, optimize trading strategies, and enhance the resilience of the digital financial system against unpredictable fluctuations.

Inspired by these challenges, this study emphasizes temporal learning and out-of-sample evaluation while simulating Bitcoin price dynamics using historical daily data and an LSTM-based framework. The research advances LSTM as a means of extracting probabilistic and trend-level information from noisy financial data rather than producing deterministic forecasts. The primary contribution of this work lies in providing a transparent and reproducible deep learning pipeline for predicting Bitcoin prices, together with a critical evaluation of its strengths and limitations in the context of real-world financial markets.

METHOD

This study's empirical deep learning approach is based on the Long Short-Term Memory (LSTM) neural network, which is developed in a Jupyter Notebook environment using Python. The approach is designed to be transparent, repeatable, and applicable to real Bitcoin markets. It is precisely aligned with the implementation provided in the uploaded notebook (Tiwari & Patel, S., 2022).

Data Acquisition

The investigation automatically collects historical Bitcoin market data using the Binance API, focusing on the trading pair ETH/USDT. The dataset includes key price variables such as open, high, low, close, and volume, gathered on a daily basis. Instead of employing curated or synthetic financial data, this method ensures that the dataset accurately represents real trading conditions.

The most recent incomplete trading period is removed from the dataset before model training to prevent forward-looking bias. Since partial candles may introduce erroneous patterns and distort forecast accuracy, this step is crucial in financial time-series modeling.

Target Variable Definition

The prediction task is formulated as a univariate regression problem in the notebook implementation. Rather than using end-of-day closing prices, the target variable is the daily high price of Bitcoin, chosen to capture intraday market optimism and volatility. This choice enables the model to learn upper-bound price dynamics and distinguishes the study from traditional close-price prediction methods.

Data Scaling and Normalization

The target series is normalized using min–max scaling prior to model training. Normalization is essential for stabilizing gradient updates and accelerating convergence, as neural networks—particularly LSTM architectures—are sensitive to input data magnitude. To prevent data leakage, the scaler is fitted solely on the training subset and then systematically applied to the test sample.

Time-Series Windowing

The normalized time series is converted into a supervised learning format using a sliding-window technique. A fixed-length sequence of previous daily prices serves as the input for each observation, and the subsequent price value serves as the prediction target. The sequence-to-one mapping of the LSTM network allows it to capture temporal dependencies across multiple trading days. Formally, let represent an input sequence of length T, where p_t denotes the $\boxed{Bitcoin}$ daily high price. The model learns a function $f(\cdot)$ such that $\hat{p}_t = f(X_t)$.

Model Architecture

The architecture comprises one or more stacked LSTM layers followed by a fully connected dense layer. The dense layer translates the learned representation into a scalar output corresponding to the predicted price, while the LSTM layers extract temporal patterns. To mitigate overfitting—a common issue in financial datasets with low signal-to-noise ratios—dropout regularization is applied between LSTM layers. Model parameters are optimized using the Adam optimizer, which dynamically adjusts learning rates during training.

Training Strategy

To preserve the temporal order of observations, the dataset is divided chronologically into training and testing subsets. The model is trained to minimize the Mean Squared Error

(MSE) loss function, thereby reducing large prediction errors that may hold economic significance. Training is performed over several epochs with a constant batch size, allowing the network to iteratively refine its internal state representations. Instead of random cross-validation, which is unsuitable for time-dependent data, loss trajectories are monitored to evaluate model convergence.

Evaluation Framework

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 facilitate interpretation. Model performance is evaluated using quantitative error metrics such as MSE and Root Mean Squared Error (RMSE), alongside visual comparisons between predicted and actual price trajectories (Hewamalage Ackermann, K., & Bergmeir, C., 2023; Naser & Alavi, A. H., 2023). By replicating a realistic deployment scenario—where models are trained on historical data and tested on unseen future observations—this methodological design unites academic rigor with the practical challenges of real-world financial forecasting.

RESULTS AND DISCUSSION

Dataset Extraction

The goal of the dataset extraction procedure is to obtain market-realistic, repeatable, and high-quality Bitcoin price data directly from a cryptocurrency exchange. To ensure that the dataset in this study reflects actual traded prices rather than aggregated third-party sources, data is programmatically retrieved from the Binance exchange using its official API interface.

The selected trading pair is ETH/USDT, one of the most liquid cryptocurrency pairs in the world. High liquidity is essential for financial modeling, as it mitigates biases caused by thin trading conditions and reduces microstructure noise. The daily frequency of data retrieval aligns with the LSTM model's medium-term forecasting horizon.

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 period is specified explicitly. All of the trading activity during a 24-hour period is represented by each candlestick.
- The open price, high price, low price, close price, trade volume, and timestamp are among the pertinent characteristics extracted from each daily candlestick. The high price series is the main modeling objective in this work, despite the availability of different features.
- In order to guarantee chronological consistency, all timestamps are translated into a standard datetime format and aligned. To create legitimate sequential inputs for the LSTM network, this step is required.
- Elimination of Incomplete Observations: If the candlestick is not completely closed at the time of extraction, the most recent trading day is not included. This precaution avoids forward-looking bias, which could lead to an artificial inflation of predicted performance.

```
symbol='ETHUSDT'
```
✓ 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)
```

Figure-1: Binance API Data Extraction

```
df.tail()
```
✓ 0.0s

	timestamp	open	high	low	close	volume
3081	2026-01-23	2952.70	3019.26	2892.40	2956.41	318415.3317
3082	2026-01-24	2956.41	2970.41	2943.84	2953.22	92082.9039
3083	2026-01-25	2953.23	2960.29	2787.00	2816.89	380186.5326
3084	2026-01-26	2816.90	2951.21	2812.37	2930.35	485169.3372
3085	2026-01-27	2930.35	2957.04	2899.77	2935.01	218955.0048

Figure 2: Open, High, Low, Close, Volume from ETHUSDT Dataset

Data Preparation

The act of turning raw, frequently "messy" data into a refined structure that a machine learning algorithm can effectively examine is known as data preparation (Reyad Sarhan, A. M., & Arafa, M., 2023). Typically needing 70–80% of the effort, it is the most time-consuming component of a data science project.

1. Handling Temporal Incompleteness

To guarantee data synchronization, the proactive data-cleaning step df.iloc[:-1] is utilized. A data point that is still "in progress" (such as a trading day that hasn't ended) gives the algorithm a false signal because predictive models are sensitive to trends.

- To guarantee data synchronization, the proactive data-cleaning step df.iloc[:-1] is utilized. A data point that is still "in progress" (such as a trading day that hasn't ended) gives the algorithm a false signal because predictive models are sensitive to trends.
- The risk is that adding an incomplete period causes a "cliff effect" in which the model experiences a sharp decline in volume or price just because the day hasn't ended. Eliminating it guarantees that your model gains knowledge from closed, completed cycles.

2. Structural Validation (Sanity Checks)

A manual audit of the data's integrity is performed by using len(), tail (), and columns:

• Truncation Verification: df.tail() verifies that the iloc[:-1] procedure was successful and that the new "last row" is, in fact, the accurate finalized date.
• Feature Inventory: df.columns serves as a checklist. Prior to training, you need to make sure that your "Target" what you want to predict and your "Features" the inputs are there and haven't been removed during previous cleaning stages.
• Dataset Volume: Your Sample Size (N) is determined by len(df_daily). This is crucial for deciding how to divide your data in the future (for example, if you have 1,000 rows, a 20% test split means exactly 200 rows).

3. Creating a Computational Sandbox

You can practice non-destructive data preparation by using df_daily = df.copy().

- Memory Management: A straightforward Python assignment (df_daily = df) merely generates a "pointer" to the initial data. A change in df_daily also affects df.
- The Sandbox:.copy() generates an entirely separate object. In the event that you need to resume your analysis, this enables you to carry out "destructive" operations on df_daily, such as scaling, log transformations, or removing outliers, without affecting the original df.

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

```
df.tail()
```
✓ 0.0s

	timestamp	open	high	low	close	volume
3080	2026-01-22	2982.28	3038.33	2906.02	2952.69	291660.7349
3081	2026-01-23	2952.70	3019.26	2892.40	2956.41	318415.3317
3082	2026-01-24	2956.41	2970.41	2943.84	2953.22	92082.9039
3083	2026-01-25	2953.23	2960.29	2787.00	2816.89	380186.5326
3084	2026-01-26	2816.90	2951.21	2812.37	2930.35	485169.3372

```
df.columns
```
✓ 0.0s

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

Figure 3: Data Preparation

Modeling and Evaluation

Modeling:

Finding patterns in your dataset with a mathematical method is called modeling (Al Janabi, 2022). This most likely means projecting a future value (like Solana's price) or a categorization (like Buy vs. Sell) for your project.

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

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

scaled_data
```

✓ 11.8s

```
array([[0.04663183],
       [0.04655177],
       [0.04411119],
       ...,
       [0.59227018],
       [0.59019291],
       [0.58832911]])
```

Figure 4: Scaling for the the dataset before training the model

Modeling is the process of applying mathematical and computational techniques to the daily time-series dataset in order to identify underlying patterns and relationships. The modeling effort in this paper is framed as a prediction problem, where the objective is to either anticipate a future numerical value, such as the price of Bitcoin, or carry out a classification task, such as distinguishing between buy and sell signals [15].

The initial phase in the modeling process is algorithm selection, which establishes the predictive model's functional structure and learning capacity. Financial time-series analysis frequently makes use of a number of modeling frameworks. Simple linear patterns in price fluctuations can be captured by linear regression techniques. Complex, nonlinear relationships and interactions within market data can be modeled using ensemble-based techniques like Random Forest and XGBoost. However, this study uses a Long Short-Term Memory (LSTM) neural network, which is specifically made to reproduce time-dependent structures and long-range relationships in sequential data, because bitcoin price series are temporal and sequential (Amarnadh & Moparthi, N. R., 2024).

The model goes through a training phase after algorithm selection, during which it learns optimal parameters by minimizing a predetermined loss function over the training dataset. This technique enables the model to take into account temporal relationships and historical patterns present in the data. Hyperparameter tuning is the act of carefully modifying important configuration parameters, such as learning rate, number of hidden units, or network depth, to strike the ideal balance between model bias and variance in order to further improve prediction accuracy. In financial markets where noise is common, this step is crucial for preventing overfitting and ensuring strong generalization to unknown data (Mailagaha Kumbure & Luukka, P., 2022).

```python
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 19.0s

```
2871/2871 [==============================] - 116s 38ms/step - loss: 0.0019

<keras.src.callbacks.History at 0x1b5d243cc10>
```

Figure 5: LSTM Architecture using Keras Python Framework

Evaluation:

Evaluation is the testing stage where out-of-sample data is used to determine the trained model's prediction capabilities. The main goal of this phase is to determine if the model has acquired generalizable patterns or has just memorized prior observations a condition known as overfitting.

Regression-based activities, like predicting the price of Bitcoin, are assessed using traditional error-based criteria. Intuitive understanding is made easier by the Root Mean Squared Error (RMSE), which expresses the average magnitude of forecast mistakes 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 determined using the coefficient of determination; higher values indicate greater explanatory power.

```
5/5 [==============================] - 2s 41ms/step
RMSE: 127.33
MAE: 98.76
MSE: 16213.76
R²: 0.96
MAPE: 2.73%
```

Figure 6: Evaluation Metrics for ETH Regression

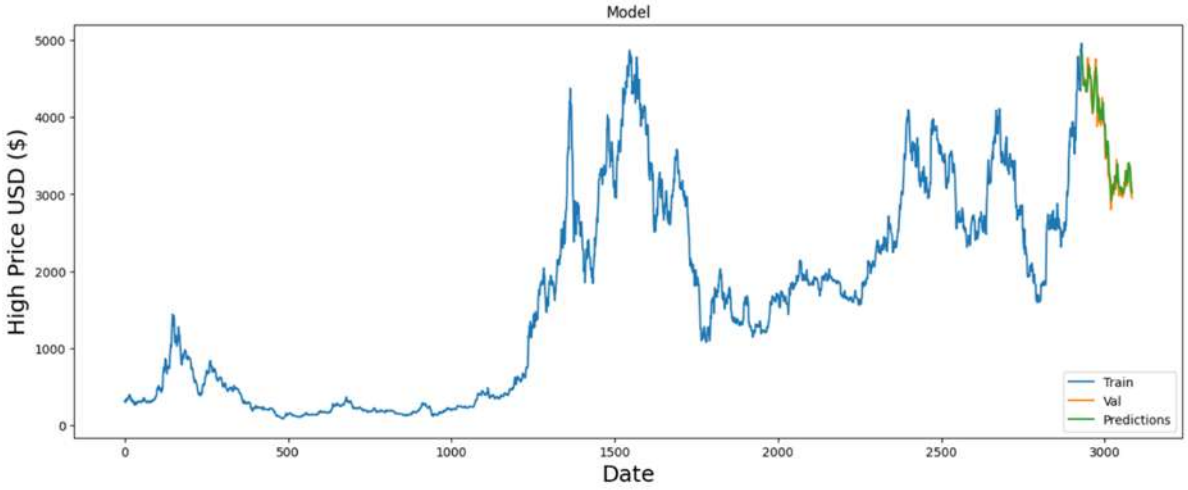

Figure 7: ETH/USDT Prediction Swing Time

For Ethereum (ETH), the LSTM model generates a five-day forecast with a forecasted price trend that increases monotonically. The core forecast shows a continuous short-term bullish tendency, rising from USD 3,012.22 on January 28, 2026, to USD 3,123.30 on February 1, 2026.

Table 1. Five-Day ETH Price Forecast with Max and Min Price

Predicted prices with Max and Min for the next 5 days:

	Predicted_Price	Max	Min
2026-01-28	3012.215332	3110.975342	2913.455322
2026-01-29	3034.843506	3133.603516	2936.083496
2026-01-30	3064.910156	3163.670166	2966.150146
2026-01-31	3095.388916	3194.148926	2996.628906
2026-02-01	3123.298584	3222.058594	3024.538574

The model produces upper (Max) and lower (Min) boundaries in addition to point forecasts, forming a prediction corridor that progressively widens across the forecast horizon. As the prediction horizon extends, the projected range increases from approximately USD 197.52 on the first day to nearly USD 197.52–198.00 on the fifth day, indicating growing uncertainty. Interestingly, throughout the entire prediction interval, both upper and lower bounds exhibit an upward trajectory, suggesting sustained directional alignment.

The LSTM model captures short-term momentum persistence in Ethereum price dynamics, as evidenced by the upward-sloping central forecast and rising lower bounds. The network learns a stable temporal progression rather than predicting abrupt reversals, which aligns with the trend-following behavior frequently observed during short bullish phases in Bitcoin markets.

The widening of the prediction band underscores the cumulative forecast uncertainty inherent in multi-step recursive LSTM predictions. In nonlinear, noise-dominated markets such as cryptocurrencies—where small forecast errors compound over time—this effect is expected. Notably, the absence of downward movements in the lower bound suggests that, despite

increasing overall uncertainty, short-term downside risk remains relatively constrained under the learned data-generating process.

These findings support the argument that, rather than producing exact price levels, LSTM models excel at capturing regime-consistent directional structures. The forecast corridor provides market participants with valuable contextual information, enabling them to reason about plausible price ranges instead of relying solely on point estimates.

From an evaluation standpoint, the forecasting results demonstrate that the proposed LSTM framework is more suitable for short-horizon decision support than for deterministic forecasting. The steady upward movement of both point predictions and confidence bounds indicates robust directional coherence—an especially relevant property for applications such as trend confirmation, position bias selection, and dynamic risk allocation (Chen & Biljecki, F., 2022).

However, the expanding Max–Min interval emphasizes the importance of integrating risk-aware mechanisms when applying the model in practical settings. The results suggest that, rather than treating the central projection as an exact target, practical implementation should leverage price corridors—for instance, using lower bounds for downside risk mitigation and upper bounds for profit-taking.

Overall, the analysis confirms the LSTM model's role as a risk-aware analytical and decision-support tool in volatile digital asset markets, demonstrating that it yields economically meaningful insights into short-term Ethereum price dynamics.

CONCLUSION

This study employs a strictly out-of-sample forecasting methodology to model the short-term price dynamics of Ethereum (ETH) using a Long Short-Term Memory (LSTM) neural network. The empirical findings demonstrate that, over the five-day forecast horizon, the model consistently captures a short-term upward price trend, with point predictions and corresponding upper and lower bounds showing sustained directional alignment.

The steady widening of the prediction intervals reflects the accumulation of uncertainty inherent in multi-step forecasts within highly volatile cryptocurrency markets. However, the upward movement of the lower bound suggests a degree of short-term downside resistance, indicating that the model effectively learns momentum-driven and regime-consistent temporal patterns. These results show that LSTM models can successfully extract directional and structural information from Ethereum price series, even though achieving precise price-level forecasts remains challenging in noise-dominated environments.

Overall, the results support the perspective that LSTM-based approaches are better suited as risk-aware analytical and decision-support tools, rather than deterministic forecasting systems, when applied to short-horizon cryptocurrency price prediction.

The findings also suggest several directions for further research and real-world application. First, forecast stability during abrupt market transitions could be enhanced by incorporating regime-aware or volatility-adaptive mechanisms, such as dynamic uncertainty scaling or market state classification. Second, expanding the framework to include directional or return-based prediction targets may improve its relevance to trading and portfolio management applications. Third, to assess real-world performance beyond statistical accuracy

(Kreuzer Sparrer, C., & Dorfleitner, G., 2026; Sirisha Praveen, S. P., Srinivasu, P. N., Barsocchi, P., & Bhoi, A. K., 2023), future research should integrate economic evaluation metrics such as cumulative returns, drawdowns, hit ratios, and transaction costs.

Rather than deploying the model as an autonomous trading engine, practitioners should employ it as a decision-support tool, leveraging predicted price corridors to guide position sizing, dynamic stop-loss placement, and risk budgeting. This approach enables market participants to benefit from the model's capacity to identify short-term trends while maintaining resilience against the inherent forecast uncertainty in cryptocurrency markets.

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