Vol. 8, No. 2, April 2026

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

A Hybrid Ensemble Stacking Framework Integrating Long Short-Term Memory and Random Forest for Bitcoin Price Forecasting

Akhlis Munazilin[1], Mochamad Agung Wibowo[2], Rizky Parlika[3]

[1,2] Doctoral Program of Information Systems, School of Postgraduate Studies, Universitas Diponegoro, Semarang, Indonesia

[1] Department of Computer Science, Faculty of science and technology, Universitas Ibrahimy, Situbondo, Indonesia

[3] Department of Informatics, Faculty of Computer Science, University of Pembangunan Nasional "Veteran" Jawa Timur, Indonesia

Received:
November 24, 2025
Revised:
March 10, 2026
Accepted:
March 31, 2026
Published:
April 12, 2026

Corresponding Author:
Author Name*:
Akhlis Munazilin
Email*:
akhlismunazilin@students.undip.ac.id

DOI:
10.63158/journalisi.v8i2.1537

Abstract. Bitcoin is a non-linear and non-stationary digital asset that has become a highly volatile asset challenging the usual prediction models. In this paper, the authors present a problem-specific Hybrid Ensemble Stacking approach, the proposed approach, which combines the benefits of Long Short-Term Memory (LSTM) in terms of capturing long-term temporal variations with the power of Random Forest (RF) to process complex technical characteristics. The model follows a two-tier structure with a split ratio of 90:10 using BTC/USD historical data of Yahoo Finance and Binance (2010-2025) to combine the predictions of base learners with the use of a Linear Regression meta-learner. Findings show that pure LSTM has a low RMSE and MAE, but the Hybrid model has the best Mean Absolute Percentage Error (MAPE) of 3.54%. This means that the stacking mechanism will provide a more balanced error percentage, that is, it will enhance stability in forecasting at the phases of price discovery. It is novel in the sense that it uses macro-technical indicators to stabilize predictions in the face of market anomalies as a stacking scheme. These results have real-life implications on developers of financial systems in creating consistent crypto-asset risk management instruments.

Keywords: Bitcoin, Hybrid Ensemble Stacking, Long Short-Term Memory, Time-series Forecasting, Cryptocurrency Forecasting.

1. INTRODUCTION

Crypto assets and Bitcoin in particular have changed the world order in the financial sector within the last ten years. Being the most capitalsized asset in the market, Bitcoin has been in focus not only of individual users but also of large organizations as an effective investment tool [1], [2]. But the biggest peculiarity of Bitcoin is that it is highly volatile, and the price might change dramatically in a few minutes as a result of the social media mood, regulatory factors, and macroeconomic forces [3]. The non-linear, non-linear and frequently noisy character of Bitcoin information renders the use of conventional statistical prediction techniques in is likely to fail to provide consistent precision [4]. Even though these hybrid models including CNN-LSTM architectures have been studied in the past to derive spatial and temporal features jointly [5], they still tend to be highly volatile to extreme prices shifts [6].

In the light of the progress of Artificial Intelligence (AI), machine learning and deep learning model have become the better choices when it comes to processing financial time series data. The tree-based algorithms include Random Forest (RF) which have been found to be useful in revealing non-linear trends that do not presuppose strict data distribution [7]. Conversely, the Long Short-Term Memory (LSTM) architecture has the special facility of commemorating the long-term patterns by way of a gating system that transcends the problem of the vanishing gradient [8]. Although both models possess their own merits, the application of either of them is frequently constrained in one way or the other: RF cannot necessarily be used to project onto data outside its historical context, whereas pure LSTM can frequently be unstable in high volatility situations without feature enrichment or further optimization [9], [10].

A number of recent researches have started examining the application of hybrid models to enhance accuracy of the forecast. The combination of social media sentiment analysis has been reported to largely enhance the accuracy of the LSTM models by sensing the psychological attitude of the market [11]. Moreover, noise has also been reduced by using data decomposition and adaptive feature selection methods prior to model training [12]. However, there is a research gap regarding how to harmoniously combine tree regression-based models with sequential neural network architectures through a stacking mechanism to create more stable price estimates that are resilient to market anomalies [13], [14].

The research gaps witnessed in this study included the fact that there was no balancing aspect between a highly sequence sensitive model like LSTMs and a resilient model to outliers like the Random Forests in one stacking structure. Relative to the conventional parallel or serial hybrid conceptualizations, the stacking ensemble scheme of the specified investigation offers a meta-learner, which intelligently learns to favor LSTM forecasts and when to be concerned with the strength of the Random Forests. The foremost contribution of the work is the development of a problem-sensitive forecasting framework which can be applied to go to extremes and non-linear tendencies of Bitcoin. Contrary to generic hybrid schemes, the paper introduces a dual level stacking framework as it includes the notion of macro-technical (MA7, MA21, RSI) in order to serve the role of noise filters and trend stabilizing agents. The innovative aspect is the presentation of what is called a meta-learner that replaces the sequence sensitive predictions provided by LSTM with the outlier-resistant characteristics of the Random Forests, which is explicitly aimed at the minimization of the Mean Absolute Percentage Error (MAPE) in the instances of unpredictable price discovery. It is not a broadly generalizable architecture that is touted as a breakthrough, but an architecture that is extremely effective with cryptocurrency time-series data.

2. METHODS

This paper uses a methodical foretelling framework, which includes information pre-processing, model architecture in two layers and performance assessment systems. The created methodology will be used to solve high volatility in crypto assets by combining sequential and tree-based algorithms into one [10], [15], [16].

2.1. Research Flowchart

The current research started by obtaining historical data on BTC/USD daily data published by Yahoo Finance and Binance. The data was pre-processed critically by managing the missing values and normalizing with MinMaxScaler. This predictive model will be developed using raw data collected, and then the features will be extracted to form technical indicators that include Moving Average (MA), Relative Strength Index (RSI) and

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

returns. The data is then split into training and test data by the use of a 90:10 ratio once the features have been created and then normalization of the data is done to bring the data value ranges together. Passing into the modeling stage, base learners are trained at the Level 0, with the LSTM and Random Forest (RF) algorithms. The outcome of this step is then combined to form a meta-set which is fed into meta-learner training at Level 1 in this case Linear Regression. The final analysis of the model performance, as well as, correctness is determined by the final evaluation of this series of procedures.

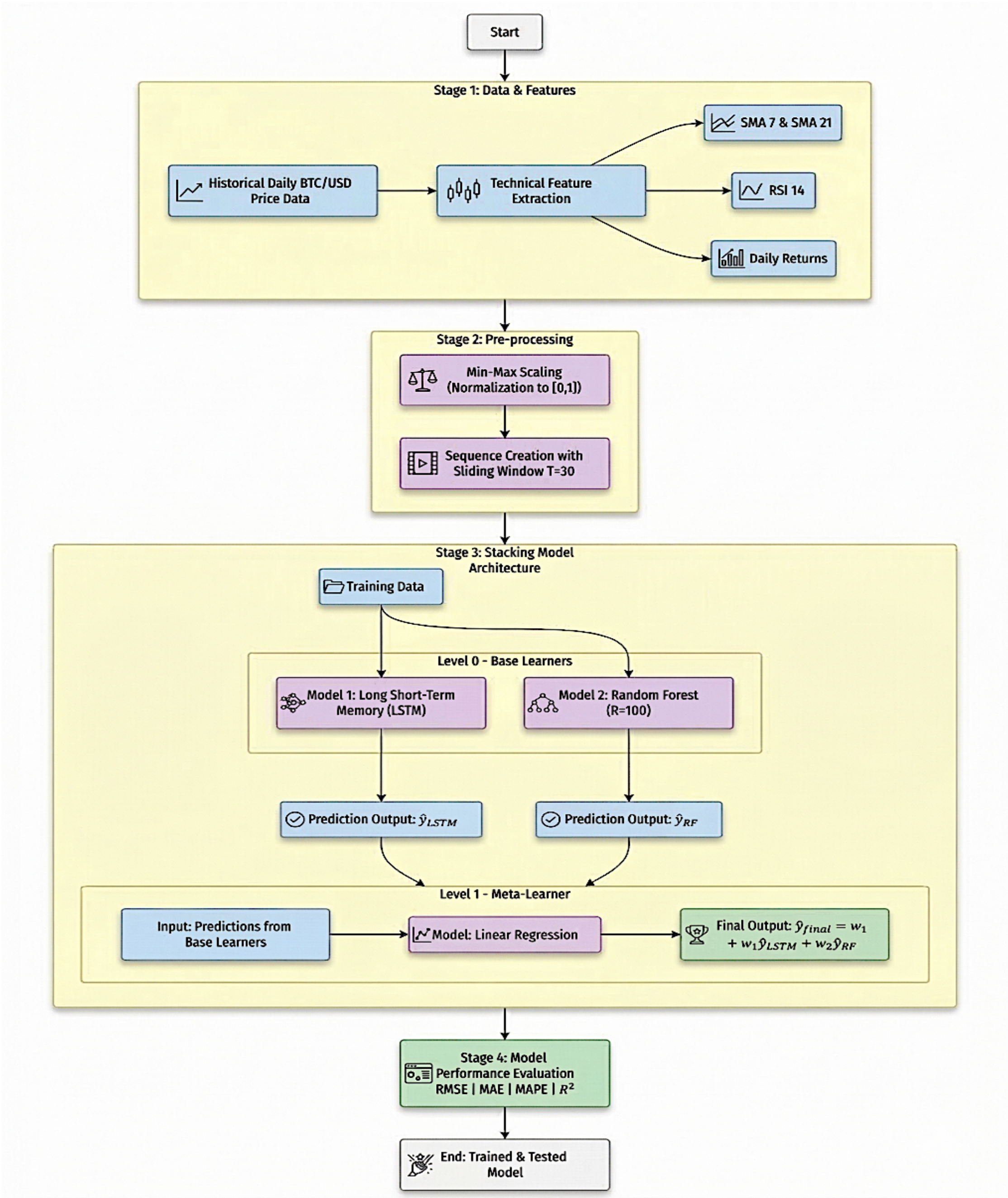

Figure 1. Research Methodology Diagram

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The methodology or system workflow of predicting the BTC/USD prices with the help of the Ensemble Learning (Stacking) approach is presented in figure 1. Each of the stages is described as follows:

Stage 1: Data and Features (Data Preparation) It starts with the gathering of daily historical data of BTC/USD. Based on this raw information we have Technical Feature Extraction which produces three key technical indicators as: SMA (Simple Moving Average): 7th and 21st day periods are used to obtain price trend. RSI 14 (Relative Strength Index): To gauge momentums and bouts of oversoldness and oversold. Daily Returns: To observe the percentage change of the prices daily.

Stage 2: Pre-processing (Pre-processing) The mined data is then pre-processed so that it can be fed into the model: Min-Max Scaling: Scales the data value to the [0,1] interval. This is quite crucial in order that the large-scale features are not dominated by the small-scale features. Sequence Creation: The information is transformed into a time series by the Sliding Window technique of length T=30. This means the model will look at the pattern of the past 30 days to predict the price of the next day.

Stage 3: Stacking Model Architecture (Model Architecture) This is the core of the system that uses the Stacking technique (two levels of models): Level 0 (Base Learners): Training data is fed into two different models in parallel: LSTM (Long Short-Term Memory): A Deep Learning algorithm that is expert in handling sequential or time series data. Random Forest (with 100 trees): A decision tree-based Machine Learning algorithm that is strong in handling non-linear relationships. These two models produce their own predictions ($\widehat{y_{LSTM}} and \widehat{y_{RF}}$). Level 1 (Meta-Learner): The prediction results from Level 0 are used as input for a new model, namely Linear Regression. The Meta-learner is tasked with "learning" the best weights from the prediction results of LSTM and Random Forest to produce the final prediction ($\widehat{y_{final}}$).

Stage 4: Model Performance Evaluation (Evaluation) After the model After training and testing, its performance is measured using four standard regression metrics: RMSE (Root Mean Square Error) & MAE (Mean Absolute Error): Measures the average magnitude of the prediction error. MAPE (Mean Absolute Percentage Error): Measures the percentage error. R^2 (R-Squared): Tests the quality of the model to explain the variation in the data.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The purpose of this flow is to integrate the capabilities of Deep Learning (LSTM) and more traditional Machine Learning (Random Forest) algorithms by applying the Linear Regression to achieve more precise and consistent predictions of the price of Bitcoins than with the help of only one of the models.

2.2. Technical Parameters and Features Details

Technical features are used to select parameters: standard capital market technical analysis:

1) Data Source & Period: BTC/USD daily historical data obtained via Yahoo Finance and Binance APIs covering the period July 2010 to June 2025.
2) Feature Formalization: All technical indicators are calculated using the closing price P_t.
3) Moving Average (7 & 21 days): Chosen to capture weekly and monthly trend momentum.
4) RSI (14 days): Uses a standard 14-day window to detect overbought/oversold conditions.
5) LSTM Parameters: Uses two hidden layers with 50 units, an Adam activation function, and a dropout rate of 0.2 to prevent overfitting.
6) Random Forest Parameters: Configure 100 trees with a max depth of 10, chosen after trial and error to balance accuracy and computational complexity.

2.3. Data Collection and Technical Features

The history of closing price of Bitcoin (BTC\/USD) is the main data that is used. The raw data is in the form of Open, High, Low, and Close (OHLC) variables.

Table 1. Dataset view

Date	Ticker	Open	High	Low	Close
07-17-2010	BTC	0.04951	0.04951	0.04951	0.04951
07-18-2010	BTC	0.04951	0.08585	0.04951	0.08584
....	...	...	...	...	...
06-20-2025	BTC	104403	106578	102385	103506
06-21-2025	BTC	103511	104056	101128	101476

In order to enhance the level of sensitivity of the model to market momentum, the extraction of technical features is carried out in the following way:

1) Simple Moving Average (SMA): It is a method of averaging the price variations in a timeframe of n days.

$$SMA_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \quad (1)$$

Where P_t is the closing price at time t, with time windows $n = 7$ and $n = 21$ [7].

2) Relative Strength Index (RSI): Momentum indicator which determines the velocity and direction of price changes.

3)

$$RSI = 100 - \left[\frac{100}{1+\frac{AvgGain}{AvgLoss}}\right] \quad (2)$$

Where $AvgGain$ and $AvgLoss$ calculated based on the average increase and decrease in prices over a 14-day period [3].

4) Daily Returns: Divides the percentage change of price per day, in order to assess relative volatility.

$$Returns_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (3)$$

2.4. Data Preprocessing

The pre-processing phase includes the normalization of data with the help of Min-Max scaling in order to shift the features into the interval [0,1]. This plays a critical role in the stability of convergence of gradient descent-based models of LSTM [17].

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (4)$$

Where x_i is the original value, whereas x_i' is a standardized value. The data is then arranged into a temporal sequence (sliding window) with a sequence length of $T = 30$.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

2.5. Hybrid Ensemble Stacking Architecture

The predictive system is built using a two-tier stacking architecture that combines the advantages of temporal and spatial feature extraction [18].

2.5.1. Level 0 (Base Learners):

1) Long Short-Term Memory (LSTM): Modeling sequential dependencies through a gate mechanism (forget, input, and output). The output of this model is $\widehat{y_{LSTM}}$. The LSTM architecture is specifically designed to address the vanishing gradient problem in long time series data by using a mechanism of memory units and gates. Each memory unit at time t is computed through the following series of operations [19]:

   a) Forget Gate (f_t): Determines which information from the previous cell state (C_{t-1}) will be discarded.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

   b) Input Gate (i_t) & Candidate State ($\widetilde{C}_t$): Determines the new information to be stored in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{7}$$

   c) Cell State Update (C_t): Updating the old cell state to a new cell state.

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{8}$$

   d) Output Gate (o_t) & Hidden State (h_t): Determines the output value based on the updated cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{9}$$

$$h_t = o_t * \tanh(C_t) \tag{10}$$

Where σ is the sigmoid activation function, W and b each represents the weight and bias matrices learned during the training process [8].

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

2) Random Forest: Performs aggregation of B decision trees to mitigate high variance in the data. The output of this model is $\widehat{y_{RF}}$. Random Forest is a bagging-based ensemble algorithm that builds a large number of independent decision trees. For Bitcoin price regression, this model aggregates predictions from each tree to produce a more stable final output [1], [7], [20]. The Random Forest prediction process is mathematically expressed as the average of the predictions of B decision tree fruits (T):

$$\widehat{y_{RF}} = \frac{1}{B}\sum_{b=1}^{B} T_b(x;\Theta_b) \tag{11}$$

Where:

$\widehat{y_{RF}}$ is the final prediction of the Random Forest model.

B is the number of trees in the forest (in this study $B = 100$).

$T_b(x;\Theta_b)$ is the prediction of the b-th tree for input x with parameter Θ_b obtained through bootstrap sampling.

This strategy effectively reduces model variance without increasing bias, making it highly robust against outliers in Bitcoin volatility data [21].

2.5.2. Level 1 (Meta-Learner):

To prevent data leakage and ensure model validity on time series data, the training procedure is set as follows:

1) Time-Series Split: The data is not shuffled randomly. The 90:10 split is done chronologically to maintain the temporal order.
2) Meta-Learner Training: The meta-learner (Linear Regression) is trained using out-of-sample predictions from the base learners. The predictions of $\widehat{y_{LSTM}}$ and $\widehat{y_{RF}}$ in the validation set are used as input features for the meta-learner to minimize the risk of overfitting.
3) Using Linear Regression to learn the optimal weights (w) of the base model predictions to minimize the error on the meta-training set.

$$\widehat{y_{final}} = w_0 + w_1\widehat{y_{LSTM}} + w_2\widehat{y_{RF}} + \varepsilon \tag{12}$$

Where w_0 is the intercept, ϵ is *residual error,* w_1 and w_2 represent the optimal weights learned to balance the stability of Random Forest and the temporal sensitivity of LSTM [22].

2.6. Performance Evaluation Metrics

The reliability of the model is validated using four main metrics to measure the deviation between the actual values (y_i) and the predicted values ($\hat{y}_i$) [4], [23]:

1) Root Mean Squared Error (RMSE): Sensitive to major errors (*outliers*).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

2) Mean Absolute Error (MAE): Measuring the absolute mean error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{14}$$

3) Mean Absolute Percentage Error (MAPE): The main indicator of accuracy is in percentage form.

$$MAPE = \frac{100\backslash\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{15}$$

4) R-Squared (R^2): Measures the extent to which the target variance can be explained by the model.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{16}$$

3. RESULTS AND DISCUSSION

3.1. Model Performance Analysis

The experiments have been performed comparing three predictive architectures, namely: a single Random Forest (RF), a single LSTM, and the proposed model Hybrid Ensemble Stacking.

1) Random Forest (RF)

This model can explain the price variation based on an ensemble tree, using technical characteristics the MA7, MA21, and RSI. Although this model remains constant when using historical data, it lacks extrapolative power when it comes to new price discovery periods.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

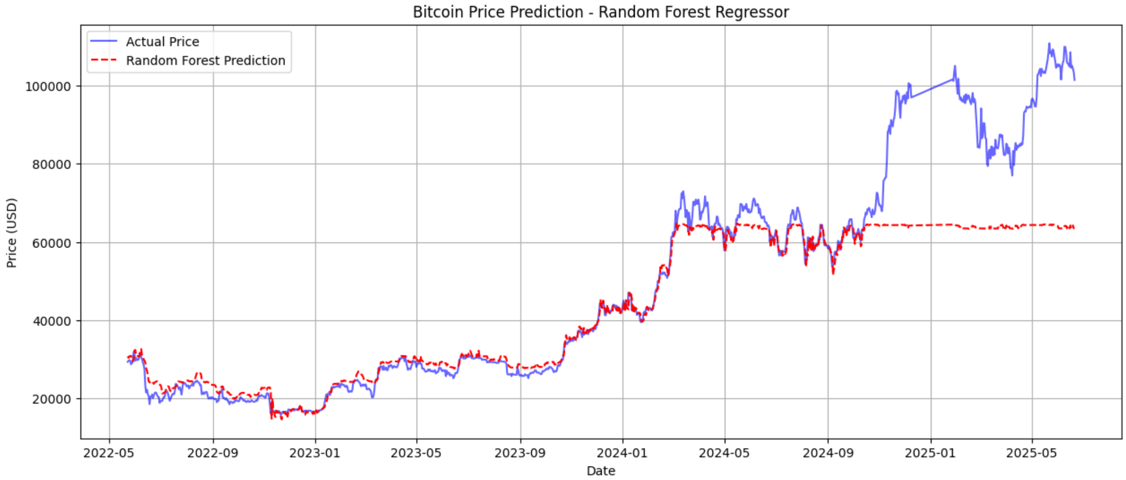

Figure 2. Prediction results with the Random Forest model

The graph plots the performance of the Random Forest Regressor model in predicting the change of Bitcoin (BTC) price with respect to the US Dollar (USD) between the middle of 2022 and the middle of 2025. There exists a sharp contrast in prediction accuracy between the training phase and the testing phase as far as methodology is concerned. The model in the first phase up to around September 2024 showed very high accuracy in the fitting properties and the prediction line (red dashed) could track the actual price movement (blue) with a very small margin of error. This means that the model has been able to pick historical patterns based on the available data in the training set.

Despite the fact that the model seemed correct at first, there was a major deviation that occurred in the end of 2024. The following are some of the critical analysis aspects of this phenomenon:

1) Extrapolation limitations: The basic problem with decision tree-based models such as the Random Forest is that they simply cannot make predictions that are out of range of the training set. With the price of Bitcoin climbing to over 100,000 dollar after reaching over 80,000 dollars and then continuing to go up, the model would have been left at an estimated output of approximately 65,000 dollars which was probably the highest possible value that the model had attained during the training process.
2) Prediction Stagnation: This trend of the red line that will flatten at the end of the graph implies that the model has reached the maximum of its predictions.

In the case of time series data having strong growth trends this is sometimes called the regressing-to-the-mean problem.

3) Architectural Mismatch: It is shown in this graph that traditional ensemble algorithms that lack a detrending component or sufficient lag property are less efficient at predicting crypto assets with exceptionally volatile behavior and long-term trends that out of their history.

The model failed to work in case of a new all-time high price situation. Although true of the historical data, it could not model the positive stock movement to the extent its parameter set had been trained.

2) Long Short-Term Memory (LSTM)

As a deep learning model, LSTM shows superiority in capturing long-term sequential dependency patterns through a memory cell mechanism with a time window (SEQ_LENGTH) of 30 days.

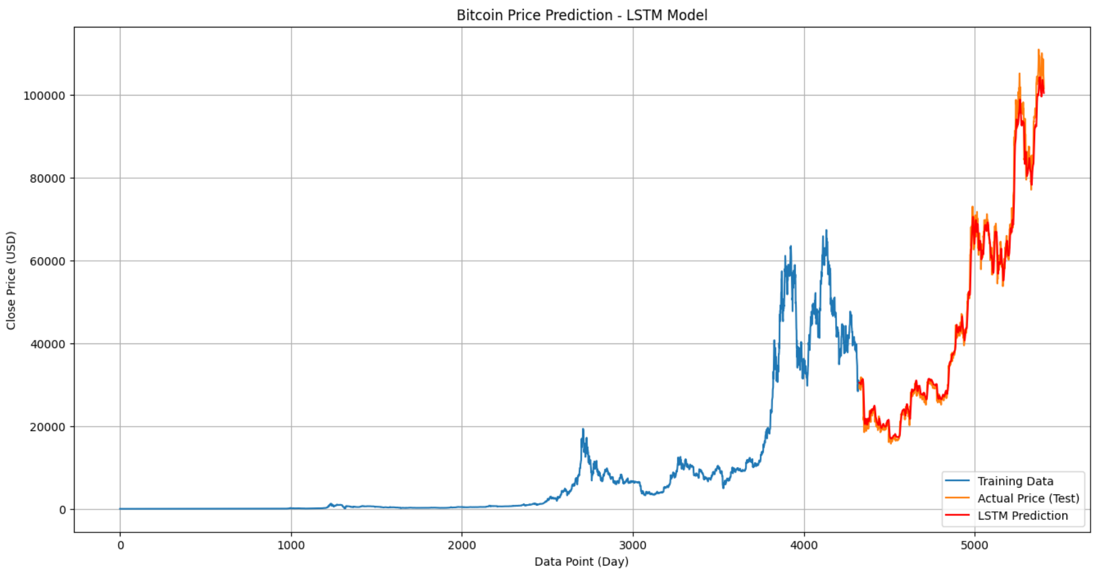

Figure 3. Prediction results using the LSTM model

The graph above (Figure 3) visualizes the performance of a Long Short-Term Memory (LSTM) model in predicting the closing price of Bitcoin (BTC) in US Dollars (USD) based on a sequence of daily data. Unlike conventional regression models, the LSTM architecture, a variant of the Recurrent Neural Network (RNN), is specifically designed to capture long-

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

term dependencies in time series data. Visually, the graph is divided into two main phases: the training phase (blue line), which covers the initial historical data up to approximately the 4,300th data point, and the testing phase (orange and red lines), which evaluates the model's generalization ability to new data.

The effectiveness of the LSTM model in this scenario demonstrates significant improvements compared to simple statistical methods or decision tree-based models, which can be described as follows:

a) Accuracy in High Volatility: It will be observed that LSTM model (red line) is particularly well-equipped to track the actual price (in orange), in the face of exceptionally large price changes in the price spikes that constantly occur upon the 5,000th data point.
b) Long-Term Trend Accuracy: LSTM was able to discover a bullish trend that hit the $100,000 mark in comparison with the static models indicating that the architecture was able to extrapolate the trend into the space where training data was not able to reach.
c) Response to Market Dynamics: The overlap of the red prediction line with the orange test data is evidence that the model has a low error rate on estimating the daily price momentum, which is a necessity of the technical analysis of crypto assets.

The success of the model is that it can remember vital information in the past by the use of the cell state and the gate mechanism hence able to learn not only the past prices but also the complex pattern of the market cycles.

3) Model Integration (Hybrid Ensemble Stacking)

This program produces a Hybrid Ensemble model, which is a combination of the predictions made by both of the base models using a Linear Regression-based meta-learner. In accordance with the automatic calculation of the evaluation function, the integration results reveal the significant improvement of the precision.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

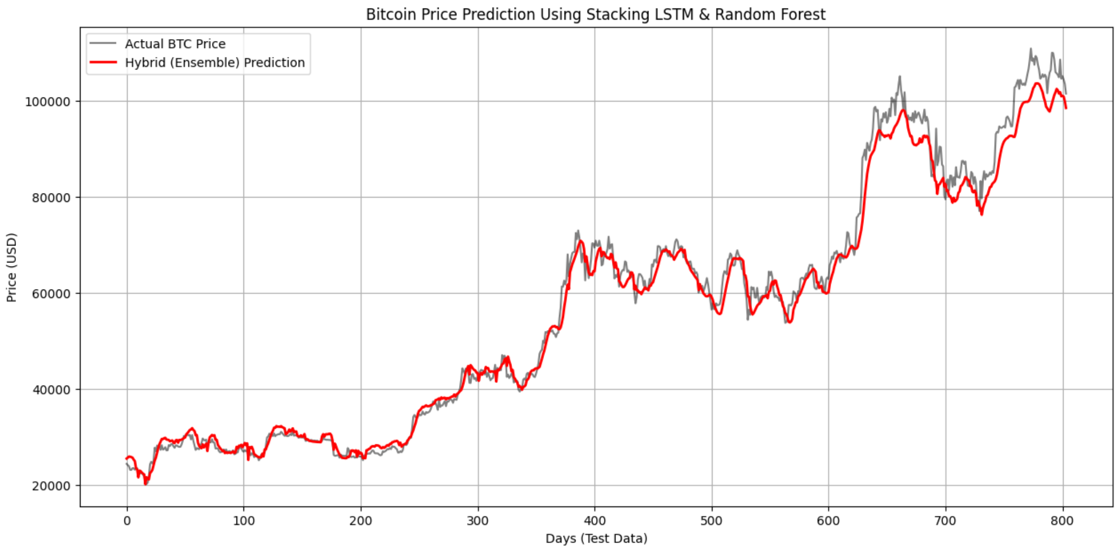

Figure 4. Prediction using integration model (Hybrid Ensemble Stacking)

The graph represents the application of a hybrid model by the Stacking Ensemble technique that integrates the Long Short-Term Memory (LSTM) and the Random Forest architecture to predict the Bitcoin prices. The goal of this method is to integrate the advantages of LSTM when seeking the long-term sequential memory and the capability of Random Forest in identifying the non-linear data relations. The hybrid prediction line (red) has a very high level of fit to the actual price (gray) visually, with the model capable of minimizing noise and still being sensitive to extreme market variability.

Combinations of the two algorithms are also effective and they have a number of technical benefits in time series analysis:

a) Optimized Generalization: With the stacking technique the lack of extrapolation to new values that is witnessed in the earlier single model of the Random Forest is effectively addressed with growth trends being captured by the LSTM.
b) Prediction Stability: The red line is also more flattened yet correct after fluctuations in prices and it means that the ensemble model is able to balance the overfitting and underfitting phenomena that are common in predicting crypto assets.
c) Extreme Trends Adaptation: This model was found to be the most useful in predicting price increments that are above the $100,000 line, and therefore,

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

the combination of the weights of the two models produces stronger predictions compared to prediction by either of the two models.

This interaction shows that the hybrid model can capture various statistical features of market data, where LSTM can emphasize the time structure, whereas Random Forest can improve the use of features to make a decision. The evaluation results using the test data set are summarized in Table 2.

Table 2. Comparison of Bitcoin Price Prediction Model Performance Metrics

No	Model	RMSE (USD)	MAE (USD)	MAPE (%)	R2
1	Random Forest	13.067,60	6.460,58	9,45%	0,77
2	LSTM	2.536,55	1.767,83	3,86%	0,99
3	Hybrid Ensemble Stacking	2.944,62	2.117,68	3,54%	0,99

Model performance evaluation was conducted by comparing the hybrid architecture to a single model using four standard metrics. Based on the experimental data summarized in Table 1, varying performance was found. The pure LSTM model recorded the lowest absolute error value with an RMSE of 2,536.55 and an MAE of 1,767.83. This indicates that, to minimize price deviation in USD, the LSTM architecture is more sensitive to large Bitcoin price fluctuations [24], [25], [26] [1], [24], [25].

All prediction results shown in the graphs are out-of-sample (test) data, ensuring that the evaluation is conducted on data the model has never seen during the training phase. Based on the results in Table 2, a significant metric trade-off is evident. Although the pure LSTM model recorded the lowest RMSE and MAE values, the Hybrid Ensemble Stacking model proved superior only on the MAPE criterion (3.54%). The improvement in MAPE with no correction in RMSE or MAE is due to the fact that the MAPE assigns errors an equal weight relative to both its value and the absolute USD errors are very sensitive (as shown by the experience when the Bitcoin broke the door to over $100,000). This implies that the stacking method places high emphasis on consistency rates of errors throughout the immensely fluctuating price ladder of digital properties.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

3.2. Visualization of Prediction

The visualization shows that the hybrid model can be used to follow the real Bitcoin price dynamics. The prediction curve (in red) has exceptionally high convergence with the true price (in black) particularly at the time of moderate volatility. The hybrid model has been proven to minimize the lag effect that is common with pure time series models. This is because the Random Forest will be used to give the momentum context to the RSI and the Moving Average indicators, whereas the LSTM will support the long-term temporal dependency structure [27], [28].

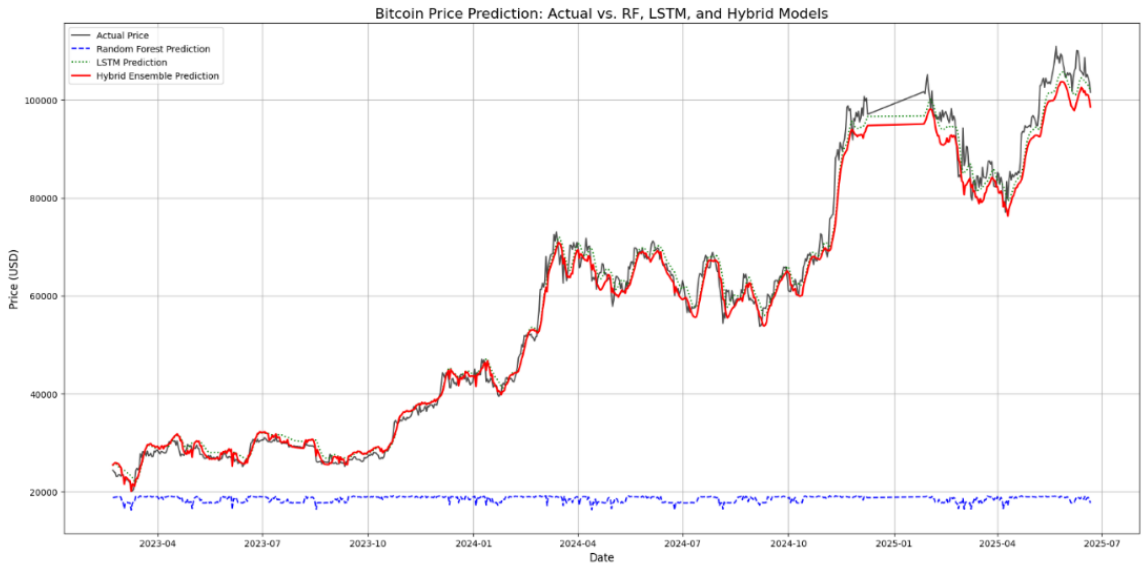

Figure 5. Prediction using Random Forest, LSTM, and Integration (Hybrid Ensemble Stacking) models

The given data visualization is an in-depth comparison of the real Bitcoin price and the predictions of three model architectures: Random Forest (RF), Long Short-Term Memory (LSTM), and Hybrid Ensemble. Strong differences in generalization capabilities of each model to the volatility of the crypto markets form methodological differences. The Random Forest model (dashed blue line) can actually illustrate a structural failure in extrapolating trends, in which the predictions come to a halt at one of the lower prices range and do not respond to any major price jumps that will happen in the future, after 2024. However, LSTM model (dotted green line) and the Hybrid Ensemble (red line) show much better performance as they accurately track the actual price changes even after Bitcoin surpassed the mark of $100,000.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The pros and cons of both strategies can be summarized as follows:

1) Random Forest Extrapolation Failure: This model can only forecast values within the range it has been trained on, and therefore it does not help in predicting upward price movement that is outside its historical range.
2) LSTM Architecture Robustness: LSTM demonstrates long-term memory capabilities that help it map long-term trends and continue to be relevant even in cases where the prices of assets have reached new all-time highs.
3) Hybrid Model Stability: The Ensemble methodology, which is a combination of LSTM and RF, has the most stable and smooth prediction line. This combination system can successfully overcome the personal inaccuracies of all the algorithms, and the estimates are more resistant to market shocks.

It has been observed that the combination of memory-based (LSTM) and tree-based (RF) models into the Ensemble system yields the most superior mode of dealing with non-linear and highly volatile time series data like Bitcoin.

3.3. Discussion

The experimental findings of the current research prove the hypothesis that the Hybrid Ensemble Stacking framework is useful to address the non-linear and non-stationary issues related to Bitcoin price. One of the findings is that the model retains a higher MAPE of 3.54 even though it does not win in RMSE and MAE. It happens so due to the stacking mechanism, which is implemented by the Linear Regression meta-learner, which puts more emphasis on relative consistency of errors at various price scales. This is especially important to the assets with such extreme value distributions as Bitcoin where absolute errors (RMSE/MAE) may be misleading in the periods of price discovery above the price of $100,000.

The input features (SMA and RSI) were also the macro-technical indicators that were incorporated, and it turned out to be a decisive element in stabilizing the prediction. This would conform to the results of Zatwarnicki (2025) who showed that technical indicators offer critical trend clues that assist machine learning models to remove market noise [29]. These indicators combined with a two-layer stacking scheme take this research beyond the realm of simple hybrid models and towards problem specific forecasting architecture as indicated by the difference in performance between our hybrid model and the individual LSTM or RF models.

Furthermore, our results show a similar pattern to the study by Quang et al. (2025), where deep learning architectures like LSTM are excellent at capturing temporal dependencies but can be prone to lag during sudden price discovery phase [30]. By introducing Random Forest as a parallel base learner, our framework mitigates this lag through ensemble averaging. Unlike the CNN-LSTM approach discussed by Wen and Ling (2023), which focuses heavily on spatial-temporal features, our stacking framework leverages the robustness of tree-based models to handle outliers that often mislead pure gradient-based neural networks [28], [31], [32].

Finally, the application of a time series safe training process based on the chronological splitting and out of sample meta learning makes sure that the findings do not contain data leakage. This validation is to confirm that the proposed model is not only correct in the percentage error, but also practical to implement in the cryptocurrency risk management system.

4. CONCLUSION

This paper concludes that the problem specific Hybrid Ensemble Stacking Framework (combining LSTM and Random Forest) is a powerful tool in predicting the price of Bitcoin. Empirical testing confirms that the pure LSTM model has more nominal accuracy in both RMSE and MAE but the proposed hybrid model has the most stable performance with a MAPE of 3.54%. This illustrates that Linear Regression meta-learner successfully trades long-term time trends of LSTM with the noise suppression features of technical indicators of the Random Forest. The applicability of the findings directly to the practice of financial information systems developers is that the findings provide a more effective instrument in managing risk with crypto-assets, particularly in the turbulent periods of price discovery. Future studies need to incorporate external sentiment factors and automated hyperparameter optimization in order to increase the model robustness against unexpected global macroeconomic shocks.

ACKNOWLEDGMENT

Gratitude is expressed to the lecturers of Universitas Diponegoro and parties who have provided support through the Indonesian Education Scholarship (BPI) from the Center for Higher Education Budget Management (PPAPT), the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia, and the Education Fund Management Institute under the Ministry of Finance of the Republic of Indonesia.

REFERENCES

[1] J. Chen, "Analysis of Bitcoin Price Prediction Using Machine Learning," *J. Risk Financ. Manag.*, vol. 16, no. 1, 2023, doi: 10.3390/jrfm16010051.

[2] A. Munazilin, M. A. Wibowo, and R. Parlika, "Bitcoin Price Prediction : A Systematic Literature Review and Bibliometric Analysis," *2025 9th Int. Conf. Inf. Technol. Inf. Syst. Electr. Eng.*, pp. 277–282, 2025, doi: 10.1109/ICITISEE68184.2025.11355086.

[3] A. Akgul, E. E. Şahin, and F. Y. Şenol, "Blockchain-based Cryptocurrency Price Prediction with Chaos Theory, Onchain Analysis, Sentiment Analysis and Fundamental-Technical Analysis," *Chaos Theory Appl.*, vol. 4, no. 3, pp. 157–168, 2022, doi: 10.51537/chaos.1199241.

[4] N. Latif, J. D. J. D. Selvam, M. Kapse, V. Sharma, and V. C. Mahajan, "Comparative Performance of LSTM and ARIMA for the Short-Term Prediction of Bitcoin Prices," *Australas. Accounting, Bus. Financ. J.*, vol. 17, no. 1, pp. 256–276, 2023, doi: 10.14453/aabfj.v17i1.15.

[5] O. Omole and D. L. Enke, "Deep learning for Bitcoin price direction prediction: models and trading strategies empirically compared," *Financ. Innov.*, vol. 10, no. 1, 2024, doi: 10.1186/s40854-024-00643-1.

[6] W. Badar, S. Ramzan, A. Raza, N. L. Fitriyani, M. Syafrudin, and S. W. Lee, "Enhanced Interpretable Forecasting of Cryptocurrency Prices Using Autoencoder Features and a Hybrid CNN-LSTM Model," *Mathematics*, vol. 13, no. 12, 2025, doi: 10.3390/math13121908.

[7] F. Orte, J. Mira, M. J. Sánchez, and P. Solana, "A random forest-based model for crypto asset forecasts in futures markets with out-of-sample prediction," *Res. Int. Bus. Financ.*, vol. 64, no. November 2022, 2023, doi: 10.1016/j.ribaf.2022.101829.

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

[8] M. Aswadi and U. Ependi, "Predicting Bitcoin and Ethereum Prices Using the Long Short- Term Memory (LSTM) Model," *J. Inf. Syst. Informatics*, vol. 7, no. 3, pp. 3046–3061, 2025, doi: 10.51519/journalisi.v7i3.1228.

[9] N. Tripathy, S. Hota, D. Mishra, S. K. Nayak, S. S. Dalai, and J. Tripathy, "Cryptocurrency Price Prediction: A Comprehensive Analysis of High-dimensional Features with Deep Learning Techniques," in *2024 International Conference on Intelligent Computing and Sustainable Innovations in Technology, IC-SIT 2024*, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/IC-SIT63503.2024.10862895.

[10] N. Tripathy, P. Satapathy, S. Hota, S. K. Nayak, and D. Mishra, "Empirical Forecasting Analysis of Bitcoin Prices: A Comparison of Machine Learning, Deep Learning, and Ensemble Learning Models," *Int. J. Electr. Comput. Eng. Syst.*, vol. 15, no. 1, pp. 21 – 29, 2024, doi: 10.32985/ijeces.15.1.3.

[11] M. Frohmann, M. Karner, S. Khudoyan, R. Wagner, and M. Schedl, "Predicting the Price of Bitcoin Using Sentiment-Enriched Time Series Forecasting," *Big Data Cogn. Comput.*, vol. 7, no. 3, 2023, doi: 10.3390/bdcc7030137.

[12] Y. Zhu *et al.*, "Price Prediction of Bitcoin Based on Adaptive Feature Selection and Model Optimization," *Mathematics*, vol. 11, no. 6, 2023, doi: 10.3390/math11061335.

[13] P. L. Seabe, C. R. B. Moutsinga, and E. Pindza, "Sentiment-driven cryptocurrency forecasting: analyzing LSTM, GRU, Bi-LSTM, and temporal attention model (TAM)," *Soc. Netw. Anal. Min.*, vol. 15, no. 1, pp. 1–27, 2025, doi: 10.1007/s13278-025-01463-6.

[14] P. L. Seabe, C. R. Bambe Moutsinga, E. Pindza, C. R. B. Moutsinga, and E. Pindza, "Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach," *Fractal Fract.*, vol. 7, no. 2, 2023, doi: 10.3390/fractalfract7020203.

[15] N. Tripathy, S. K. Nayak, and S. Prusty, "A comparative analysis of Silverkite and inter-dependent deep learning models for bitcoin price prediction," *Front. Blockchain*, vol. 7, 2024, doi: 10.3389/fbloc.2024.1346410.

[16] R. Bourday, I. Aatouchi, M. A. Kerroum, and A. Zaaouat, "Cryptocurrency Forecasting Using Deep Learning Models: A Comparative Analysis," *HighTech Innov. J.*, vol. 5, no. 4, pp. 1055–1067, 2024, doi: 10.28991/HIJ-2024-05-04-013.

[17] A. Ladhari and H. Boubaker, "Deep Learning Models for Bitcoin Prediction Using Hybrid Approaches with Gradient-Specific Optimization," *Forecasting*, vol. 6, no. 2, pp. 279 – 295, 2024, doi: 10.3390/forecast6020016.

[18] P. L. Seabe, E. Pindza, C. R. B. Moutsinga, M. Aphane, C. R. Bambe Moutsinga, and M. M Aphane, "Temporal Attention-Enhanced Stacking Networks: Revolutionizing Multi-Step Bitcoin Forecasting," *Forecasting*, vol. 7, no. 1, 2025, doi: 10.3390/forecast7010002.

[19] M. R. Kabir, D. Bhadra, M. Ridoy, and M. G. Milanova, "LSTM–Transformer-Based Robust Hybrid Deep Learning Model for Financial Time Series Forecasting," *Sci*, vol. 7, no. 1, 2025, doi: 10.3390/sci7010007.

[20] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[21] K. Murray, A. Rossi, D. Carraro, and A. Visentin, "On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles," *Forecasting*, vol. 5, no. 1, pp. 196–209, 2023, doi: 10.3390/forecast5010010.

[22] Z. Ye, Y. Wu, H. Chen, Y. Y. Pan, and Q. Jiang, "A Stacking Ensemble Deep Learning Model for Bitcoin Price Prediction Using Twitter Comments on Bitcoin," *Mathematics*, vol. 10, no. 8, 2022, doi: 10.3390/math10081307.

[23] M. Z. Maliha, A. S. Trisha, A. M. T. Khan, P. Das, M. I. Hossain, and R. Rahman, "A Deep Learning Approach to Predict Cryptocurrency Price by Evaluating Sentiment and Stock Market Correlations," *Lect. Notes Networks Syst.*, vol. 867 LNNS, pp. 3 – 17, 2024, doi: 10.1007/978-981-99-8937-9_1.

[24] E. Koosha, M. Seighaly, and E. Abbasi, "Measuring the Accuracy and Precision of Random Forest, Long Short-Term Memory, and Recurrent Neural Network Models in Predicting the Top and Bottom of Bitcoin price," *J. Math. Model. Financ.*, vol. 2, no. 2, pp. 107 – 128, 2022, doi: 10.22054/jmmf.2023.15183.

[25] M. Bagheri and P. S. Giudici, "Accurate, Secure and Explainable bitcoin forecasting," *Phys. A Stat. Mech. its Appl.*, vol. 678, 2025, doi: 10.1016/j.physa.2025.130974.

[26] R. Bourday, I. Aattouchi, and M. Ait Kerroum, "A Transfer Learning–Enhanced Hybrid Deep Learning Framework for Bitcoin Price Forecasting Using Market Sentiment and Time Series Data," *Int. J. Inf. Eng. Electron. Bus.*, vol. 17, no. 5, pp. 1–17, 2025, doi: 10.5815/ijieeb.2025.05.01.

[27] Y. Wang, M. F. Ghazali, R. Ab Razak, and M. A. S. Zaidi, "Complex system and PS-LSTM prediction of cryptocurrencies, stocks, bonds, exchange rates and commodities," *Phys. A Stat. Mech. its Appl.*, vol. 679, 2025, doi: 10.1016/j.physa.2025.130976.

[28] N. Shi Wen and L. Sook Ling, "Evaluation of Cryptocurrency Price Prediction Using LSTM and CNNs Models," *Int. J. Informatics Vis.*, vol. 7, no. 3–2, pp. 2016–2024, 2023.

[29] M. Zatwarnicki and K. Zatwarnicki, "Timing Usage of Technical Analysis in the Cryptocurrency Market," *Appl. Sci.*, vol. 15, no. 23, pp. 1–30, 2025, doi: 10.3390/app152312802.

[30] P. D. Quang, N. H. Duy, P. Q. Khoai, and B. D. Duong, "Integrating Moving Average Indicators with Long Short-Term Memory Model in Bitcoin Price Forecasting," *J. Appl. Data Sci.*, vol. 6, no. 3, pp. 1850–1864, 2025, doi: 10.47738/jads.v6i3.766.

[31] N. Kose, Y. E. Gur, and E. Ünal, "Deep Learning and Machine Learning Insights Into the Global Economic Drivers of the Bitcoin Price," *J. Forecast.*, vol. 44, no. 5, pp. 1666–1698, 2025, doi: 10.1002/for.3258.

[32] K. Zhen, D. Xie, and X. Hu, "A multi-feature selection fused with investor sentiment for stock price prediction," *Expert Syst. Appl.*, vol. 278, p. 127381, 2025, doi: 10.1016/j.eswa.2025.127381.