Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

Comparison of Time Series Algorithms Using SARIMA and Prophet in Predicting Short-Term Bitcoin Prices

Muhammad Zidan Brilliant[1], Triyanna Widiyaningtyas*[2], Wahyu Caesarendra[3]

[1,2]Departement of Electrical Engineering and Informatics, Universitas Negeri Malang, Indonesia
[3]Department of Mechanical and Mechatronics Engineering, Faculty of Engineering and Science, Curtin University Malaysia, Malaysia

Email: [2]triyannaw.ft@um.ac.id

Received : May 24, 2025; Revised : Jun 29, 2025; Accepted : Jul 20, 2025; Published : Aug 18, 2025

Abstract

Digital finance, particularly Bitcoin, has become a global phenomenon with high volatility, posing great challenges for traders in predicting short-term prices. This study compares the performance of the SARIMA and Prophet algorithms in predicting short-term Bitcoin prices using daily closing price data from October 1, 2014, to October 1, 2024. The study utilizes two different data timeframes, a 10-year dataset (2014-2024) and the last 5 years (2019-2024) for comparative analysis. The SEMMA methodology is used to analyze and compare the two algorithms, which consist of the stages Sample, Explore, Modify, Model, and Assess. The experimental results show that SARIMA provides more stable and consistent results with an MAPE value of 1.24% and RMSE of 896.15 in Scenario 1 and an MAPE value of 1.27% and RMSE of 920.24 in Scenario 2. In contrast, Prophet shows different performance in each scenario. In Scenario 1, Prophet shows optimal results but not so good with an average MAPE of 1.74% and an RMSE value of 1214.86. On the other hand, Prophet showed good performance in Scenario 2 with a lower average MAPE of 0.71% and a smaller RMSE of 489.94, indicating Prophet's ability to handle newer and more dynamic datasets. Both models show their respective advantages; SARIMA is better for long and stable historical data, while Prophet is more effective for shorter and dynamic data. This research provides practical insights for traders and investors in choosing the right prediction model, with results for further study in predicting crypto asset prices.

Keywords: *Bitcoin, Price Prediction, Prophet, SARIMA, SEMMA, Time Series.*

1. INTRODUCTION

The world of digital finance has undergone a significant transformation with the emergence of cryptocurrencies, particularly Bitcoin [1]–[3]. Since it was first introduced by Satoshi Nakamoto, Bitcoin has become a global phenomenon that has caught the attention of many market participants [4], [5]. Known for its high volatility, Bitcoin not only brings great risk to traders, but also offers great profit opportunities [6]–[8]. For traders using swing trading or intraday strategies, which focus on daily or weekly price movements, short-term Bitcoin price prediction becomes a very important aspect [9]–[11]. Bitcoin price prediction is not just about historical data or analytical algorithms-it also requires a thorough understanding of human dynamics, global economics, and technological developments. Therefore, the use of appropriate price prediction models can help in making better decisions. The results of the Bitcoin price prediction can provide information for traders/investors on whether the current trend is up, down, or sideways. Thus, daily traders can determine entry/exit levels based on the bitcoin price projections generated by the system, and long-term investors can also estimate potential future returns for evaluating entry/exit.

One widely used approach to predicting the price of financial assets is time series analysis [12]–[14]. Although this method has been applied in various studies to predict Bitcoin prices, market

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

uncertainty and extreme price fluctuations make the application of classical time series models, such as ARIMA, less effective [15], [16]. This is due to the assumptions of stationarity and linearity that do not always apply in Bitcoin data [17], [18].

Previous research, such as that conducted by [19], shows that ARIMA models can be used for short-term predictions with favorable results. However, these models cannot handle the complexity of more dynamic and non-linear data, which is a big challenge in the highly volatile Bitcoin market.

Recent research, such as that conducted by [20], compared the performance of several models, including ARIMA, SARIMA, and Linear Regression, in predicting Bitcoin price. The results show that SARIMA is more effective in handling seasonal patterns in Bitcoin price data. However, despite SARIMA's advantage in handling seasonal data, there has been no research that directly compares SARIMA's performance with modern algorithms such as Prophet [21]–[23], which is designed to handle more complex and dynamic time series data [24], [25]. SARIMA works well on stationary time series data, which is data that has a constant mean, variance, and covariance over time. Therefore, SARIMA can evaluate Bitcoin volatility by using differencing to transform non-stationary data into stationary data [20]. Meanwhile, Prophet assumes that the main trend changes smoothly, with few changepoints [26]. Therefore, if there is a spike in Bitcoin price fluctuations, it is necessary to increase the changepoint_prior_scale to make the model more flexible to sudden changes.

While several studies have evaluated Bitcoin price prediction methods, some gaps need to be addressed. First, most of the previous studies used data with a relatively short time of less than five years. This limited time may not be sufficient to capture the long and complex cycles of the Bitcoin market. Secondly, while there have been comparisons between several traditional models, no studies have specifically compared the performance of SARIMA with more modern algorithms, such as Prophet, which is designed to cope with uncertainty and non-linear trends in time series data.

This study aims to fill the gap by offering several novelties. First, this study will use Bitcoin price data over a longer time, from October 1, 2014, to October 1, 2024. The use of longer time series allows for a more in-depth analysis of the more complex patterns and cycles of the Bitcoin market. Secondly, this study will compare the performance of two time series algorithms, namely SARIMA and Prophet, in predicting short-term Bitcoin prices (1-7 days). A direct comparison between the two provides a more comprehensive insight into the strengths and weaknesses of each method in handling volatility and non-linear trends in Bitcoin data.

2. METHOD

This research adopts the SEMMA methodology as the main framework to analyze and compare Bitcoin price prediction algorithms. SEMMA stands for five main stages: Sample, Explore, Modify, Model, and Assess, which are designed to facilitate data exploration, predictor variable selection, model building, and model performance evaluation as shown in Figure 1.

2.1. Sample

At this stage, historical Bitcoin price data was collected from Yahoo Finance using the Python yfinance library to obtain structured data. The time used is from October 1, 2014, to October 1, 2024. The data collected includes important variables such as opening price (Open), highest price (High), lowest price (Low), closing price (Close), and trading volume (Volume), with a total data count of 3,654 rows and 6 columns. This data was chosen to ensure a complete representation of the various Bitcoin market conditions over the last ten years.

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

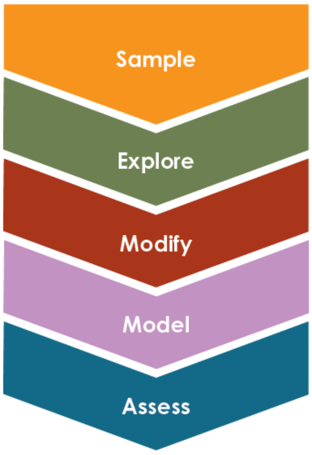

Figure 1. The SEMMA methodology

2.2. Explore

The exploratory stage aims to analyze historical Bitcoin price data, identifying long-term trends, daily fluctuations, and seasonal patterns that may affect price movements. At this stage, an important step is the visualization of Bitcoin's daily closing price over the period from October 1, 2014, to October 1, 2024. This exploratory analysis helps in understanding the volatility of Bitcoin price, which is a key challenge in building accurate short-term prediction models. Table 1 shows the 10-year Bitcoin historical data.

Table 1. 10 Years Bitcoin Historical Data

Date	Open (USD)	High (USD)	Low (USD)	Close (USD)	Volume
2014-10-01 00:00:00	387.43	391.38	380.78	383.61	26229400
2014-10-02 00:00:00	383.99	385.50	372.95	375.07	21777700
2014-10-03 00:00:00	375.18	377.70	357.86	359.51	30901200
2014-10-04 00:00:00	359.89	364.49	325.89	328.87	47236500
2014-10-05 00:00:00	328.92	341.80	289.30	320.51	83308096
…	…	…	…	…	…
2024-09-30 00:00:00	65634.66	65635.05	62873.62	63329.50	37112957475
2024-10-01 00:00:00	63335.61	64110.98	60189.28	60837.01	50220923500

2.3. Modify

The modification stage includes cleaning, transforming, and sharing data in preparation for modeling. The data was cleaned of missing values and anomalies that could affect the prediction results. The first step ensures that the data is free of missing values and anomalies that could affect the prediction results. As Figure 2 shows, after checking, there is no empty or missing data.

```
Total number of missing values:
ds    0
y     0
dtype: int64
```

Figure 2. Check Missing Value

The transformation is done to ensure the data is stationary. Before applying a SARIMA model, it is important to ensure that the time series data is stationary, because this model works on the assumption that the mean, variance, and covariance do not change over time [27], [28]. A Stationarity test is

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

conducted using the Augmented Dickey-Fuller Test (ADF) to ensure the data meets the stationary criteria. The result of the ADF Test is shown in Figure 3.

```
ADF Statistic: -1.3422664860232743
p-value: 0.6096204927939071
Data is not stationary. Perform differencing.
```

Figure 3. ADF Test before Differencing

From Figure 3, it can be seen that the bitcoin data used is still not stationary. To change the data to be stationary, data transformation is carried out, such as differencing, so that the existing data can become stationary. Differencing is a technique to eliminate trends and seasonality by calculating the difference between the current observation and the previous observation. The purpose of differencing in SARIMA is to make data stationary, and improve prediction accuracy. Figure 4 is the result of differencing the Bitcoin data.

```
ADF Statistic: -11.479406635070555
p-value: 5.0374041188818834e-21
Data is already stationary.
```

Figure 4. ADF Test after Differencing

The historical data is divided into two scenarios to evaluate the model’s performance on different datasets. Scenario 1 utilizes the complete dataset (for ten years), and scenario 2 employs the last five years' dataset. By limiting the data range to the last 5 years, this scenario aims to capture recent patterns that may not be visible in older historical data. The dataset is split into two parts, viz, data training and data testing, with a comparison of 80% of training and 20% of testing. This chronological data division aims to replicate real-world prediction scenarios, where the most recent data is used to test models that have been trained on historical data.

1. Figure 5 is the graphical result of scenario 1, using the complete dataset from October 1, 2014 to October 1, 2024, divided into 80% training data (October 1, 2014 - September 30, 2022) and 20% testing data (October 1, 2022 - October 1, 2024), resulting in 2,923 rows of training data and 731 rows of testing data.

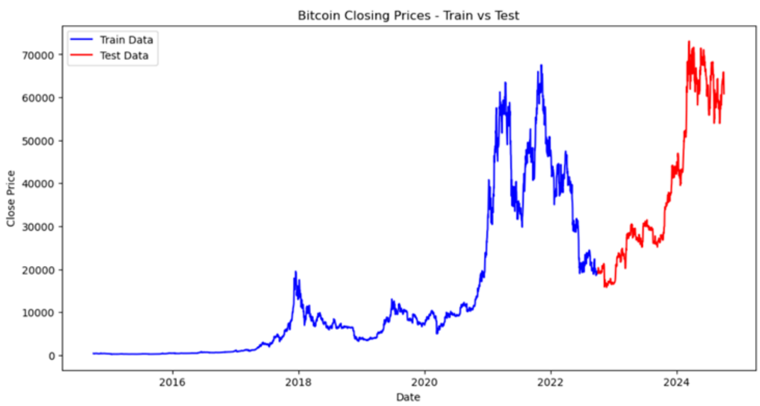

Figure 5. Training and Testing Data Sharing Chart with 10 Years of Data

2. Figure 6 is the graphical result of scenario 2, using the last 5 years of data (October 1, 2019 - October 1, 2024), divided into 80% training data (October 1, 2019 - September 30, 2023) and 20% testing data (October 1, 2023 - October 1, 2024), resulting in 2,923 rows of training data and 731 rows of testing data.

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

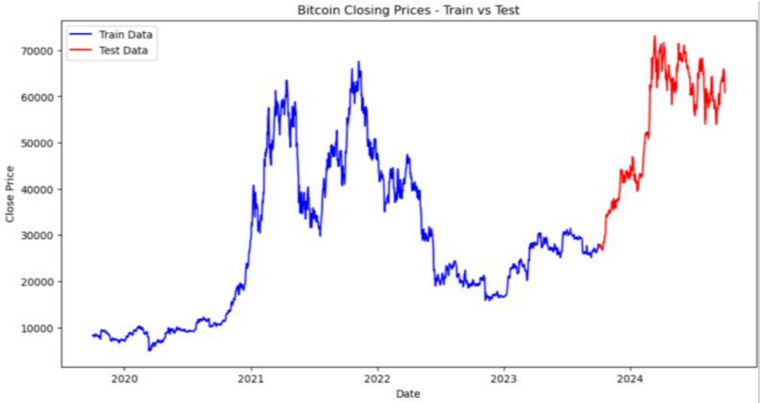

Figure 6. Training and Testing Data Sharing Chart with 5 Years of Data

2.4. Model

At this stage, the Bitcoin price prediction model is built using two time series algorithms: SARIMA and Prophet. Both algorithms are optimized and evaluated to produce the most accurate model for predicting the short-term Bitcoin price. The SARIMA model is implemented to model autoregressive (AR), moving average (MA), differencing (I), and seasonal (S) components. Optimization is performed using a Grid Search approach to test various combinations of (p, d, q) and (p, d, q, s) parameters for the seasonal component [20], [29]. p denotes the order of the AR model, indicating the number of past lags of the variable included in the model, d represents the degree of differencing needed to make the time series stationary, q indicates the number of lagged residuals, and s is the seasonal component. The seasonal period parameter is set to capture weekly patterns with $s = 7$. The optimization process is carried out to obtain a model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values.

The main reasons for choosing grid search in SARIMA optimization are its simplicity, its ability to systematically evaluate all possible parameter combinations, and its compatibility with evaluation criteria such as AIC/BIC. Equation 1 is the basic formula of SARIMA.

$$\left(1-\emptyset_1 B-\emptyset_2 B^2-\cdots-\emptyset_p B^p\right)\left(1-\beta_1 B^t-\beta_2 B^{2t}-\cdots-\beta_p B^{pt}\right)(1-B)^d(1-B^t)^D(Y_t-\mu)=$$

$$\left(1+\emptyset_1 B+\emptyset_2 B^2+\cdots+\emptyset_p B^p\right)\left(1+\delta_1 B^t+\delta_2 B^{2t}+\cdots+\delta_p B^{pt}\right)(1-B)^d(1-B^t)^D\varepsilon_t \quad (1)$$

The Prophet model is designed to capture seasonal patterns and non-linear trends. The model does not require stationary data and can work with non-stationary data. The model is configured with annual, weekly, and daily seasonal patterns, as well as trend changepoints [26]. The changepoint configuration uses a prior scale value of 17.61, which has proven effective in previous studies [30]. Equation 2 is the basic formula of the Prophet.

$$y(t)=g(t)+s(t)+h(t)+\varepsilon(t) \quad (2)$$

$g(t)$ signifies the trend element, which may be expressed as piecewise linear or logistic form. $s(t)$ captures periodic fluctuations like daily, weekly, or seasonal trends. Additionally, $h(t)$ addresses holidays with unpredictable schedules, and $\varepsilon(t)$ represents the error component.

2.5. Assess

This stage evaluates the performance of the SARIMA and Prophet models using two main metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). MAPE

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

measures the prediction error in percentage terms, where the smaller the MAPE value, the better the model is at predicting Bitcoin price [23]. The MAPE formula is shown in Eq. 3.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \widehat{Y_i}}{Y_i}\right| \times 100 \qquad (3)$$

where n indicates the size of the sample, $\widehat{Y_i}$ represents the predicted value, and Y_i is the observed value. MAPE metrics with values <10% are considered excellent, while 10%-20% are acceptable in the context of volatile time series such as cryptocurrency prices [31]. The MAPE indicator classification is shown in Table 2.

Table 2. MAPE Indicator Classification

MAPE (%)	Prediction Accuracy
< 10%	*Excellent*
10% ~ 19%	*Good*
20% ~ 49%	*Reasonable*
≥ 50%	*Not Accuracy*

RMSE measures the prediction error in the same units as the Bitcoin price, is more sensitive to outliers, and gives an idea of the prediction accuracy in absolute terms [32]. The RMSE formula is shown in Eq. 4.

$$RMSE = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{t}=1}^{\mathrm{N}}(y_t - \widehat{y_\imath})^2} \qquad (4)$$

3. RESULT

This section presents the results of research and testing, including model implementation and prediction performance evaluation using the SARIMA and Prophet algorithms.

3.1. SARIMA Model

Parameter optimization is done using the grid search method. The best parameters obtained are Order (0, 2, 2) and Seasonal Order (0, 1, 1, 7), with an AIC value of 52,880.72 and BIC of 52,905.09. These parameters were chosen because they have the most optimal and low AIC and BIC results. Table 3 shows the grid search's results to find the best 5 parameters and select the most optimal and best 1 parameter.

Table 3. Parameter Results of Grid Search SARIMA Model

No	Order (p, d, q)	Seasonal Order (P, D, Q, s)	AIC	BIC
1	0, 2, 2	1, 1, 1, 1, 7	52875.364	52905.824
2	0, 1, 2	1, 1, 1, 1, 7	52875.452	52905.914
3	**0, 2, 2**	**0, 1, 1, 1, 7**	**52880.719**	**52905.087**
4	0, 1, 2	0, 1, 1, 1, 7	52881.209	52905.578
5	1, 1, 2	0, 1, 1, 1, 7	52880.596	52911.057

The SARIMA model is evaluated in two scenarios. This evaluation aims to determine the model's performance after training and testing. The results of the SARIMA model in both scenarios are shown in Figures 7 and 8.

P-ISSN: 2723-3863
E-ISSN: 2723-3871
Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

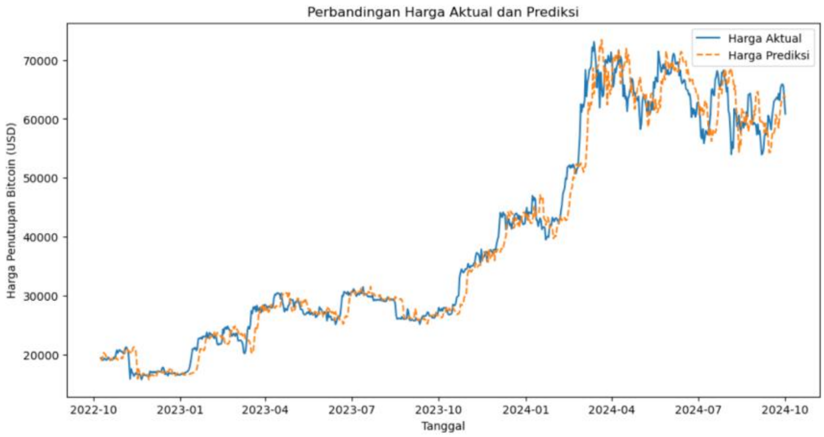

Figure 7. SARIMA Testing Results Scenario 1

Figure 7 is the visualization result of scenario 1, SARIMA showed an MAPE value of 0.02% and an RMSE of 1,169.12. SARIMA can capture the pattern of Bitcoin price fluctuations very well, which is indicated by the very low MAPE value in the first scenario.

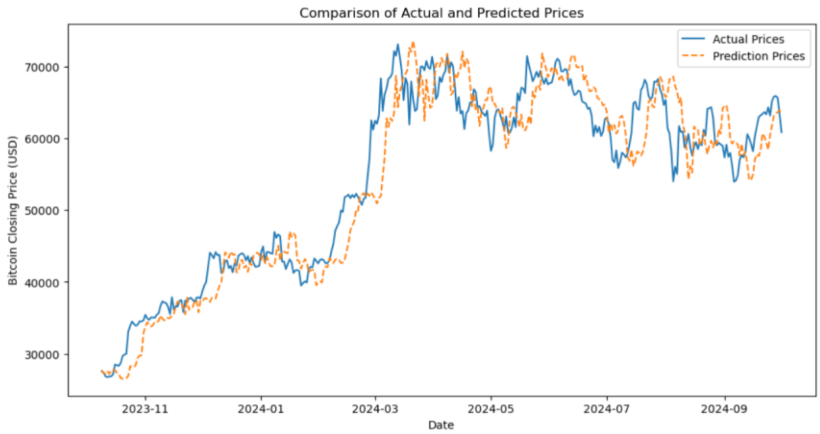

Figure 8. SARIMA Testing Results Scenario 2

Figure 8 is the visualization result of scenario 2; the SARIMA model produced an MAPE of 0.02% and an RMSE of 1,553.26. Still, as in scenario 1, SARIMA's performance is quite consistent with similar MAPE and RMSE results in both scenarios.

Overall, SARIMA can capture the pattern of Bitcoin price fluctuations very well, as shown by the very low MAPE values in both scenarios. The performance difference between scenarios 1 and 2 is not significant, although the RMSE in scenario 2 is slightly higher.

3.2. Prophet Model

The Prophet model was configured with a Changepoint_prior_scale parameter of 17.61 was adopted from Hamdani et al. [30]. This configuration allows Prophet to handle sudden changes in data trends. The model is designed to handle non-stationary data, making it suitable for Bitcoin price dynamics.

Evaluation of the Prophet model is carried out in two scenarios. This evaluation aims to determine the model's performance after training and testing. Figures 9 and 10 illustrate the results of the Prophet model in both scenarios.

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

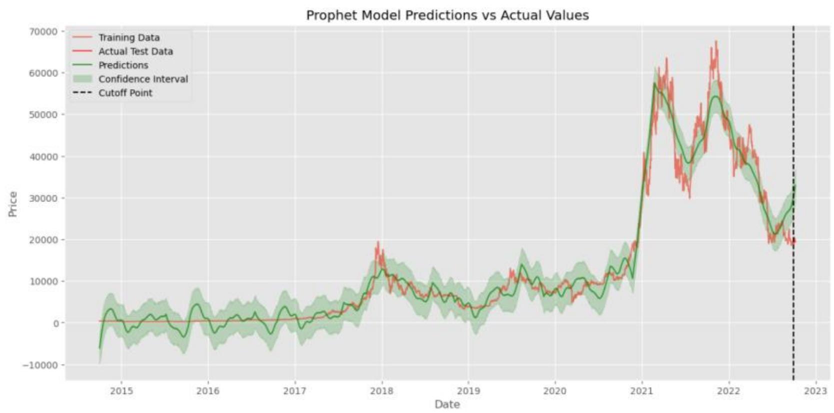

Figure 9. Prophet Testing Results Scenario 1

Figure 9 is the visualization result of scenario 1, Prophet shows poor performance results, producing high MAPE and RMSE values with an MAPE value of 61.88% and RMSE of 1,2218.36. This shows that the model is not optimal in handling larger datasets.

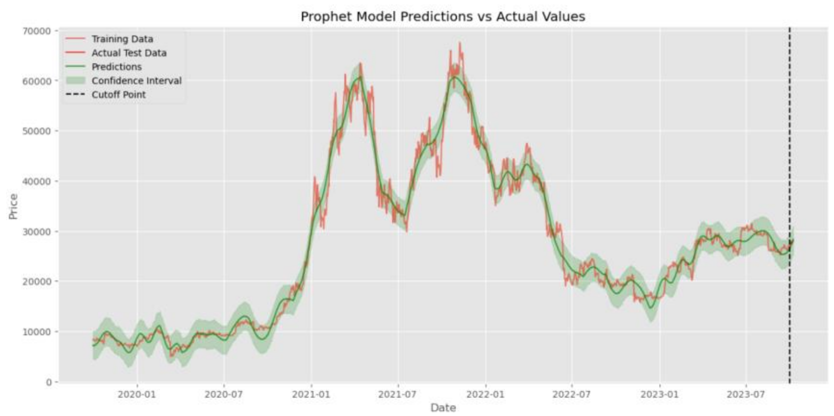

Figure 10. Prophet Testing Results Scenario 2

Figure 10 is the visualization result of scenario 2, prophet shows better performance than the first scenario, a much better performance with a lower RMSE value and a smaller MAPE, which results in a MAPE of 1.23% and RMSE of 421.34, which indicates that prophet with the configuration of the Changepoint_prior_scale value of 17.61 is better at predicting Bitcoin prices with shorter datasets. Prophet uses changepoints from training data. If the new dataset has many sudden trend changes, the model is not flexible enough to adjust. Underfitting can occur if the number of changepoints is too small, or overfitting if too many.

4. DISCUSSIONS

The test results aim to analyze and evaluate the prediction results of the SARIMA and Prophet algorithms in two predetermined scenarios. The evaluation utilizes the MAPE and RMSE metrics. The visualization of prediction results shows the ability of each model to predict short-term Bitcoin prices.

4.1. Scenario 1: 7-Day Forward Prediction

In Scenario 1, the two algorithms show different prediction characteristics. SARIMA has a daily error range of 0.32% to 2.53% with an MAPE value of 1.24% and an RMSE of 896.15, with a prediction focus that tends to be closer to the actual price at the beginning of the period. In contrast, Prophet displays a daily error range of 0.26% to 2.95%, with higher variability at the beginning of the prediction period, resulting in an MAPE value of 1.74% and an RMSE of 1,214.86. It is interesting to note that

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

Prophet reached the lowest daily error of 0.26% on October 7, 2024, indicating the potential for high accuracy at this particular point in time. Table 4 displays the performance results of the two algorithms.

Table 4. MAPE and RMSE Results of 7-Day Forward Prediction Scenario 1

Algorithm	Date	Prediction (USD)	Actual (USD)	Error per day (%)	MAPE (n=7)	RMSE (n=7)
SARIMA	**02/10/2024**	**61030.62**	**60836.32**	**0.32**		
	03/10/2024	61020.96	60632.48	0.64		
	04/10/2024	61063.89	60754.63	0.51		
	05/10/2024	61108.61	62067.61	1.55	1.24%	896.15
	06/10/2024	61145.05	62084.99	1.51		
	07/10/2024	61232.18	62819.11	2.53		
	08/10/2024	61213.80	62221.64	1.62		
Prophet	02/10/2024	62360.30	60836.32	2.51		
	03/10/2024	62419.99	60632.48	2.95		
	04/10/2024	62540.09	60754.63	2.94		
	05/10/2024	62669.82	62067.61	0.97	1.74%	1214.86
	06/10/20/24	62798.69	62084.99	1.15		
	07/10/2024	**62985.33**	**62819.11**	**0.26**		
	08/10/2024	63073.72	62221.64	1.37		

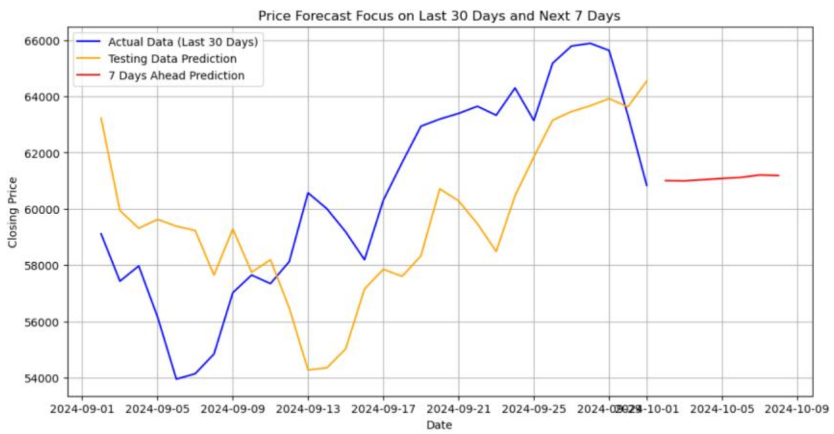

Figure 11. Scenario 1: Graph of SARIMA Model Results for Short-Term Prediction

In the first scenario, the SARIMA model shows a fairly accurate predictive ability in estimating the price of Bitcoin. Analysis of the prediction range from October 2, 2024, to October 8, 2024, reveals that the model can produce consistent estimates and is close to the actual price. It can be seen in Figure 11 that the MAPE value obtained is 1.24%, and the RMSE has a value of 896.15. The lowest daily error of 0.32% was recorded on October 2, 2024, and the highest daily error of 2.53% was recorded on October 7, 2024. This relatively small variation in prediction error indicates that SARIMA has a stable performance in predicting Bitcoin prices in the first scenario.

The Prophet model in the first scenario displays slightly different prediction characteristics from SARIMA. The same prediction range, from October 2, 2024, to October 8, 2024, produces estimates with varying degrees of accuracy. It can be seen in Figure 12 that the MAPE value obtained ranged from 1.74%, and the RMSE value was 1214.86. With the lowest daily error of 0.26% on October 7, 2024, and the highest daily error of 2.95% on October 3, 2024. Despite having some prediction points with higher

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

errors, Prophet shows potential in predicting Bitcoin price, especially on some dates with very low prediction errors.

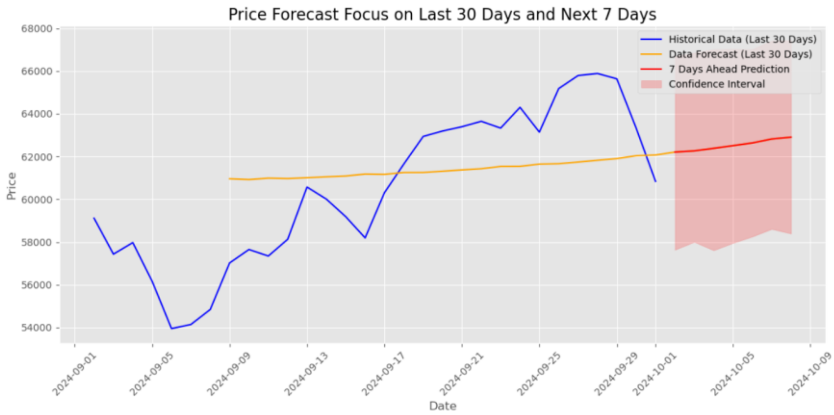

Figure 12. Scenario 1 Graph of Prophet Model Results for Short-Term Prediction

4.2. Scenario 2: 7-Day Forward Prediction

In Scenario 2, both showed improved performance. SARIMA maintains a daily error range ranging from 0.38% to 2.55%, with a prediction pattern that is consistent with the previous scenario, resulting in a similar MAPE value of 1.27% and an RMSE of 920.24, although the average MAPE value increases, but only an insignificant increase, so that it can be said that SARIMA's performance is optimal in both scenarios. Meanwhile, Prophet displays a significant improvement with a daily error range of 0.18% to 1.27% with an MAPE value of 0.71% and an RMSE of 489.94, which is substantially lower than Scenario 1. Prophet's peak performance was recorded on October 6, 2024, with the lowest MAPE of 0.18%, indicating superior adaptability in this scenario. Table 5 displays the performance results of the two algorithms.

Table 5. MAPE and RMSE Results of 7-Day Forward Prediction Scenario 2

Algorithm	Date	Prediction (USD)	Actual (USD)	Error per day (%)	MAPE (n=7)	RMSE (n=7)
	02/10/2024	**61065.18**	**60836.32**	**0.38**		
	03/10/2024	61006.28	60632.48	0.62		
	04/10/2024	61033.47	60754.63	0.46		
SARIMA	05/10/2024	61063.30	62067.61	1.62	1.27%	920.24
	06/10/2024	61103.21	62084.99	1.58		
	07/10/2024	61215.98	62819.11	2.55		
	08/10/2024	61165.46	62221.64	1.70		
	02/10/2024	61228.68	60836.32	0.64		
	03/10/2024	61328.43	60632.48	1.15		
	04/10/2024	61525.55	60754.63	1.27		
Prophet	05/10/2024	61736.19	62067.61	0.53	0.71%	489.94
	06/10/2024	**61971.40**	**62084.99**	**0.18**		
	07/10/2024	62291.89	62819.11	0.84		
	08/10/2024	62438.46	62221.64	0.35		

In the second scenario, SARIMA maintained a similar performance pattern to the first scenario. It can be seen in Figure 13 that the predictions were made over the same time, from October 2, 2024, to October 8, 2024, resulting in an MAPE value of 1.27% and an RMSE value of 920.24. The lowest daily error of 0.38% was recorded on October 2, 2024, while the highest daily error was 2.55% on October 7,

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

2024. The consistency of SARIMA's performance in both scenarios shows that this model has stable and reliable prediction capabilities under various conditions.

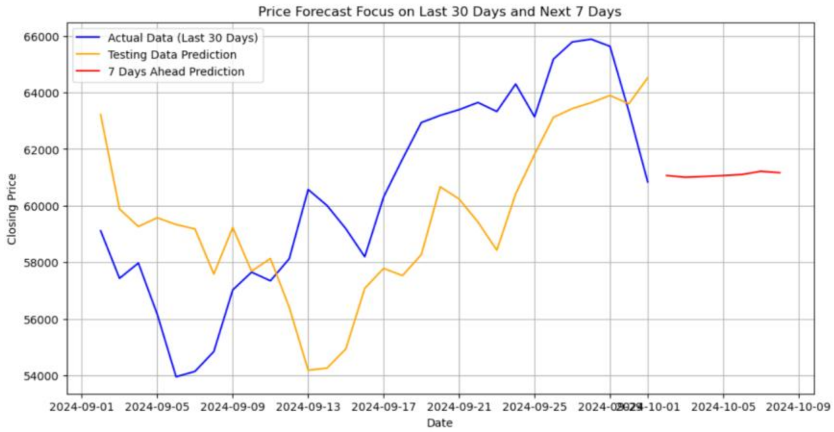

Figure 13. Scenario 2: Graph of SARIMA Model Results for Short-Term Prediction

In the second scenario, the Prophet model showed a significant performance improvement compared to the first scenario. It can be seen in Figure 14 that the prediction range remained consistent from October 2, 2024, to October 8, 2024, but with a lower variation in prediction error. The MAPE value is only 0.71% with an RMSE value of 335.59. The lowest daily error value was 0.18% on October 6, 2024, and the highest daily error was 1.27% on October 4, 2024. This performance improvement indicates that Prophet has good adaptability to changes in data patterns in different scenarios.

Evaluation of the performance of both algorithms using MAPE and RMSE metrics shows that SARIMA is more stable and consistent in predicting Bitcoin prices, both with long-term and short-term datasets. While Prophet also shows good performance in both scenarios, there is also a significant increase in performance in scenario 2, which uses Bitcoin price data from the last 5 years, where Prophet can adjust better to more recent and dynamic price trends.

Experimental results show that Bitcoin volatility affects the prediction results of both algorithms (SARIMA and Prophet). SARIMA has a low ability to handle dynamic trends, relying on differencing and ARIMA. Meanwhile, Prophet with changepoints and flexibility is better at handling dynamic data trends.

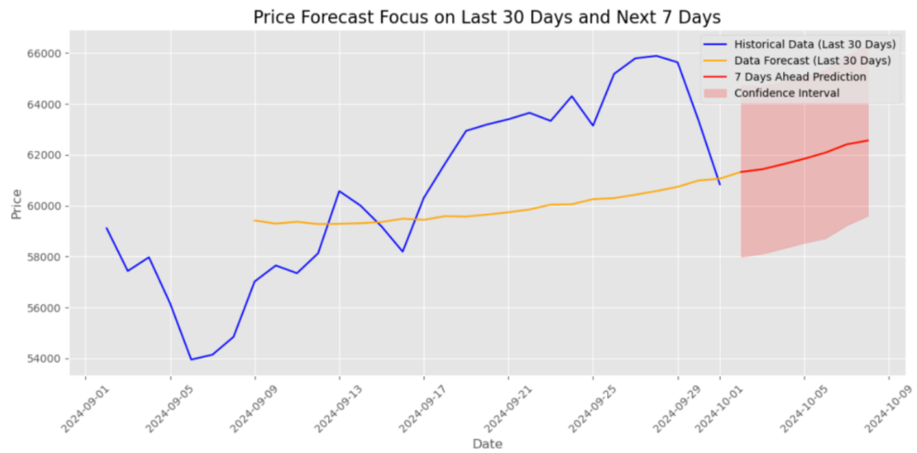

Figure 14. Scenario 2: Graph of Prophet Model Results for Short-Term Prediction

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

5. CONCLUSION

Based on the experimental results, both algorithms show varying performance depending on the dataset scenario used. SARIMA showed stable performance with fairly low MAPE and RMSE in both scenarios. In Scenario 1, the MAPE value is 1.24% with detailed error values per day ranging from 0.32% to 2.53% and with an RMSE value range of 896.15. While in Scenario 2, the MAPE value is 1.27% with a daily error value in the range of 0.38% to 2.55% and an RMSE value of 920.24. This model can accurately capture the pattern of Bitcoin price fluctuations, although there is a slight increase in the average MAPE and RMSE values in Scenario 2.

Prophet, while capable of handling sudden changes in Bitcoin price trends, performed very well in both scenarios as well, although Prophet's performance in scenario 1 was not as good as the SARIMA model. In scenario 1, Prophet produced a MAPE value of 1.74% and detailed daily errors ranging from 0.26% to 2.95% with an RMSE value of 1214.86. However, in Scenario 2, Prophet shows a significant improvement, with a lower MAPE, which is a daily error ranging from 0.18% to 1.27%, with an MAPE value of only 0.71% and an RMSE value of 489.94. This shows that Prophet is more effective in handling smaller and newer datasets.

Overall, this study concludes that both SARIMA and Prophet have their own advantages according to the characteristics of the dataset used. SARIMA is better for longer and more stable historical data, while Prophet is more effective in predicting Bitcoin prices with shorter datasets, although in scenarios with long-term datasets, it is still considered to have good performance as well. Both models, despite having weak points in some periods, show strong potential in predicting the short-term Bitcoin price. This bitcoin prediction will be useful for day traders to determine entry/exit levels based on price projections. Meanwhile, long-term investors can estimate potential future returns to evaluate entry/exit from positions.

To improve the shortcomings of both methods, further research can explore other bitcoin prediction models, such as the use of more sophisticated hyperparameter optimization techniques (e.g. Bayesian Optimization or Random Search) to find more optimal parameter combinations. This approach can improve the efficiency and accuracy of the model, both for SARIMA and Prophet, so that the model can adapt better to the existing dataset.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest between the authors or with research object in this paper.

ACKNOWLEDGMENT

This work was supported by the Universitas Negeri Malang in an undergraduate thesis research scheme under Grant No. 24.2.663/UN32.14.1/LT/2025. The authors are deeply grateful for the facilities, guidance, and encouragement extended to them throughout the research process.

REFERENCES

[1] S. Otabek and J. Choi, “From Prediction to Profit: A Comprehensive Review of Cryptocurrency Trading Strategies and Price Forecasting Techniques,” *IEEE Access*, vol. 12, no. June, pp. 87039–87064, 2024, doi: 10.1109/ACCESS.2024.3417449.

[2] L. Jin, B. Zheng, X. Jiang, L. Xiong, J. Zhang, and J. Ma, “Dynamic cross-correlation in emerging cryptocurrency market,” *Phys. A Stat. Mech. its Appl.*, vol. 668, no. April, p. 130568, 2025, doi: 10.1016/j.physa.2025.130568.

[3] N. Ramya, R. Sanjay Roshan, R. Vishal Srinivas, and D. Krishna Prasad, “Crypto-Currency Price Prediction using Machine Learning,” *2022 6th Int. Conf. Trends Electron. Informatics, ICOEI*

2022 - Proc., no. Icoei, pp. 1455–1458, 2022, doi: 10.1109/ICOEI53556.2022.9776665.
[4] K. John and J. Li, "Bitcoin price volatility: Effects of retail traders, illegal users, and sentiment," *J. Corp. Financ.*, vol. 94, no. January, p. 102837, 2025, doi: 10.1016/j.jcorpfin.2025.102837.
[5] T. H. A. Joubert, "Unraveling Bitcoin price unpredictability: The role of hard forks," *Int. Rev. Financ. Anal.*, vol. 96, no. PB, p. 103662, 2024, doi: 10.1016/j.irfa.2024.103662.
[6] X. He, Y. Li, and H. Li, "Revolutionizing Bitcoin price forecasts: A comparative study of advanced hybrid deep learning architectures," *Financ. Res. Lett.*, vol. 69, no. PA, p. 106136, 2024, doi: 10.1016/j.frl.2024.106136.
[7] R. Dubey and D. Enke, "Bitcoin price direction prediction using on-chain data and feature selection," *Mach. Learn. with Appl.*, vol. 20, no. May, p. 100674, 2025, doi: 10.1016/j.mlwa.2025.100674.
[8] S. Long, Y. Xie, Z. Zhou, B. Lucey, and A. Urquhart, "From whales to waves: Social media sentiment, volatility, and whales in cryptocurrency markets," *Br. Account. Rev.*, no. July 2024, pp. 1–16, 2025, doi: 10.1016/j.bar.2025.101682.
[9] Z. I. Ramadhan and H. Widiputra, "Comparative Analysis of Recurrent Neural Network Models Performance in Predicting Bitcoin Prices," *J. RESTI (Rekayasa Sist. Teknol. Inf.)*, vol. 10, no. 3, pp. 377–388, 2024, [Online]. Available: http://jurnal.iaii.or.id
[10] O. Ahmed Al-Zakhali and A. M. Abdulazeez, "Comparative Analysis of Machine Learning and Deep Learning Models for Bitcoin Price Prediction," *Indones. J. Comput. Sci.*, vol. 13, no. 1, pp. 407–419, 2024, doi: 10.33022/ijcs.v13i1.3722.
[11] N. Tripathy, S. Hota, D. Singh, B. M. Acharya, and S. K. Nayak, "A comprehensive analysis of Bitcoin volatility forecasting using time-series econometric models," *Appl. Soft Comput.*, vol. 178, no. April, p. 113339, 2025, doi: 10.1016/j.asoc.2025.113339.
[12] A. Isufaj, C. De Castro Martins, M. Cavazza, and H. Prendinger, "Applying time delay convergent cross mapping to Bitcoin time series," *Expert Syst. Appl.*, vol. 277, no. January, p. 127125, 2025, doi: 10.1016/j.eswa.2025.127125.
[13] V. Mizdrakovic *et al.*, "Forecasting bitcoin: Decomposition aided long short-term memory based time series modeling and its explanation with Shapley values," *Knowledge-Based Syst.*, vol. 299, no. April, p. 112026, 2024, doi: 10.1016/j.knosys.2024.112026.
[14] Y. Indulkar, "Time series analysis of cryptocurrencies using deep learning fbprophet," *2021 Int. Conf. Emerg. Smart Comput. Informatics, ESCI 2021*, pp. 306–311, 2021, doi: 10.1109/ESCI50559.2021.9397004.
[15] Q. Phung Duy, O. Nguyen Thi, P. H. Le Thi, H. D. Pham Hoang, K. L. Luong, and K. N. Nguyen Thi, "Estimating and forecasting bitcoin daily prices using ARIMA-GARCH models," *Bus. Anal. J.*, 2024, doi: 10.1108/baj-05-2024-0027.
[16] K. Dhinakaran, P. Baby Shamini, J. Divya, C. Indhumathi, and R. Asha, "Cryptocurrency Exchange Rate Prediction using ARIMA Model on Real Time Data," *Proc. Int. Conf. Electron. Renew. Syst. ICEARS 2022*, no. Icears, pp. 914–917, 2022, doi: 10.1109/ICEARS53579.2022.9751925.
[17] A. Ibrahim, R. Kashef, and L. Corrigan, "Predicting market movement direction for bitcoin: A comparison of time series modeling methods," *Comput. Electr. Eng.*, vol. 89, no. November 2020, p. 106905, 2021, doi: 10.1016/j.compeleceng.2020.106905.
[18] K. Kashif and R. Ślepaczuk, "LSTM-ARIMA as a hybrid approach in algorithmic investment strategies," *Knowledge-Based Syst.*, vol. 320, no. July 2024, p. 113563, 2025, doi: 10.1016/j.knosys.2025.113563.
[19] U. Sampat Kumar, S. P. Aanandhi, S. P. Akhilaa, V. Vardarajan, and M. Sathiyanarayanan, "Cryptocurrency Price Prediction using Time Series Forecasting (ARIMA)," *2021 4th Int. Semin. Res. Inf. Technol. Intell. Syst. ISRITI 2021*, pp. 598–602, 2021, doi: 10.1109/ISRITI54043.2021.9702842.
[20] J. Zhu, "Bitcoin Price Prediction: ARIMA & SARIMA vs Linear Regression," *Adv. Econ. Manag. Polit. Sci.*, vol. 61, no. 1, pp. 47–54, 2023, doi: 10.54254/2754-1169/61/20230776.
[21] S. Periketi, R. Kulkarni, and U. N. Dulhare, "LSTM and Prophet Model Fusion Framework for Bitcoin Candlestick Visualization and Price Prediction Forecasting," *Proc. 17th INDIACom; 2023 10th Int. Conf. Comput. Sustain. Glob. Dev. INDIACom 2023*, pp. 1190–1194, 2023.

Vol. 6, No. 4, Agustus 2025, Page. 1971-1984
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.4.4773

[22] K. Ramani, M. Jahnavi, P. J. Reddy, P. Venkatachakravarthi, P. Meghanath, and S. K. Imran, "Prediction of Bitcoin Price through LSTM, ARIMA, XGBoost, Prophet and Sentiment Analysis on Dynamic Streaming Data," *2023 9th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2023*, vol. 1, pp. 1514–1518, 2023, doi: 10.1109/ICACCS57279.2023.10113014.

[23] M. D. Angelo, I. Fadhiilrahman, and Y. Purnama, "Comparative Analysis of ARIMA and Prophet Algorithms in Bitcoin Price Forecasting," *Procedia Comput. Sci.*, vol. 227, pp. 490–499, 2023, doi: 10.1016/j.procs.2023.10.550.

[24] P. Kodicherla and N. Velagandula, "Univariate Time Series Analysis of Cryptocurrency Data using Prophet, LSTM and XGBoost," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 10, no. 12, pp. 2005–2013, 2022, doi: 10.22214/ijraset.2022.48411.

[25] K. Nigam and M. Singh, "Prediction of the Variation in Price of Bitcoin Using Machine Learning," *Proc. Int. Conf. Contemp. Comput. Informatics, IC3I 2023*, vol. 6, pp. 344–347, 2023, doi: 10.1109/IC3I59117.2023.10397988.

[26] T. Toharudin, R. S. Pontoh, R. E. Caraka, S. Zahroh, Y. Lee, and R. C. Chen, "Employing long short-term memory and Facebook prophet model in air temperature forecasting," *Commun. Stat. Simul. Comput.*, vol. 52, no. 2, pp. 279–290, 2023, doi: 10.1080/03610918.2020.1854302.

[27] J. Cheng, S. Tiwari, D. Khaled, M. Mahendru, and U. Shahzad, "Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models," *Technol. Forecast. Soc. Change*, vol. 198, no. October 2023, p. 122938, 2024, doi: 10.1016/j.techfore.2023.122938.

[28] K. Albeladi, B. Zafar, and A. Mueen, "A Novel Deep-Learning Based Approach for Time Series Forecasting Using SARIMA, Neural Prophet and Fb Prophet," 2023, doi: 10.20944/preprints202311.0794.v1.

[29] R. Maurya, D. Kaur, A. P. Singh, and S. Ranjan, "Stock Price Prediction Using Time Series," *Commun. Comput. Inf. Sci.*, vol. 2053 CCIS, pp. 309–320, 2024, doi: 10.1007/978-3-031-56700-1_25.

[30] A. F. Hamdani, D. Swanjaya, and R. Helilintar, "Facebook Prophet Model with Bayesian Optimization for USD Index Prediction," *JUITA J. Inform.*, vol. 11, no. 2, p. 293, 2023, doi: 10.30595/juita.v11i2.17880.

[31] E. Vivas, H. Allende-Cid, and R. Salas, "A systematic review of statistical and machine learning methods for electrical power forecasting with reported mape score," *Entropy*, vol. 22, no. 12, pp. 1–24, 2020, doi: 10.3390/e22121412.

[32] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not," *Geosci. Model Dev.*, vol. 15, no. 14, pp. 5481–5487, 2022, doi: 10.5194/gmd-15-5481-2022.