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Comparison of Support Vector Regression and Extreme Learning Machine Methods for Predicting Bitcoin Prices

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ABSTRACT

Bitcoin can be used for transactions, mining, and investments. Transactions with Bitcoin are highly secure with the help of Bitcoin miner validation. Miners who validate transactions are rewarded with Bitcoins which then adds supply to the Bitcoin network. However, over time, these rewards will run out. The depletion of Bitcoin supply can affect the price of Bitcoin. In addition, investing in Bitcoin is very risky with the fluctuating price of Bitcoin. Therefore, it is necessary to predict the price. In this research, prediction is done using Support Vector Regression (SVR) and Extreme Learning Machine (ELM). The dataset for Bitcoin price (USD) comes from Yahoo Finance. The types of Bitcoin prices predicted are Open, High, Low, and Close prices. Across all series and both splits, ELM outperforms SVR. Under the 80/20 split, the average error of ELM is MAE 418.698 USD, RMSE 633.953 USD, R^2 of 0.987, versus SVR's MAE 1061.449 USD, RMSE 1227.499 USD, R^2 of 0.955. A reduction of 60.6% (MAE) and 48.4% (RMSE). With the 60/40 split, ELM remains strong (MAE 550.783 USD, RMSE 850.656 USD, R^2 0.989 while SVR deteriorates (MAE 1843.534 USD, RMSE 2093.542 USD, R^2 of 0.935, yielding 70.1% and 59.4% average reductions in MAE and RMSE, respectively. ELM consistently tracks both levels and day to day movements, with typical errors of only a few hundred dollars. These results indicate that ELM is the more reliable choice and is capable of capturing non-linearities for Bitcoin price prediction.

I. INTRODUCTION

Bitcoin is one of the cryptocurrencies (digital currencies) that can be used for various purposes such as purchases, mining, and investment [1]. This currency was introduced as a new method or alternative way of conducting transactions. Transactions using cryptocurrency are generally secure, and no personal information is required during the process [2]. Supervision and regulation for Bitcoin and other cryptocurrencies are generally absent [3]. In contrast, physical money used in daily life is monitored and regulated by banks [4]. Such regulation and supervision of physical money aim to control its availability in the public sphere [5].

The technology used by Bitcoin is blockchain, which is a transaction database structured as a linked list [6]. Each block in a blockchain consists of a set of transactions, digital signatures, a hash of the block itself, and a hash of the previous block [7]. Every transaction within the block is given a digital signature using a function that takes the block's contents along with a private key [8]. The private key must be kept secure and not shared to prevent misuse. With the use of digital signatures, transactions can be verified for authenticity by matching them with the corresponding public key [9].

Blocks or lists of transactions are distributed across the entire Bitcoin network and can be viewed by anyone [10]. The widespread distribution of blocks may cause some individuals to distrust the validity of certain blocks or transactions. For example, a person may attempt to send a block or transaction to two different addresses simultaneously with the intention of spending the same cryptocurrency (double spending) [11]. The sender must make the transaction valid by generating a hash validation faster than the miner. Recipients of invalid blocks are advised to wait for additional blocks until the blockchain grows longer and to reject blocks coming from a double-spending sender. A longer blockchain can be considered as representing valid transactions [12]. Validation to determine a legitimate block requires searching for a unique hash result. Such a unique result increases confidence in the authenticity of a block. The hash value is obtained using the contents of the block and a nonce (number only used once) [13]. A valid hash typically begins with the largest possible number of leading zeros in its bits. The search for such a hash value requires considerable time but is essential for transaction validation and block creation, a process known as proof of work [14]. The creators of new blocks, commonly referred to as miners, attempt to find valid hash values. Miners are rewarded with cryptocurrency (block reward) for validating new blocks [15]. These block rewards increase the circulation of Bitcoin, and with periodic reductions in rewards (halving), Bitcoin becomes increasingly scarce over time, which may subsequently influence its price [16].

Several studies have been conducted on Bitcoin price prediction. Study [17] employed Linear Regression using Bitcoin price data from October 2021 to October 2023, achieving an R^2 value of 0.994. Another study [18] utilized Long Short-Term Memory (LSTM) on three cryptocurrencies. The highest evaluation result was obtained for BNB with an R^2 score of 96.7 and an MAE of 25.683, while the Bitcoin prediction with an R^2 score of 85.7 and an MAE of 5818.39. These studies show that the evaluation levels of cryptocurrency price prediction vary.

SVR Linear Kernel is chosen because of relatively small-to-moderate datasets, requires fewer parameters to tune than deep neural networks, and can provide stable, interpretable results when the dominant relationships are approximately linear. ELM is selected for its extremely fast training and its ability to capture non-linear patterns with minimal tuning effort. Compared to LSTM, which often requires large amounts of data and hyperparameter optimization adjustments. SVR and ELM offer a pragmatic balance between predictive capability, computational efficiency, and reproducibility. The novelty of this research lies in the comparative analysis between SVR and ELM for Bitcoin price prediction, which remains relatively underexplored in prior studies. Unlike most existing works that emphasize deep learning models such as LSTM or traditional approaches like linear regression, this study highlights two lightweight yet powerful algorithms that can provide a balance between accuracy, efficiency, and interpretability. Therefore, this research focuses on using SVR and ELM, with the expectation that these two methods can provide alternative perspectives.

Investments in Bitcoin or other cryptocurrencies generally involve high risk. This risk is even greater than that of other investments, such as stocks [19]. The risk arises from the highly volatile and unstable price of Bitcoin [20]. Several factors contribute to Bitcoin's price fluctuations, such as increases or decreases driven by positive or negative sentiment, and the acceptance or rejection of cryptocurrencies by companies, which can cause Bitcoin's price to rise or fall [21], [22]. Moreover, the absence of a regulatory body overseeing Bitcoin makes its price more prone to fluctuation. Given the high-risk and volatile nature of Bitcoin's price, it is necessary to conduct experiments to attempt predicting Bitcoin prices, particularly using Machine Learning algorithms, and to compare which algorithm performs best.

II. METHOD

The method used in this research is a comparison between the Support Vector Regression (SVR) with a Linear Kernel and the Extreme Learning Machine (ELM), both of which are applied to predict Bitcoin prices. The dataset used consists of Bitcoin prices in United States Dollars (USD), obtained from Yahoo! Finance [23]. The applications and libraries employed in this study include Jupyter Lab (Python 3.10), Pandas, Numpy, Matplotlib, Sklearn for SVR, and PyRCN for ELM. The research methodology is illustrated in the flowchart (Figure 1).

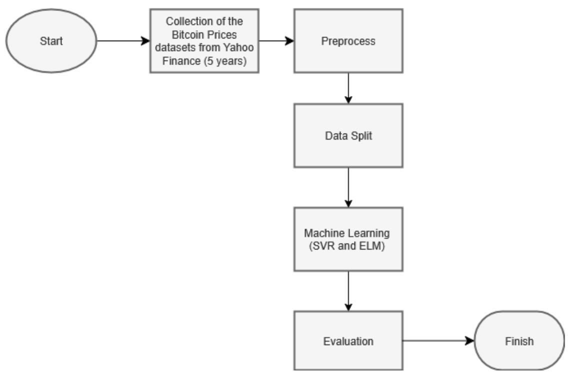

Figure 1. Research Flowchart

A. Dataset

The Bitcoin price dataset used in this research was obtained from Yahoo Finance, which provides a web page containing the historical data of Bitcoin prices over the past 10 years. The Bitcoin prices are presented in United States Dollars (USD). The type of historical data used is the daily price, consisting of the columns Open, High, Low, Close, Adjusted Close, and Volume. These columns respectively represent the opening price, the highest price, the lowest price, the closing price, the adjusted closing price, and the trading volume for each day.

B. Preprocess

The dataset was downloaded from the Yahoo Finance web page in .csv format, containing 1,827 records of daily Bitcoin price data. The dataset has no missing rows. The period covered is the last five years (January 1, 2019 to January 1, 2024). The columns Adj Close and Volume were removed from the dataset and the columns Open, High, Low, and Close were selected for predicting Bitcoin price. Before applying the machine learning algorithms, the dataset underwent a normalization stage to prepare it for training and evaluation. The normalization technique that is applied is Min–Max normalization to rescale the Bitcoin prices into the range of 0 and 1 so that all features contribute equally to the learning process. This transformation is particularly important for algorithms such as Support Vector Regression (SVR) and Extreme Learning Machine (ELM), which are sensitive to the magnitude of input values. If features remain on their original scales (for example, Bitcoin prices span from a few thousand to over sixty thousand US dollars), the model may place disproportionately high importance on attributes with larger numeric ranges, resulting in biased learning and unstable predictions. The first five rows of the dataset are shown in Table I and also Figure 2 presents the graph of these four prices.

TABLE I
SAMPLE OF THE FIRST 5 ROWS OF THE DATASET

Date	Open	High	Low	Close
2019-01-01	3746.71	3850.91	3707.23	3843.52
2019-01-02	3849.21	3947.98	3817.40	3943.40
2019-01-03	3931.04	3935.68	3826.22	3836.74
2019-01-04	3832.04	3865.93	3783.85	3857.71
2019-01-05	3851.97	3904.90	3836.90	3845.19

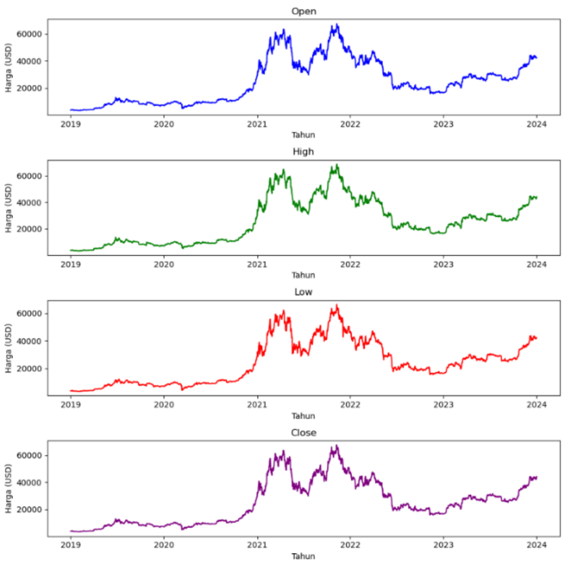

Figure 2. Graph of Open, High, Low, and Close Prices

C. Data Split

The data is split sequentially. The early part becomes the training set and the late part becomes the testing set, so that the time sequence is maintained. After that, each subset is converted into supervised samples using a sliding window (fixed time step) to form input-target pairs. In the first scenario, 80% of the data is used for training and 20% is used for testing (80/20), while in the second scenario, 60% of the data is used for training and 40% is used for testing (60/40). In both scenarios, the time step that is used is 3. The reason for choosing a time step of 3 is to allow the model to capture short-term dependencies and patterns in the data without making the input dimension too large. Using a time step that is too small may cause the model to lose important sequential information, while using too large may increase computational complexity and introduce noise from less relevant past data. Thus, a time step of three provides a balanced trade-off between capturing temporal dependencies and maintaining model efficiency.

D. SVR and ELM

Support Vector Regression (SVR) is an algorithm derived from Support Vector Machine (SVM) that is specifically designed for regression and prediction tasks. While SVM is primarily applied to classification problems, SVR extends the concept to regression by enabling the prediction of continuous value. Similar to SVM, SVR predicts continuous values by constructing a main regression line (hyperplane) and margin lines referred to as the epsilon-insensitive tube, based on the data points [24]. Data points that fall outside the tube are considered slack variables, which, together with the support vectors located near the margin lines, determine the maximum error line and the minimum error line [25]. The values of the variables, data points, and margins are illustrated in Figure 3.

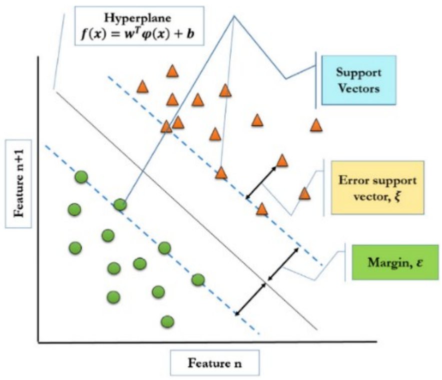

Figure 3. SVR Linear Kernel Illustration [26]

The equations for the linear kernel function and for determining the minimum error are presented in Equation (1) and Equation (2), respectively [27]. In these equations, w denotes the weight, b represents the bias, and c is the coefficient, while ξ_i and ξ_i^* correspond to the minimum slack distances of the data points above and below the margin. These parameters collectively define the structure of the regression function and the tolerance limits within which prediction errors are minimized.

$$f(x) = w\phi(x) + b \quad (1)$$

$$min\left(\frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n}(\xi_i + \xi_i^*)\right) \quad (2)$$

Besides SVR, the ELM algorithm is also utilized in this study. Extreme Learning Machine (ELM) is a neural network algorithm with a simpler structure, in which only a single hidden layer is used, compared to conventional neural network algorithms that typically employ multiple hidden layers [28]. In this algorithm, the weights and biases are initialized randomly, eliminating the need for manual initialization. Similar to other neural network algorithms, ELM consists of an input layer, a hidden layer (only one), and an output layer, as illustrated in Figure 4.

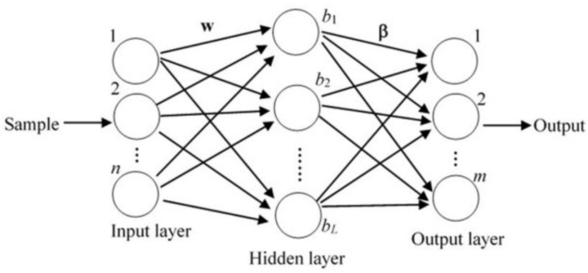

Figure 4. Illustration of the ELM architecture [29]

In the input layer, the training data are fed in according to the number of n features in the dataset. Subsequently, in the hidden layer, calculations are performed by initializing the weights and biases using Equation (3), while the output weights or the output layer are computed using Equation (4) [30].

$$y_j = \sum_{i=1}^{n}\beta_i g_i(w_i x_j + b_i) \quad (3)$$

Explanation of Equation (3):
- n represents the number of hidden nodes.
- β_i is the weight vector between the hidden layer and the output layer.
- g denotes the activation function.
- w_i is the weight vector between the input layer and the hidden layer.
- x_j is the input vector.
- b_i is the bias vector.

$$\beta = H^+T \quad (4)$$

Explanation of Equation (4):
- H^+ is the pseudo-inverse matrix of the hidden layer.
- T is the target output matrix.

E. Evaluation

The use of algorithms for prediction requires an evaluation process to assess their performance. In this study, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2) are employed to evaluate and compare the performance of SVR with a Linear Kernel and ELM. MAE measures the average absolute difference between the actual values and the values predicted by the algorithm. RMSE evaluates the average prediction error in the same units as the actual and predicted values. Finally, R^2 assesses the goodness-of-fit between the model's predicted results and the actual values in the dataset [31]. Lower MAE and RMSE values indicate fewer prediction errors in the model, while an R^2 value closer to 1 signifies that the model's predictions closely match the actual results. The equations for calculating MAE, RMSE, and R^2 are provided in Equations (5), (6), and (7), respectively [32].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (7)$$

Explanation for Equations (4), (5), and (6):
- n is the number of samples.
- y_i is the actual value of the i-th sample.
- $\hat{y}_i$ is the predicted value of the i-th sample.
- $\bar{y}$ is the mean of the actual values.

III. RESULTS AND DISCUSSION

A. SVR

In this study, SVR with a Linear Kernel is employed to predict Bitcoin prices. Under the 80% training and 20% testing data split. The Mean Absolute Error (MAE) for the Open price is 1037.425, indicating that the average difference between the predicted Bitcoin price and the actual value is 1037.425 USD. The Root Mean Squared Error (RMSE) for the Open price is 1186.852 USD. Furthermore, the average Coefficient of Determination (R^2) obtained from the experiment is 0.958, demonstrating that the SVR model provides a good fit, with the predicted price trend closely

Figure 5. SVR Prediction
(80% training data, 20% testing data)

matching the actual price trend. The evaluation results of SVR under the 80% training and 20% testing split are presented in Table II.

TABLE II
EVALUATION VALUES OF SVR
(80% TRAINING DATA AND 20% TESTING DATA)

Price	MAE	RMSE	R^2
Open	1037.425	1186.852	0.958
High	1311.776	1484.047	0.937
Low	869.294	1052.886	0.968
Close	1027.300	1186.212	0.958

Apart from the Open price, the results are generally satisfactory; however, the High price exhibits the largest error values, with an MAE value of 1311.776 USD and an RMSE of 1484.047. The R^2 value for the High price is also lower than that of the Open price, at 0.937, indicating a slightly weaker fit between the predicted and actual prices. The higher MAE and RMSE, along with the lower R^2 for the High price, where the respective values of MAE, RMSE, and R^2 were 1311.776, 1484.047, and 0.895179. The plots corresponding to the first split (80% training and 20% test) is shown in Figure 5.

The separation between the predicted (orange) and actual (blue) lines is most visible around local and global peaks, which explains the larger MAE and RMSE for the High price. Even so, during longer calm periods the two lines move in parallel, showing that the model still follows the direction of change for this graph. For the Low price, accuracy is the best among all four. Overall, the figures and metrics point to a clear pattern. The linear SVR captures the broad trend well but smooths extreme moves. It tends to undershoot at rapid peaks and overshoot just after abrupt drops, producing asymmetric residuals near turning points. Despite this limitation at extremes, the consistently high R^2 values confirm that the model reproduces day-to-day Bitcoin price dynamics reliably for Open, Low, and Close, with High remaining the most challenging price. Quantitatively, these errors are small relative to the prevailing price level: with Bitcoin trading mostly between 20,000 and 45,000 USD over the study window, MAE values of 0.87 to 1.31 thousand USD correspond to 2 to 5% deviations. Together with R^2 in the 0.937 to 0.968 range, this indicates that the linear SVR is adequate for short-term monitoring and trend-tracking tasks, where reproducing the overall direction and scale of movements is more critical than matching intraday extremes.

With the 60% training and 40% testing split, accuracy drops across all four prices (Table III). Errors increase from the 80/20 case and the fit weakens, with R^2 now ranging from 0.909 (High) to 0.955 (Low). The Open and Close price remain in the middle of all prices, while High is the hardest to predict and Low the easiest. For Open, MAE and RMSE rise to 1909.039 and 2143.612 USD, and R^2 declines to

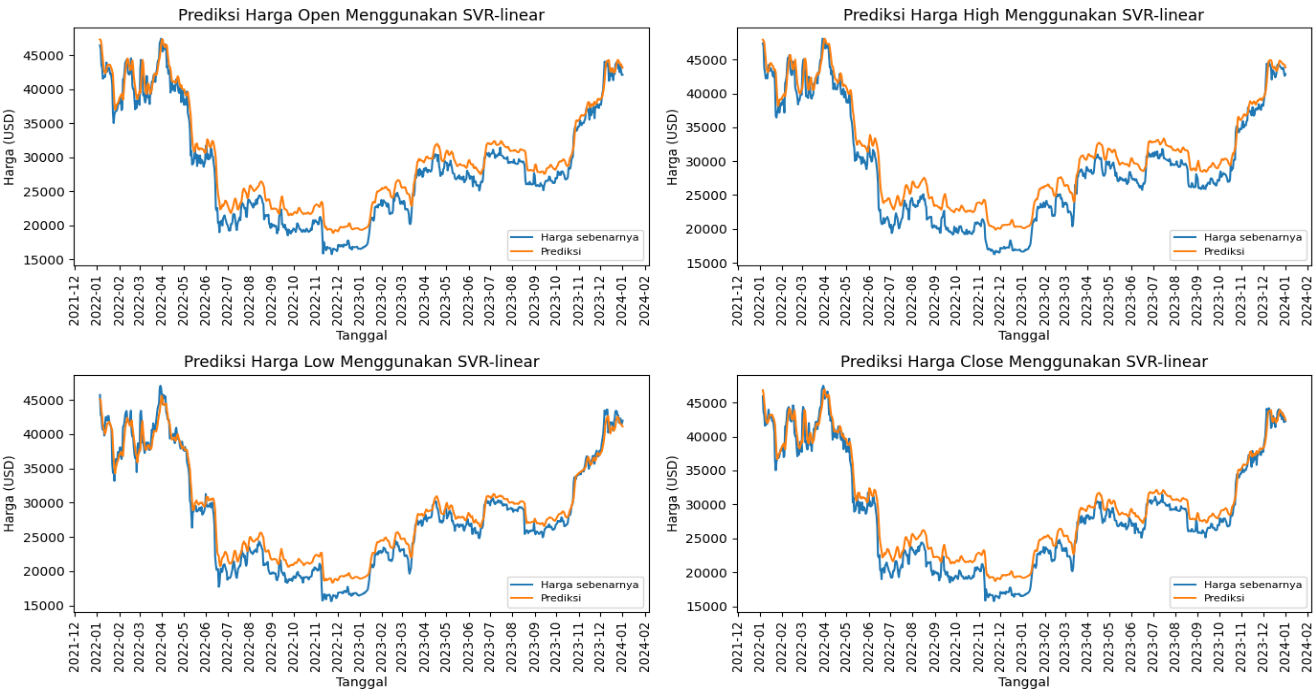

Figure 6. SVR Prediction
(60% training data, 40% testing data)

0.933. High records the largest errors. Low posts the best scores, while Close sits between Open and High. A representative prediction under this split is shown in Figure 6.

TABLE III
EVALUATION VALUES OF SVR
(60% TRAINING DATA AND 40% TESTING DATA)

Price	MAE	RMSE	R^2
Open	1909.039	2143.612	0.933
High	2303.619	2550.286	0.909
Low	1444.468	1715.071	0.955
Close	1717.009	1965.200	0.943

Visually based in Figure 6, the model continues to track the broad trend but shows larger gaps near turning points than under the 80/20 split. During the early 2022 decline, the prediction often sits above the actual (mild overshoot), whereas during the late 2023 rally it frequently sits below the actual (undershoot). This smoothing behavior is most evident in the High panel, which helps explain the lower R^2 and higher MAE/RMSE for that graph. The Low remains the easiest to follow: the orange curve hugs the troughs closely for long stretches, consistent with its best scores in Table III. RMSE is larger than MAE in every graph, indicating that a handful of large deviations concentrated near turning points and peaks contribute disproportionately to the loss. In relative terms, MAE values of about 1.4 to 2.3 thousand USD against a 16 to 45 thousand USD price range translate to roughly 3 to 8% deviations, so the model still tracks levels reasonably well even as precision deteriorates. Residuals are small and centered during stable periods, expand in magnitude during rapid transitions, and exhibit a mild asymmetry: more negative around fast peaks and more positive just after sharp pullbacks. Together, these patterns show that the 60/40 split remains adequate for following the overall direction and approximate magnitude of Bitcoin prices, while accuracy naturally weakens near extremes most notably for the High.

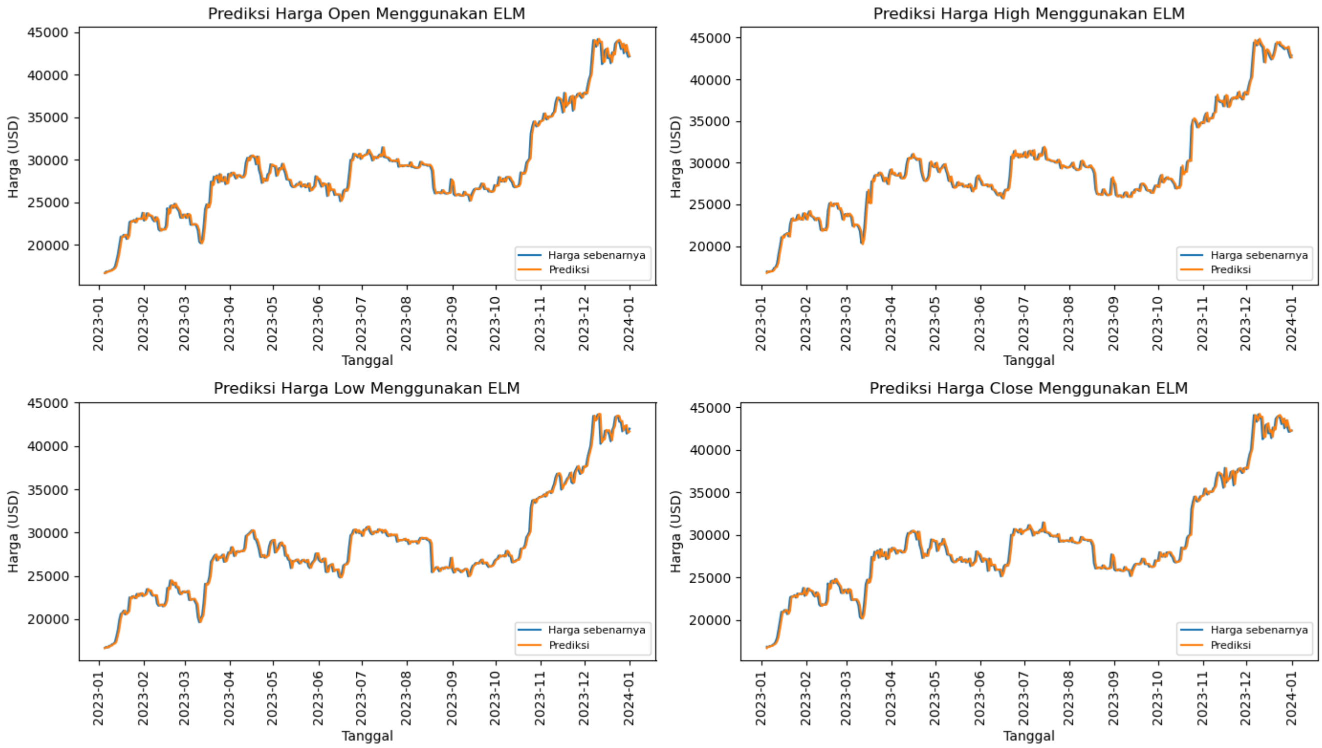

Figure 7. ELM Prediction
(80% training data, 20% testing data)

B. ELM

Under the 80% training and 20% testing split, the Extreme Learning Machine (ELM) achieves uniformly strong results across all four prices (Table IV). For Open, the errors are MAE of 441.709 USD and RMSE of 655.432 USD with R^2 of 0.987. For High, performance is even slightly better. The Low attains the best accuracy overall, with MAE of 369.472 USD, RMSE of 584.855 USD, and the highest R^2 of 0.989. The Close is comparable to Open. These values indicate that ELM explains nearly all variation in the test data and keeps absolute errors well below one thousand USD for every prices.

TABLE IV
EVALUATION VALUES OF ELM
(80% TRAINING DATA AND 20% TESTING DATA)

Price	MAE	RMSE	R^2
Open	441.709	655.432	0.987
High	424.156	640.470	0.988
Low	369.472	584.855	0.989
Close	439.455	655.053	0.987

The plots (Figure 7) show the orange prediction line almost overlapping the blue actual line for most of the year. Rises and pullbacks are tracked closely, and separations are short-lived and modest in size. Peaks during the late year are reproduced with small gaps, and troughs earlier in the year are also followed tightly. Compared with earlier linear SVR figures, the ELM curves exhibit less smoothing at local extremes and smaller deviations immediately after sharp moves. The visual impression of tight alignment matches the high R^2 values reported in Table IV, confirming that the model captures both level and direction with high fidelity. The improvement over the linear SVR is large in absolute and relative terms. Compared to the 80/20 linear SVR, ELM reduces MAE by an average of 60.6% and RMSE an average of 48.4%, while R^2 rises from 0.937 - 0.968 to 0.987 - 0.989. ELM's single hidden layer provides a non-linear feature mapping, allowing the model to learn curved relationships between recent lags and the next day price that a purely linear kernel cannot represent. Training is solved by a fast least-squares step once the hidden parameters are set, which tends to fit the dominant patterns efficiently without long optimization. The error structure also changes: RMSE remains above MAE, but the gap narrows because extreme misses become rarer and smaller. Taken together, these patterns suggest that ELM captures non-linearities in Bitcoin's dynamics more effectively, yielding tighter predictions for Open, High, Low, and Close.

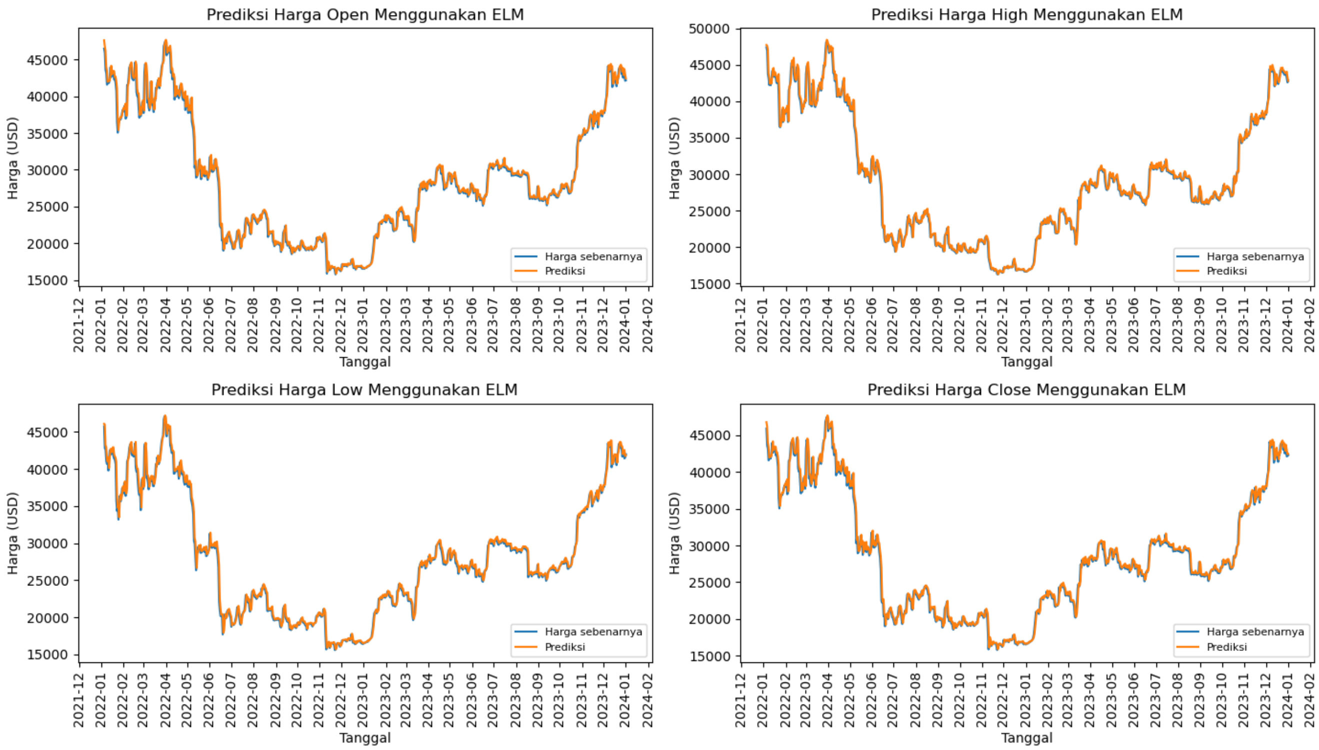

Figure 8. ELM Prediction
(60% training data, 40% testing data)

With 60% training and 40% testing data, ELM maintains very strong accuracy across all prices (Table V). The Open price records MAE 581.245 USD and RMSE of 882.390 USD with R^2 of 0.989. The High is slightly better, achieving MAE of 527.437 USD, RMSE of 800.995 USD, and the highest R^2 of 0.991. The Low and Close are similarly accurate. Errors remain well below one thousand USD for every price, and R^2 values near one indicate that ELM explains nearly all of the variance in the test data even with a longer test window.

TABLE V
EVALUATION VALUES OF ELM
(60% TRAINING DATA AND 40% TESTING DATA)

Price	MAE	RMSE	R^2
Open	581.245	882.390	0.989
High	527.437	800.995	0.991
Low	515.377	838.206	0.989
Close	579.074	881.035	0.989

In Figure 8 (ELM 60/40), the orange prediction line almost overlaps the blue actual line throughout the period, including the deep 2022 decline and the late 2023 rebound. Deviations appear briefly around sharp turns but close quickly, and both peaks and troughs are reproduced with small gaps. The High shows the tightest tracking among the four, matching its best R^2, while Low remains stable with only short, minor under or overshoots. RMSE exceeds MAE in every price, which means occasional larger misses still exist, yet the magnitude is modest relative to the overall price level. Taken together, the figures corroborate the table: ELM captures both the level and the day-to-day movement of Bitcoin prices with high fidelity. Compared with the 80/20 split, MAE and RMSE increase slightly under 60/40 (as expected with more test window), but R^2 is marginally higher (0.989 - 0.991 than 0.987 - 0.989). This can occur because R^2 is variance-scaled: the 40% test window has larger price variance, so explaining a similar share of movement yields a higher R^2 even when absolute errors are larger. Again, the robustness of ELM across both splits suggests that its non-linear hidden layer captures curved relationships between recent lags and next-day prices that linear models smooth out. Moreover, the closed-form training step of ELM tends to fit dominant patterns efficiently, which helps preserve accuracy when the test window is increased. Overall, the 60/40 results show that ELM remains reliable for monitoring trend and level across Open, High, Low, and Close, with only modest degradation in absolute error despite the longer test horizon.

C. Overview of SVR and ELM

Based on the results, ELM consistently outperforms SVR on all prices in both splits. ELM shows superior performance compared to SVR because its single hidden layer architecture with non-linear activation functions is better able to capture the fluctuating patterns of Bitcoin prices. Under a 60% training and 40% testing data partition, ELM continues to outperform SVR in Bitcoin price prediction, which can be attributed to the fast and efficient pseudo-inverse learning process that enhances model stability across varying data splits and improves generalization capability despite the reduction in training data. Overall, ELM provides substantially lower errors and higher R^2 than SVR in both data splits, with average MAE in the hundreds of dollars (near the actual prices) and strong fidelity to daily movements. SVR remains serviceable for trend tracking but smooths extremes and loses more accuracy as the test horizon lengthens.

IV. Conclusion

This study compared a linear-kernel Support Vector Regression (SVR) with an Extreme Learning Machine (ELM) for day-ahead Bitcoin price prediction using only lagged prices. Across all price series (Open, High, Low, Close) and in both train–test splits, ELM consistently outperformed SVR. The 80/20 split, the average performance of SVR was MAE of 1061.449 USD, RMSE of 1227.499 USD, and R^2 of 0.955, whereas ELM achieved MAE of 418.698 USD, RMSE of 633.953 USD, and R^2 of 0.987. This evaluation means that ELM's MAE of roughly 419 USD indicates that predictions are typically within a few hundred dollars of the actual price, while SVR's 1.06 thousand USD. Relative to SVR, ELM reduces MAE by about 60.6% and RMSE by 48.4% and explains a larger share of the variance. With the 60/40 split (less training, longer test window), ELM remains robust with MAE of 550.783 USD, RMSE of 850.656 USD, R^2 of 0.989, compared with SVR's MAE of 1843.534 USD, RMSE of 2093.542 USD, R^2 of 0.935. Thus, ELM still delivers 70.1% lower MAE and 59.4% lower RMSE than SVR on average. Errors stay in the hundreds of dollars for ELM, while SVR's errors are typically in the low thousands. These outcomes indicate that ELM predictions are consistently closer to the actual prices, and that the model captures both level and day to day movements with high fidelity. In terms of interpretation, the MAE values indicate that ELM predictions are consistently closer to the actual Bitcoin prices, since a lower MAE reflects that the model can predict with relatively small deviations. The RMSE results further strengthen this conclusion because smaller RMSE values show that the ELM model not only produces accurate predictions on average but also avoids large fluctuations in error, meaning its predictions are more stable and its non-linear function significantly improves the evaluation. Based on these findings, ELM can be considered a more reliable algorithm for Bitcoin price prediction.

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