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Comparative Analysis of Machine Learning and Deep Learning Models for Bitcoin Price Prediction

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Abstract

This research endeavors to forecast Bitcoin prices by employing a suite of machine learning and deep learning models. Five distinct models were employed: Random Forest, Linear Regression, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), each evaluated based on their R-squared scores. Notably, the models showcased diverse performances, with the ensemble learning approach of Random Forest exhibiting near-perfect accuracy, closely followed by GRU and SVM. The deep learning architectures, LSTM and GRU, demonstrated remarkable predictive capabilities, showcasing their adeptness in capturing intricate temporal patterns within the cryptocurrency price data. This study sheds light on the comparative performance of these models, emphasizing their strengths and limitations in predicting Bitcoin prices.

A. Introduction

The advent of cryptocurrencies, particularly Bitcoin, has revolutionized the financial landscape, introducing a decentralized digital currency that operates outside the purview of traditional financial institutions. Since its inception in 2009, Bitcoin has experienced unprecedented growth, propelling it into the spotlight as a volatile yet lucrative investment avenue [1]. Its remarkable price volatility, characterized by rapid fluctuations and unforeseeable market movements, has intrigued investors, traders, economists, and technologists alike, fostering an ongoing quest to comprehend and forecast its price dynamics [2].

Amidst the burgeoning interest in cryptocurrencies, the ability to predict Bitcoin's price movements has emerged as a fundamental pursuit in financial forecasting and investment decision-making. Traditional financial markets, often governed by macroeconomic indicators and historical trends, face a distinctive challenge when applied to the realm of cryptocurrencies due to their unique characteristics. Bitcoin, in particular, exhibits non-linear and erratic price behavior, influenced by diverse factors encompassing technological advancements, regulatory developments, market sentiment, adoption trends, and macroeconomic events [3].

The dynamic nature of Bitcoin's price dynamics presents a conundrum for traditional financial modeling approaches [4]. However, the surge in computational power and the evolution of machine learning and deep learning techniques offer a promising avenue for analyzing and predicting cryptocurrency prices. Leveraging historical price data, trading volumes, market sentiment analysis, blockchain metrics, and a plethora of technical indicators, these methodologies strive to unravel the intricate patterns embedded within Bitcoin's market behavior [5].

This research paper endeavors to explore and scrutinize the efficacy of various machine learning and deep learning models in predicting Bitcoin prices. The selected models encompass a spectrum of approaches, each with its unique capabilities and adaptability to capture Bitcoin's complex price movements.

The Random Forest algorithm, an ensemble learning technique comprising multiple decision trees, excels in handling large datasets and nonlinear relationships. By aggregating predictions from diverse decision trees, it mitigates overfitting and provides robust estimations, potentially navigating Bitcoin's erratic price fluctuations [6]. A fundamental yet powerful technique in predictive modeling, Linear Regression establishes a linear relationship between input variables and Bitcoin prices. Its simplicity and interpretability offer insights into the overall trend in price movements, enabling stakeholders to discern directional shifts [7]. SVM, operating by mapping data into higher-dimensional spaces, aims to delineate Bitcoin price movements into distinct categories. Known for its ability to identify complex patterns and nonlinear relationships, SVM holds promise in deciphering Bitcoin's market trends [8].

Venturing into the realm of deep learning, LSTM and GRU, two recurrent neural network architectures, are tailored to capture sequential dependencies within time-series data. Renowned for their capability to model long-term dependencies, these architectures exhibit potential in discerning Bitcoin's intricate temporal patterns and irregularities [9].

The research herein encompasses an extensive empirical study, employing historical Bitcoin price data sourced from reputable exchanges within a defined time frame. The data undergoes preprocessing normalization, and partitioning into training and testing sets. Subsequently, each model is meticulously implemented, fine-tuned through rigorous experimentation, and evaluated using pertinent performance metrics.

The findings of this study aim to shed light on the performance, strengths, limitations, and comparative analysis of Random Forest, Linear Regression, SVM, LSTM, and GRU models in forecasting Bitcoin prices. The assessment hinges on established evaluation metric by R-squared (R2) scores, to ascertain their predictive accuracy and robustness.

In essence, this research contributes to the ongoing discourse surrounding Bitcoin price prediction, offering insights into the applicability and efficacy of diverse machine learning and deep learning methodologies in navigating the enigmatic landscape of cryptocurrency markets. Through comprehensive analysis and empirical validation, this study endeavors to provide a nuanced understanding of the capabilities and limitations of these models in forecasting Bitcoin prices.

B. Literature Review

The prediction of Bitcoin price has become a popular and significant topic in recent years, considering the increasing attractiveness of this virtual currency to investors. Researchers have explored various techniques and methodologies from the domains of statistical, machine learning, and deep learning to predict Bitcoin price accurately.

Hari Andi [10] presents a method to predict the price of Bitcoin based on a normalization dataset and LSTM. Machine learning and AI-assisted trading processes are increasingly used to access abnormal profits from the Bitcoin market, and their algorithms and architectural structure produce strong results. The author collects Bitcoin data and uses it to train the LSTM model, normalizing the data to aid in achieving accurate forecasting. Ho et al. [11] investigates the use of machine learning and neural networks for predicting Bitcoin prices. The researchers implemented the linear regression and Long Short-Term Memory models and trained them on Bitcoin data from August 2017 to August 2020. The analysis was focused on four main features: open, close, high, and low prices. The linear regression model demonstrated the highest accuracy.

Ferdiansyah el al. [12] The authors tested their LSTM-based model using historical Bitcoin price data over a five-year period from 2014 to 2019, obtained from Yahoo Finance and CryptoCompare. Performance was measured using the Root Mean Square Error, and they experimented with different numbers of epochs and dropout rates. The model achieved an RMSE of approximately 288 with 500 epochs. Awoke et al. [13] The prediction models that were implemented were LSTM and GRU, both of which are deep learning approaches. According to the findings of the study, the GRU model is the superior mechanism for predicting the price of cryptocurrencies across time series, and it also requires less time to compile results. When it comes to recognizing long-term dependencies, LSTM and GRU models are more capable than others. Poongodi et al. [14] uses a machine learning technique to predict Bitcoin prices. On applying the ARIMA model for predicting the price of Bitcoin, the author obtained a satisfactory accuracy. The paper concludes by highlighting that despite some challenges, Bitcoin is increasingly preferred for investment and transactions, with a notable shift towards centralization from its original decentralized nature.

Ye et al. [15] To forecast the price of Bitcoin for the next 30 minutes, a unique ensemble deep learning model was put forth that makes use of sentiment indexes, technical indicators, and price data. This model combines the stacking ensemble technique with two different neural network types—long short-term memory (LSTM) and gate recurrent unit (GRU)—to increase decision accuracy. In this paper, the source data of public opinion is derived from texts found on social media platforms rather than from news websites. This is due to the fact that social media platforms provide real-time updates of comments. There is a significant difference in performance between the daily prediction and the near-real time prediction, as demonstrated by the results of the experiments. Ji et al. [16] For the purpose of predicting the price of Bitcoin, they investigated and compared a number of cutting-edge deep learning techniques, including a DNN, a LSTM model, a CNN, a deep residual network, and their respective combinations. The findings of the experiments demonstrated that although LSTM-based prediction models performed marginally better than the other prediction models when it came to predicting the price of Bitcoin (regression), DNN-based models fared the best when it came to predicting price increases and decreases (classification).

These papers collectively provide a comprehensive overview of the various machine learning models and methodologies employed for Bitcoin price prediction, showcasing the evolution of techniques and the ongoing efforts to improve prediction accuracy in the cryptocurrency domain.

C. Methodology

Bitcoin, the first and most popular cryptocurrency, has garnered significant attention in recent years. Investors, traders, and enthusiasts are constantly seeking ways to predict the future price movements of Bitcoin. The preprocessing technique and various models have been employed to forecast Bitcoin prices, including Random Forest, Linear Regression, SVM, LSTM, and GRU models. Fig. 1 shows the data flow of our proposed methodology.

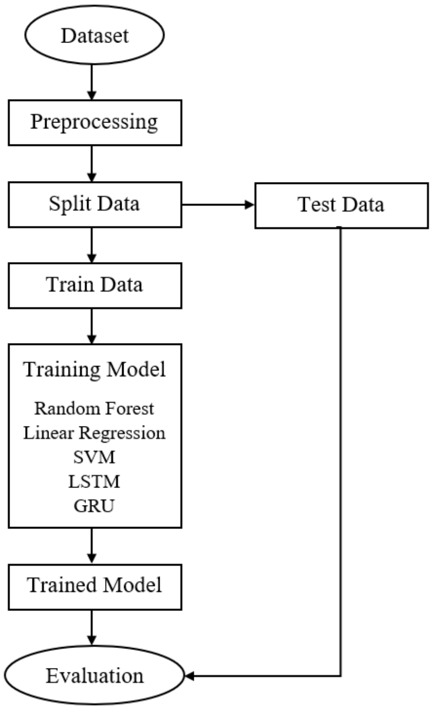

Figure 1. Data Flow of Proposed Models

The research employed a comprehensive set of tools and libraries within the Python ecosystem for data retrieval, manipulation, modeling, and evaluation. The data collection phase utilized 'yfinance,' a robust library enabling seamless access to financial data from Yahoo Finance [17], facilitating the retrieval of Bitcoin price information spanning the entirety of 2022. For data preprocessing, manipulation, and model creation, fundamental libraries like 'pandas' and 'numpy' were instrumental in structuring, cleaning, and transforming the dataset into a suitable format for modeling. The scikit-learn library provided a diverse suite of machine learning algorithms, allowing the implementation and evaluation of models such as Random Forest, Linear Regression, and SVM, while 'TensorFlow' and 'Keras' facilitated the creation and training of complex deep learning architectures like LSTM and GRU [18]. These tools collectively provided a robust framework for data handling, model development, and performance evaluation in the pursuit of accurate Bitcoin price prediction.

1. Preprocessing technique

The MinMaxScaler function in Python, part of the scikit-learn library, serves the purpose of transforming data features into a specified range, commonly between 0 and 1. This scaling method is advantageous in machine learning as it helps algorithms converge faster and avoid certain biases that can arise from features with different scales [19]. This process preserves the shape of the distribution while transforming the values. The formula utilized by MinMaxScaler to normalize data features within the range of [0, 1] is as follows:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, X represents the original feature value. X_{min} is the minimum value of the feature. X_{max} is the maximum value of the feature. X_{scaled} is the transformed feature value within the range [0, 1].

2. Random Forest

Random Forest is an ensemble learning technique for regression tasks that generates the mean prediction of individual trees while constructing multiple decision trees during training [20] see figure 2. The methodology of random forest involves fine-tuning hyperparameters such as the number of trees in the forest we used (100), maximum tree depth we used none (If None, Next, the nodes are further increased until either all of the leaves are pure or until there are fewer samples than the minimum required.), and the minimum number of samples required to split a node we used (2). prediction $\hat{Y}$ for a given input X in Random Forest is obtained by averaging predictions of individual trees T :

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^{N} T_i(X) \tag{2}$$

where N is the number of trees in the forest. The hyperparameters of the Random Forest model, such as the number of trees, maximum depth, and minimum samples per leaf, are optimized to minimize the mean squared error (MSE) or maximize the coefficient of determination (R-squared).

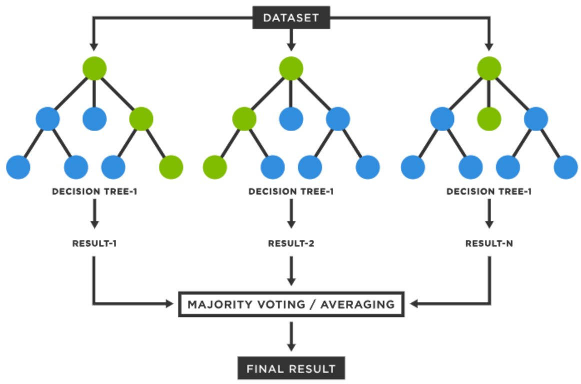

Figure 2. Random Forest general example [21]

3. Linear Regression

By fitting observed data to a linear equation, linear regression is a fundamental statistical technique used to characterize the relationship between dependent and independent variables [22] see figure 3. In this research, Linear Regression is employed to predict Bitcoin prices based on historical data. Linear Regression models the relationship between the dependent variable Y and independent variables X through a linear equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{3}$$

Where β_0 is the intercept, β_i represents the coefficients of input features, X_i are the independent variables, and ϵ is the error term.

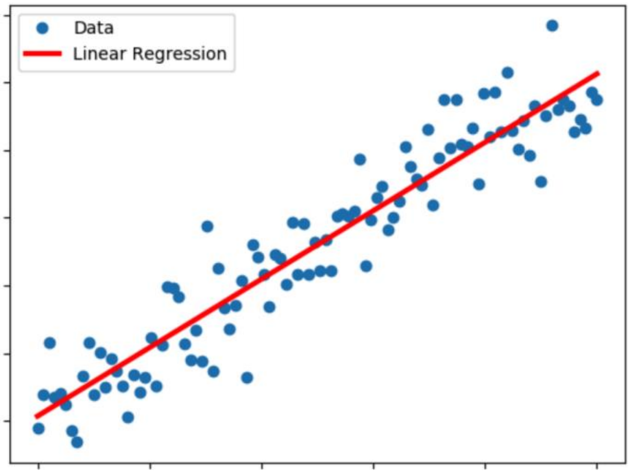

Figure 3. Linear Regression General Example [23]

4. SVM

The Support Vector Machine is a very effective supervised learning technique that is now being utilized for classification and regression tasks [24] see figure 4. In this study, SVM is adapted for Bitcoin price prediction. The methodology involves selecting the appropriate kernel (radial basis function) and tuning hyperparameters such as the regularization parameter (C=1.0) and the kernel-specific parameters (gamma for RBF kernel=scale).

The objective of SVM is to locate the hyperplane that best separates data points into various classes or, in the case of regression problems, makes the data fit with the greatest possible margin. In the case of regression, the SVM regression equation aims to minimize the errors while staying within the margin:

$$Minimize\ \frac{1}{2}\ \|\omega\|^2 + C\sum_{i=1}^{n}(\varepsilon_i + \varepsilon_i^*) \qquad (4)$$

subject to the constraints:

$$y_i - \omega^T.x_i - b\ \leq\ \epsilon + \varepsilon_i \qquad (5)$$

$$\omega^T.x_i + b - y_i \leq\ \epsilon + \varepsilon_i^* \qquad (6)$$

where ω is the weight vector, x_i represents the input features, y_i is the target variable, b is the bias term, ε_i and ε_i^* are slack variables, C is the regularization parameter, and ϵ controls the margin width.

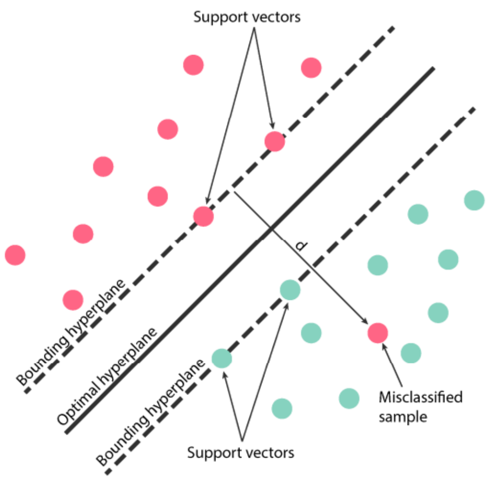

Figure 4. SVM General Example [25]

5. LSTM

LSTM is a type of RNN designed to capture long-term dependencies in sequential data. For Bitcoin price prediction, LSTM models are employed to learn temporal patterns from historical price sequences [26] see figure 5. The LSTM architecture comprises multiple memory cells and gates that regulate the flow of information through the network. Hyperparameters such as the number of LSTM units=50, batch size=32, epochs=1000, and learning rate= 0.001, are fine-tuned through experimentation to optimize the model's performance.

LSTM models capture temporal dependencies in sequential data. The key equations in LSTM involve the computation within a single LSTM cell, including the forget gate, input gate, and output gate. These gates control the flow of information and are calculated as follows:

$$f_t = \sigma(W_f \, . \, [h_{t-1}, x_t] + b_f) \quad (7)$$

$$i_t = \sigma(W_i \, . \, [h_{t-1}, x_t] + b_i) \quad (8)$$

$$\tilde{C}_t = tanh(W_C \, . \, [h_{t-1}, x_t] + b_C) \quad (9)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (10)$$

$$o_t = \sigma(W_o \, . \, [h_{t-1}, x_t] + b_o) \quad (11)$$

$$h_t = o_t * \tanh(C_t) \quad (12)$$

where f_t is the forget gate, i_t is the input gate, $\tilde{C}_t$ is the candidate cell state, C_t is the cell state, o_t is the output gate, h_t is the hidden state, x_t is the input at time step t, h_{t-1} is the previous hidden state, σ represents the sigmoid function, * denotes element-wise multiplication, and W and b are weight and bias parameters, respectively.

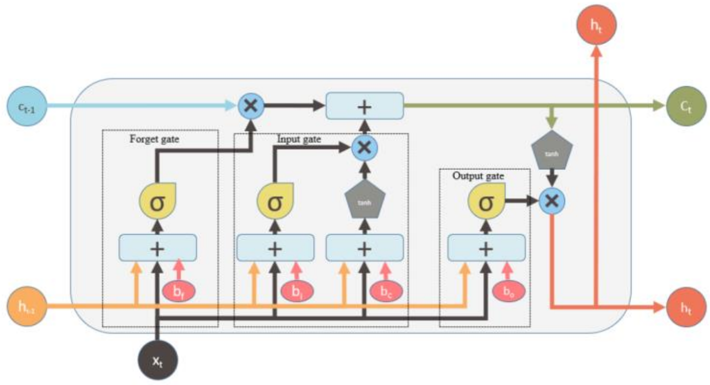

Figure 5. A traditional LSTM Model [27]

6. GRU

GRU is a variant of recurrent neural networks designed to address some of the limitations of traditional RNNs like the vanishing gradient problem [28] see figure 6. Hyperparameter tuning involves optimizing parameters like the number of GRU units=50, batch size=32, epochs=1000, and learning rate= 0.001, are fine-tuned through experimentation to optimize the model's performance.

GRU simplifies the architecture of LSTM by combining the forget and input gates into a single update gate and merging the cell state and hidden state. The equations governing the operations within a GRU unit are as follows:

$$z_t = \sigma(W_z \, . \, [h_{t-1}, x_t] + b_z) \quad (13)$$

$$r_t = \sigma(W_r \,.\, [h_{t-1}, x_t] + b_r) \quad (14)$$
$$\tilde{h}_t = tanh(W_h \,.\, [r_t * h_{t-1}, x_t] + b_h) \quad (15)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (16)$$

where z_t is the update gate, r_t is the reset gate, $\tilde{h}_t$ is the candidate activation, h_t is the hidden state at time step t, x_t is the input, h_{t-1} is the previous hidden state, σ denotes the sigmoid function, * represents element-wise multiplication, and W and b are weight and bias parameters, respectively.

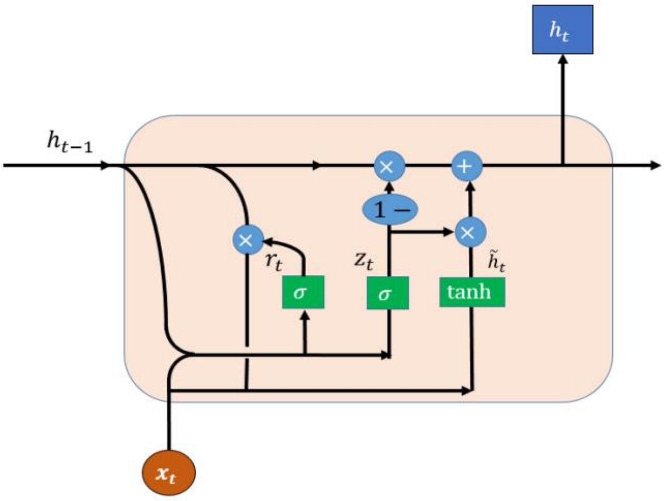

Figure 6. A traditional GRU Model [29]

These detailed descriptions outline the methodologies and steps involved in implementing each machine learning and deep learning model for Bitcoin price prediction, including data preprocessing, hyperparameter tuning, and model architecture design.

D. Results and Discussion

The performance of the models was evaluated using the Yahoo Finance dataset spanning from January 1st, 2022, to December 31st, 2022. Five different models were employed: Random Forest, Linear Regression, SVM, LSTM, and GRU. Each model underwent rigorous training and testing, with evaluation metrics centered around R-squared (R2) scores.

In a regression model, the coefficient of determination, which is also commonly referred to as R-squared (R2), is a statistical metric that evaluates the proportion of the variation in the dependent variable that can be predicted based on the independent variables [30]. It is calculated as the ratio of the explained variance to the total variance of the response variable and ranges between 0 and 1. The formula for R2 is depicted as follows:

$$R^2 = 1 - \frac{Sum\ of\ Squared\ Residuals}{Total\ Sum\ of\ Squares} \quad (17)$$

Here, the numerator represents the sum of squared differences between the predicted values and the actual values (residuals), while the denominator indicates the total variability of the dependent variable around its mean. An R2 score closer to 1 implies that a higher proportion of the variance in the target variable is captured by the model, suggesting a better fit. Conversely, an R2 score closer to 0 indicates that the model fails to explain much of the variability in the dependent variable. R2 serves as a crucial metric in evaluating the goodness of fit for regression models, providing insights into their predictive performance. The Table 1 show the R-squared of all used models.

Table 1. R-Squared Compression

No	Models	R-squared
1	Random Forest	0.988
2	Linear Regression	0.842
3	SVM	0.945
4	LSTM	0.926
5	GRU	0.952

The Random Forest model exhibited outstanding performance in predicting Bitcoin prices, achieving an exceptional R-squared score of 0.988. Its ensemble of decision trees allowed it to grasp intricate relationships among features, enabling precise predictions. The robustness of this model in handling high-dimensional data and capturing complex patterns is evident from its near-perfect predictive accuracy.

Linear Regression, a fundamental yet interpretable model, achieved a respectable R-squared score of 0.842 in predicting Bitcoin prices. Its simplicity and ease of interpretation make it a valuable tool for initial analysis. However, its linear nature might limit its ability to capture the complex, non-linear relationships inherent in cryptocurrency markets, resulting in slightly lower predictive accuracy compared to more sophisticated models.

The Support Vector Machine (SVM) model displayed commendable performance, yielding an R-squared score of 0.945. SVM's capability to handle non-linear relationships through kernel functions enabled it to capture intricate patterns in the data, contributing to its high predictive accuracy. However, fine-tuning hyperparameters might further enhance its adaptability to the intricate dynamics of cryptocurrency price fluctuations.

Both Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), prominent architectures within the domain of recurrent neural networks (RNNs), demonstrated exceptional predictive capabilities. LSTM achieved a remarkable R-squared score of 0.926, while GRU outperformed with an even higher score of 0.952. These deep learning models leverage their inherent memory mechanisms to capture long-term dependencies and temporal patterns in sequential data.

E. Conclusion

The evaluation of various machine learning and deep learning models for Bitcoin price prediction yielded intriguing insights into their individual strengths and effectiveness in capturing the complex dynamics of cryptocurrency markets. Notably, the Random Forest model displayed an exceptional R-squared score, demonstrating its robustness in comprehending intricate relationships within the

Bitcoin price data. However, while Random Forest showcased unparalleled accuracy, its computational complexity might hinder its scalability for real-time deployment.

Contrastingly, Linear Regression and SVM, while achieving respectable R-squared scores, demonstrated a trade-off between simplicity and predictive power. These models, known for their interpretability and computational efficiency, captured essential patterns in the data but fell short in grasping the nuanced complexities of cryptocurrency price fluctuations.

The standout performers, LSTM and GRU, both deep learning architectures, showcased remarkable predictive capabilities with R-squared scores. Their recurrent nature allowed them to capture long-term dependencies and intricate temporal patterns within the sequential Bitcoin price data, outperforming traditional machine learning models. Despite their exceptional accuracy, their computational intensity might limit their practical deployment in real-time scenarios.

This research highlights the necessity for a balanced approach between model complexity, interpretability, and computational efficiency in cryptocurrency price prediction. Further investigations could explore hybrid models that leverage the strengths of various approaches, integrating external factors such as sentiment analysis and market dynamics for enhanced predictive accuracy. This study lays the groundwork for future advancements in the development of robust models for cryptocurrency price forecasting, facilitating informed decision-making in financial markets.

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G. References

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