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ASSESSING BITCOIN PRICE PREDICTION WITH MACHINE LEARN PROTOCOLS

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Abstract
Cryptocurrency is an alternative payment method developed with encryption techniques. To predict Bitcoin values using both weekly and monthly datasets, this study compares four machine learning models: GRU, Weighted LSTM, LSTM, and LSTM with Attention. The models' accuracy and dependability in capturing the dynamics of cryptocurrency prices were assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared (RSCORE). While LSTM with Attention did well with an RSCORE of 0.7173, LSTM with Attention had the highest RSCORE of 0.9173 in the weekly dataset, indicating higher ability in modelling short-term sequential patterns. Additionally, weighted LSTM performed well (RSCORE of 0.8002), surpassing GRU (RSCORE of 0.5728), which had trouble keeping up with the volatility of Bitcoin prices. Both LSTM and LSTM with Attention performed best in the monthly dataset, each with the lowest MSE (0.0304) and an RSCORE of 0.8173. With an RSCORE of 0.7002, weighted LSTM came next, using temporal weighting to enhance predictions. Because of its limited capacity to grasp intricate temporal connections, GRU continuously fared poorly in both datasets. According to the analysis, LSTM is the most dependable model for both short-term and long-term forecasts, and for weekly forecasts, LSTM with Attention provides improved interpretability. These results provide a framework for applying machine learning approaches to financial time series forecasting, highlighting the significance of choosing suitable models based on data frequency, volatility, and prediction aims.
Keywords: Cryptocurrency, Bitcoin Forecasting, Machine Learning, Long Short-Term Memory (LSTM), Time Series Prediction
JEL Codes: C45, E42; G17

INTRODUCTION

Cryptocurrency is an alternative payment method developed with encryption techniques. Cryptocurrencies serve as a virtual accounting system in addition to being a form of money. Satoshi Nakamoto introduced the concept of Bitcoin currency in the finance industry, which is arguably one of the most challenging sectors (Nakamoto, 2008). This marked the beginning of the digital transformation that we regularly experience in all domains. Since the launch of Bitcoin and other digital currencies like Ethereum, XRP, and Stellar have appeared incredibly quickly. Bitcoin continues to hold the largest share of all cryptocurrencies and completely controls the digital economy. Its market capitalization is currently close to $250 billion USD with over 300,000 transactions taking place per day in November 2020 (Coindesk, 2021). Bitcoin transactions are conducted between two people without the involvement of a third-party financial institution, in contrast to traditional cash.

The prediction of cryptocurrency prices, especially Bitcoin, is crucial since cryptocurrencies are the newest financial invention and are significantly affecting the global economy. Predicting cryptocurrency prices and holding blockchain conferences to inform the public about the next revolution are of special interest to fintech experts and technologists. Evidence of this connection between changes in stock prices and social media has been found in earlier research. Additionally, because of the abundance of publicly accessible data on social trends and the cryptocurrency market. Forecasting the price of bitcoin is one of the most difficult issues that corporations, financial institutions, and individual investors deal with (Kao et al., 2013). The reliability of bitcoin price predictions is influenced by several variables, such as investor psychology, political environments, and economic conditions.

The research claims that due to this complexity, there is a lot of interest in using machine learning algorithms that can predict prices. These algorithms are a collection of techniques for using data to learn mathematical models without having to explicitly teach the computer to do a certain function. There is a need for various models that can capture more intricate data representations for the cryptocurrency industry. The time-series challenge of cryptocurrency price prediction can be resolved by deep learning models, particularly recurrent neural networks. In recent years, several studies have been conducted by different authors to use machine learning and deep learning algorithms to forecast the value of stocks and securities (H. et al., 2020). Four distinct machine learning models - LSTM, WLSTM, GRU, and LSTM with Attention - will be taken into consideration in this investigation. This paper's major sections are arranged as follows. The related works in this paper are presented in Section 2. The suggested methodology for bitcoin price forecasting is displayed in Section 3. The tests, findings, and discussion are presented in Section 4. Lastly, Section 5 provides the conclusion and future research directions.

LITERATURE REVIEW

Conceptual Review

Machine learning has increasingly become a central tool in financial forecasting, particularly in stock markets and more recently in the cryptocurrency space. Its strength lies in its ability to model non-linear, high-dimensional data, features that are particularly relevant for assets like Bitcoin, which are highly volatile and influenced by a wide array of exogenous and endogenous factors. In forecasting applications, deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have gained popularity due to their capacity to learn from sequential patterns and long-term dependencies. Several recent studies have extended traditional models by incorporating variations such as Weighted LSTM, LSTM with Attention, and hybrid models that integrate machine learning and deep learning techniques. Fanai and Abbasimehr (2023), for instance, demonstrated that hybrid deep learning models, combinations of LSTM, GRU, Weighted LSTM, and LSTM with Attention, can significantly improve forecasting accuracy, particularly when temporal data are involved. These models outperform simpler models by capturing hidden patterns, especially in highly volatile environments like the cryptocurrency market.

Similarly, Zhao et al. (2023) integrated LSTM with k-nearest neighbors (KNN) and AdaBoost, showing that hybrid models perform better than standalone machine learning methods. Ensemble approaches such as the AdaBoost-GRU model used by Kwak and Lim (2021) also demonstrated improved efficiency and robustness when applied to financial markets. Fang et al. (2023) contributed further by proposing a model that integrates LSTM with batch normalization, dropout layers, and a binary classifier to reduce overfitting and enhance trend prediction in temporal financial data.

Dimensionality reduction has been another important aspect of improving forecasting performance. Traditional techniques like Principal Component Analysis (PCA), though useful, are limited to linear patterns and may not fully capture the non-linear complexities in financial data (Zhong & Enke, 2017). This limitation has been addressed through the use of autoencoders, which are better suited for non-linear feature extraction. For instance, Gradxs and Rao (2023) employed deep stacked autoencoders in fraud detection and demonstrated their superiority over PCA in capturing complex relationships within the data.

Despite advancements in machine learning and deep learning applications to financial data, research specific to cryptocurrency forecasting—particularly Bitcoin—remains relatively limited. Most of the recent empirical studies focus on stock markets or generalized financial time series, with only a few tailored to the unique characteristics of cryptocurrencies. Moreover, there has been limited effort to compare multiple LSTM variants across different temporal frequencies such as weekly and monthly data, which is essential for understanding the practical usability of these models in different trading contexts.

This study addresses these gaps by comparing four models, GRU, Weighted LSTM, LSTM, and LSTM with Attention, across weekly and monthly Bitcoin price datasets. By doing so, it contributes to both methodological advancement and practical understanding of machine learning applications in cryptocurrency forecasting, offering insights into model performance under varying temporal resolutions and volatility conditions.

Theoretical Review

The theoretical foundation of this study rests primarily on two complementary frameworks: the Efficient Market Hypothesis (EMH) and the Adaptive Market Hypothesis (AMH). The EMH posits that financial markets are informationally efficient, meaning that asset prices fully reflect all available information, making it impossible to consistently achieve excess returns using historical price data. However, the EMH has been heavily critiqued in the context of cryptocurrency markets, where irrational investor behavior, speculative bubbles, and information asymmetry are more pronounced.

In contrast, the AMH, proposed by Andrew Lo, offers a more dynamic understanding of market behavior. It suggests that market efficiency is not static but evolves over time in response to changing market conditions, investor behavior, and technological advancements. Under the AMH framework, markets may exhibit periods of inefficiency that can be exploited by adaptive learning algorithms. Machine learning models, particularly those capable of learning from historical trends and adapting to new data, align well with the AMH perspective. In the context of cryptocurrencies, where the market is relatively immature and prone to behavioral anomalies, these models are especially relevant.

This study also draws on time series modeling theory, particularly in relation to recurrent neural networks (RNNs) such as LSTM and GRU. These models are grounded in the theory of sequential learning and are specifically designed to capture long-range dependencies within time-series data. LSTM, with its memory cell structure and gating mechanisms, addresses the vanishing gradient problem and is therefore particularly effective for financial forecasting tasks that require the model to remember information over long time lags.

The inclusion of attention mechanisms further extends this theoretical base by allowing models to selectively focus on the most relevant portions of the input sequence, thereby improving interpretability and predictive accuracy. Attention mechanisms are grounded in cognitive theories of selective focus and have been widely adopted in natural language processing before being adapted for time-series forecasting.

Moreover, hybrid model theory suggests that combining different models, each with its own strengths, can enhance overall forecasting performance by capturing multiple dimensions of the data. This theoretical approach supports the use of ensemble models and integrated frameworks that combine deep learning with traditional ML techniques, as evidenced by studies like Kwak and Lim (2021) and Zhao et al. (2023).

Empirical Literature

In several fields of study and application, machine learning has advanced significantly. Our concentration in this part is restricted to financial applications because it would be extremely difficult to cover every piece of literature from other fields. By reducing redundancy in bitcoins market data, dimensionality reduction techniques can lead to more accurate price predictions. For daily stock market return, Zhong and Enke (2017) used ANNs with dimensionality reduction approaches. However, they used various forms of principal component analysis (PCA), which only captures linear/planar intricacy within the data, in their dimensionality reduction strategies. Non-linear complexity are the primary factor influencing the stock market. By considering a number of variables, including market history, commodity prices, and foreign currency rates, Kohli et al. (2019) predict the movements of the Bombay Stock currency (BSE). They discovered that the BSE was most impacted by gold prices. Their investigation showed that the AdaBoost algorithm outperformed the others.

There has been a lot of study recently on predicting stock and currency market prices (Watanabe et al., 2009). In 2019, Kang et al. developed an architecture for Generative Adversarial Networks that uses Multi-Layer Perceptrons (MLP) as discriminators and Long Short-Term Memory (LSTM) as generators. Zhan and associates (2019) Multiple metrics have been used to evaluate the models, and the suggested GAN model has proven to be superior to another model based on all metrics used in this study. The GAN model has been compared with the LSTM, Artificial Neural Network (ANN), and Support Vector Regression (SVR). Greater efficiency and speed of innovation would be possible with big data. Examples of financial innovation that have supported financial development and economic progress include venture capital, equity funds, and exchange-traded funds. Bhatti and associates (2021).

Bitcoin was developed with differing degrees of success using short term temporal (LSTM) networks and Bayesian optimized recurrent neural networks (RNN), according to M. and Szafarz (2013). Edwin Sin and Lipo Wang (2017) The well-known time series forecasting ARIMA model was used to compare with deep learning models; the highest classification of LSTM is 52%, and the RMSE is 8%. In deep learning for time sequence forecasting, LSTM connection is contemporary. Less research has been done on economic forecasting, particularly with regard to cryptocurrencies. In order to forecast the daily price of Bitcoin, we thus provide a novel LSTM model prediction framework that makes use of two distinct LSTM models (the conventional LSTM model and the LSTM with ARIMA model). The daily variations of bitcoin data during the time frame of January 1, 2018, to July 28, 2018, comprising 208 data points, were used to assess the design's performance. Madan, Isaac, and others (2015). The outcomes validate the ARIMA model's optimal square footage estimate. error (MSE). For the price of Bitcoin, RMSE, MAPE, and Mean Absolute Error (MAE) are used. Edwin Sin and Lipo Wang (2017), Our AR(2) model's LSTM performs better than the conventional LSTM model. In order to overcome the difficulty of diverse input selection in LSTM models without requiring precise data, this study presents a novel method for predicting Bitcoin values. The findings show that it might be applied to several commercial scenarios, including real-time financial data, medical data, and cryptocurrency prediction.

For non-linear feature extraction, many kinds of autoencoders are employed. Deep stacked autoencoders have been employed in behavior-based credit card fraud detection by Gradxs and Rao (2023). They have paired a deep balanced stacking autoencoder with Harris Grey Wolf Network. Fanai and Abbasimehr (2023) have employed deep classifiers and hybridise LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), WLSTM (Weighted LSTM) and LSTM with attention. Two popular recurrent neural networks for processing sequential data are LSTM with attention (LSTMA). d autoencoders to detect credit card fraud. Their tests demonstrate the autoencoder's advantage over PCA. Multiple feature consideration is also crucial for accurate prediction; in this case, hybridisation is helpful. numerous features of several techniques can be combined into a single model by hybridising numerous DL models. This aids in capturing hidden intricacies that were previously overlooked. Zhao et al. have integrated LSTM with k-nearest neighbours (KNNs) and adaptive boosting (AdaBoost, 2023).

The combined approach's performance was notable when compared to conventional ML models. In their experiments on the KOSPII market, Kwak and Lim (2021) found that the AdaBoost and GRU ensemble model was more efficient than the LSTM, GRU, and ARIMA models. For trading-signal prediction, Shen et al. (2018) previously experimented with GRU by substituting SVM for the final layer. Their research revealed that hybridising ML and DL models significantly improved performance. According to Hossain et al. (2018), LSTM-GRU hybridisation improves pricing predictability. Song and Choi (2023) investigated several DL model hybridisations and found that they significantly increased efficiency when compared to other conventional models. Fang and associates in order to predict trends in financial temporal data, (2023) have put forth a hybrid forecasting framework that combines LSTM, a binary classifier, a batch normalisation layer, and a dropout layer.

METHODOLOGY

The study uses the Long Short-Term Memory (LSTM) machine learning algorithm to examine and evaluate the dataset for the purpose of identifying the best model for Bitcoin prediction (Pritam Ahire, 2021). The model presents a holistic strategy for forecasting Bitcoin prices, utilizing past data and sophisticated modeling methods to offer valuable perspectives for cryptocurrency traders and investors (Roth, 2105). For model training, assessment, and testing, the data is then divided into subsets for training, validation, and testing. Validation and testing datasets are used to evaluate the trained model, and predictive capability is measured using performance metrics such as Mean Absolute Error and Root Mean Squared Error, Mean Percentage Error and R-score, as provided by Table 1:

Table 1: Predictive accuracy measures

Accuracy Measure	Accuracy Scale
MAE	$\frac{1}{m}\sum_{t=1}^{m}\lvert e_t\rvert$
MSE	$\frac{1}{n}\sum_{t}^{n}(y_t - \hat{y}_t)^2$
RMSE	$\left(\frac{1}{m}\sum_{t=1}^{m}(e_t)^2\right)^{1/2}$
R^2(score)	$1 - \frac{\sum_t^n(\hat{y}_t - y_t)^2}{\sum_t^n(y_t - \bar{y}_t)^2}$
MAPE	$\frac{100}{m}\sum_{t=1}^{m}\lvert\frac{e_t}{y_t}\rvert$

Note: mean absolute error (MAE); mean squared error (MSE); root mean squared error (RMSE); R-squared (R^2) score; mean absolute percentage error (MAPE).
Source: Author (2024)

After validation, the model is implemented for batch or real-time predictions and incorporated into trading platforms or online apps for user convenience. Continuous monitoring and periodic model updates ensure adaptability to evolving market conditions, while risk management strategies like stop-loss orders and portfolio diversification mitigate potential losses associated with Bitcoin trading. We trained three distinct models for three different forms of cryptocurrency price prediction using historical cryptocurrency prices. Then, to evaluate the suggested schemes' performances, we compare the accuracy of our proposed model to that of current models by following five stages: (1) collecting historical cryptocurrency data; (2) data exploration and visualization; (3) training the models; (4) testing the models; and (5) extracting and comparing the results.

Data Collection
The paper approaches the data gathering through Yahoo finance gathered past Bitcoin price data based on monthly and weekly from 2015 till date using the Python data scrapping. Moreso, the study imported Yahoo finance library taking as (yfinance). The study obtains the log of the original data (close price series) was taken to help stabilize the variance captured facts to detach any errors or lack of consistency. Pick up lost values, outliers, and fact inconsistencies appropriately. Normalize or scale the data to ensure uniformity and stability during model training. This was done to make it easy for the adopted models to learn pattern of the bitcoins close price effectively. The paper took the difference of the logged data to enhance optimal training of the data and effective prediction.

Model Selection
The choice of models selection for this study was bourned out of careful study of these models such as LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), WLSTM (Weighted LSTM) and LSTM with attention. Two popular recurrent neural networks for processing sequential data are LSTM with attention (LSTMA). By using three gates to control information flow and lessen the vanishing gradient issue, LSTM is excellent at learning long-term dependencies. In instance, on shorter sequences or jobs that require faster training, GRU, a simpler variant of LSTM, achieves equivalent performance while been computing more

economically by combining the forget and input gates into a single update gate. WLSTM (Weighted LSTM) and LSTM with Attention have been introduced to further improve performance. By giving input features weights, WLSTM enables the model to efficiently manage noisy or unbalanced data and highlight important information. By including an attention component, LSTM with Attention enables the model to concentrate on the most pertinent segments of the input sequence while making predictions. This enhances the model's capacity to identify significant patterns and connections, particularly in jobs involving lengthy sequences like machine translation, natural language processing, and time series forecasting.

Model Training
To train the models, fit them, and adjust their parameters, the dataset was divided into training and test subsets at an 80:20 ratio. LSTM BTC, WLSTM, GRU, and LSTM with Attention Model are executed on all five of the unique forms that comprise the facts set. Every fact set covers the period from January 2015 to December 2024. The Monthly Basis Data Set is the first data set. Moreso

Min-Max-Scaler ensures all features are proportionally adjusted within a specified range, with features between 0 and 1. By rescaling data, this helped to prevent features such as outliers with larger magnitudes from dominating the learning process, making it particularly beneficial for models sensitive to feature scales. This preprocessing step often leads to more effective model performance and faster convergence during training.

Model Evaluation: Assess the performance of the trained models using appropriate evaluation metrics such as MAE, MAPE, RMSE and R-SCORE. Compare the tests of distinct approach to analyze the better approach for Bitcoin cost.

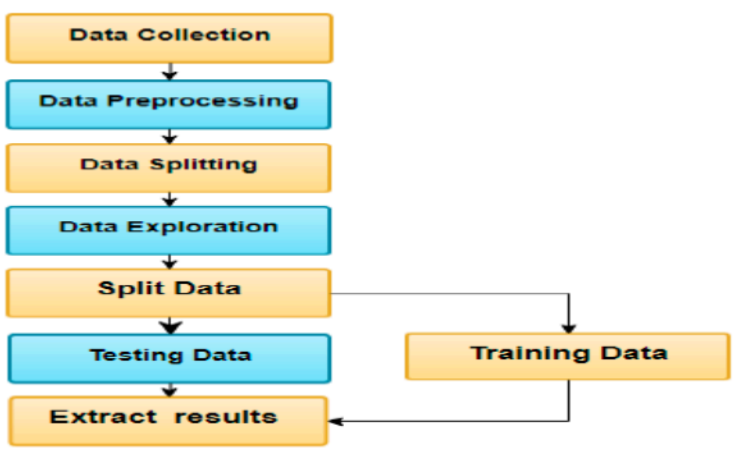


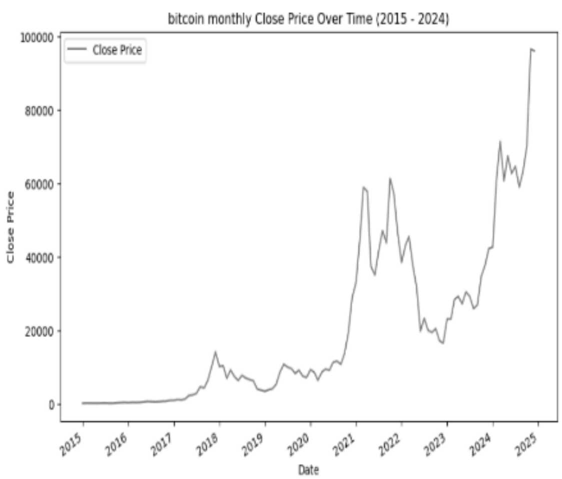
Figure 1. Methodology of processing data and model selection.

RESULTS AND DISCUSSION
Using both weekly and monthly data, the performance evaluation of GRU, Weighted LSTM, LSTM, and LSTM with Attention on Bitcoin price prediction reveals the advantages and disadvantages of each algorithm. With the lowest MSE (0.0304), MAE (0.1436), RMSE (0.1743), and greatest RSCORE (0.8173) for the monthly dataset, LSTM and LSTM with Attention produce the best results, demonstrating strong handling of long-term patterns and exceptional prediction

abilities. With an RSCORE of 0.7002, weighted LSTM also does well, gaining from its capacity to highlight important data aspects. With an RSCORE of 0.4728, GRU, on the other hand, performs the worst in the monthly sample, demonstrating its inability to identify long-term correlations in the erratic price dynamics of Bitcoin.

With an RSCORE of 0.9173 and the lowest MSE (0.0404) and RMSE (0.2743) for the weekly dataset, LSTM performs better than other models, showcasing its exceptional capacity to identify short-term sequential patterns. With an RSCORE of 0.8002, weighted LSTM comes second, demonstrating that temporal weighting successfully enhances performance. With a low MAE (0.2436), LSTM with Attention efficiently catches important time points; nevertheless, its RSCORE of 0.7173 indicates that it might have trouble with overfitting or volatility in weekly data. With an RSCORE of 0.5728 and the greatest RMSE (0.4960), GRU once again scores the worst, highlighting its shortcomings in managing intricate short-term oscillations. Lastly, Because of its steady accuracy and strong generalisation across a range of time granularities, we advise utilising LSTM for both weekly and monthly Bitcoin price forecasts. Particularly for short-term forecasts, LSTM with Attention is a good choice for situations that call for interpretability and the necessity to highlight important time points. Because weighted LSTM can allocate emphasis to inputs, it is appropriate for addressing noisy or unbalanced data. Despite its computational efficiency, GRU is best suited for jobs where speed and ease of use are more important than prediction accuracy.

The paper first analyzes the data set the price at various time intervals, based on weekly (Figure 2) and monthly (Figure 3) periodicities. Figure 2 shows the visualization of Bitcoin price.



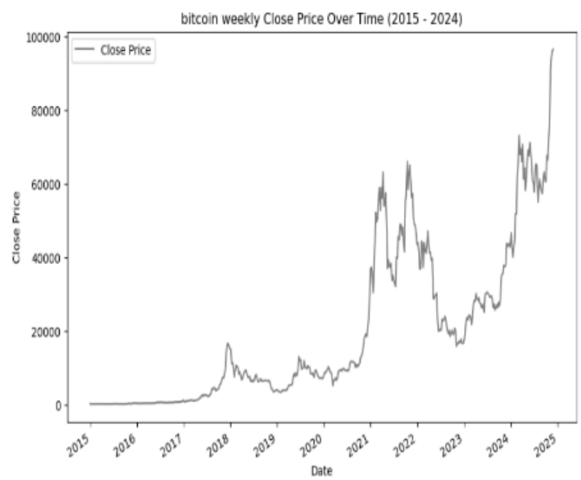
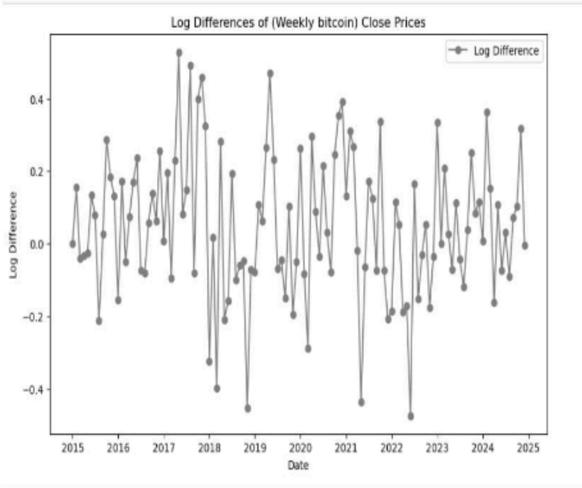


Figure 2: BTC monthly close price (2015-2024)   Figure 3: BTC weekly close price (2015-2024).



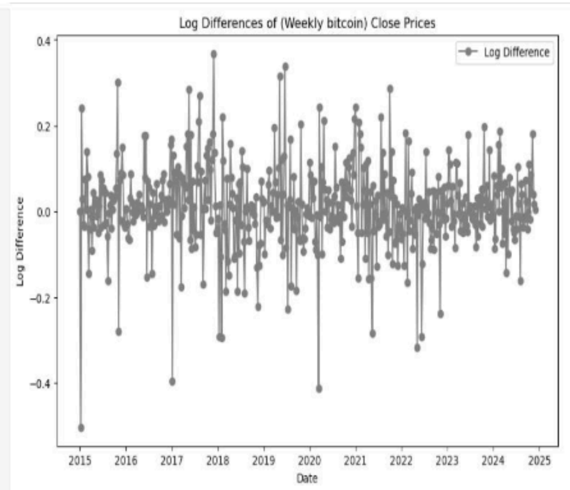


Figure 4: Log difference of BTC monthly close price. Figure 5: Log difference of BTC weekly close price.

Table 2 show the performance analysis of the proposed Models with respect to MSE, MAE, RMSE and RSCORE for the two datasets: monthly and weekly

Table I. Performance analysis of proposed models w.r.t different error and results (monthly data)

	Evaluation Metrics			
Models	MSE	MAE	RMSE	RSCORE
GRU	0.0876	0.2628	0.2960	0.4728
WLSTM	0.0498	0.1833	0.2232	0.7002
LSTM	0.0304	0.1436	0.1743	0.8173
LSTMA	0.0304	0.1436	0.1743	0.8173

Source: Author (2025)

Table 2. Performance analysis of proposed models w.r.t different error and results (weekly data)

	Evaluation Metrics			
Models	MSE	MAE	RMSE	RSCORE
GRU	0.0876	0.4628	0.4960	0.5728
LSTM	0.0598	0.2833	0.3232	0.8002
LSTM	0.0404	0.3436	0.2743	0.9173
LSTMA	0.0404	0.2436	0.3743	0.7173

Note: Weighted LSTM (WLSTM); LSTM with Attention (LSTMA)
Source: Author (2025)

Significant insights into the capabilities of each machine learning model are provided by comparing the weekly and monthly Bitcoin price forecasts made by GRU, Weighted LSTM, LSTM, and LSTM with Attention. We can evaluate the accuracy and dependability of these models in capturing the dynamics of cryptocurrency prices by using metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared (RSCORE).

With similar RSCORE values of 0.8173, the LSTM and LSTM with Attention models perform exceptionally well in the weekly dataset, surpassing GRU and Weighted LSTM by a significant margin. This demonstrates how well the models can identify sequential dependencies in short-term data trends. Especially, With an RSCORE of 0.7002 as opposed to 0.4728 for GRU, weighted LSTM exhibits a noticeable improvement over GRU. These outcomes highlight the advantages of using temporal weighting, which enables Weighted LSTM to more effectively concentrate on important data in the dataset.

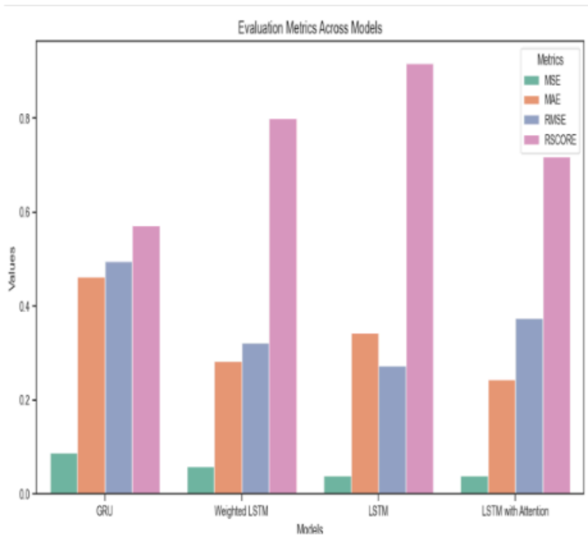
A clear performance hierarchy can be shown in the monthly dataset, with LSTM showing the best predicting ability (RSCORE of 0.9173). This implies that LSTM can catch longer-term patterns with amazing accuracy thanks to monthly aggregation, which reduces noise and volatility. The capacity of weighted LSTM to adjust to aggregated data is demonstrated by its strong performance in the monthly dataset (RSCORE of 0.8002). With an RSCORE of 0.7173, LSTM with Attention performs somewhat worse in the monthly sample, despite its interpretability and capacity to highlight important time steps. Compared to the conventional LSTM, this could be explained by overfitting or ineffective attention processes that fail to capture longer-term relationships.

Through the datasets, GRU constantly performs the worst. When it comes to managing extremely volatile financial data, such as Bitcoin prices, its RSCORE numbers (0.4728 for weekly and 0.5728 for monthly) show its limitations. The inability of GRU to capture the subtle temporal patterns required for precise predictions in this scenario is probably a result of its simplicity, which compromises depth for computing efficiency.

The change from weekly to monthly data shows how model performance is affected by data granularity. The higher RSCORE in monthly forecasts, despite LSTM's continued dominance in both datasets suggests that the reduced noise aids in model generalization. Weighted LSTM shows a similar trend, benefiting from the smoother patterns of monthly data. On the contrary, LSTM with Attention performs best in the weekly dataset, indicating that its mechanism of emphasizing specific time points is more effective in capturing short-term fluctuations than long-term trends.

All things considered, these results show the advantages and disadvantages of various designs for predicting the price of bitcoin. The most dependable model across datasets is LSTM because of its strong handling of sequential data and efficient generalisation. Although not as effective as LSTM, weighted LSTM outperforms GRU, suggesting that adding weight greatly improves temporal modelling. Although it performs competitively in weekly predictions and improves interpretability, LSTM with Attention has certain disadvantages when applied to aggregated data. Despite its computational efficiency, GRU is not deep enough for this kind of complicated prediction problem.

This study emphasises how crucial it is to choose models according to the frequency of data and the goals of the predictions. LSTM with Attention provides a competitive advantage for short-term forecasts when catching instantaneous fluctuations is crucial. LSTM performs better than other models for longer-term trends. The differences in RSCORE between weekly and monthly forecasts further highlight how important it is to take volatility and data granularity into consideration when evaluating model performance. The analysis's conclusions offer a useful framework for integrating machine learning methods into financial time series forecasting.



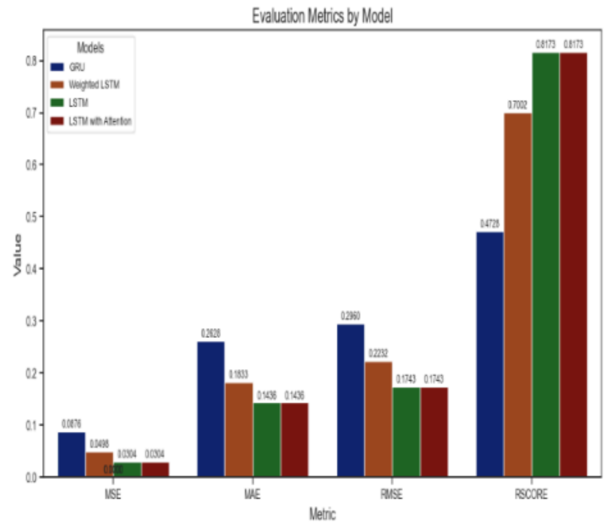


Figure 6: Plot of evaluation metric (monthly) Figure 6: Plot of evaluation metric (weekly)

Discussion of Findings

The findings of this study provide significant insights into the practical application and policy considerations surrounding cryptocurrency price forecasting. By comparing the performance of GRU, Weighted LSTM, LSTM, and LSTM with Attention models on weekly and monthly Bitcoin price data, it becomes evident that model selection must be carefully tailored to the data frequency and forecasting objectives. The consistent superiority of the LSTM model across both datasets underscores its robustness in capturing the complex, sequential dependencies inherent in Bitcoin price movements. This makes LSTM particularly well-suited for longer-term forecasting and investment strategies, where understanding broader market trends is crucial. On the other hand, the LSTM with Attention model demonstrates a distinct advantage in short-term predictions by emphasizing important temporal features, enabling better capture of rapid price fluctuations. This feature is especially valuable for traders and financial analysts focused on short-term market dynamics, where timely and precise signals can significantly impact trading outcomes.

The improved performance of Weighted LSTM relative to GRU highlights the importance of incorporating temporal weighting mechanisms to effectively manage the volatility and irregularities of cryptocurrency prices. For quantitative analysts and algorithmic traders, this suggests that adding layers of temporal emphasis can refine predictive accuracy, potentially leading to better risk management and enhanced trading strategies. Conversely, the relatively poor showing of the GRU model emphasizes the limitations of simpler architectures in dealing with the high complexity and noise present in Bitcoin price data. This serves as a caution to practitioners who might prioritize computational efficiency over model depth and sophistication, reminding them that simpler models may fall short in capturing essential market nuances in volatile environments.

Furthermore, the contrast between weekly and monthly data reveals that model performance benefits from data smoothing, with monthly aggregation reducing noise and allowing models to generalize better over longer-term trends. This has practical implications for financial institutions and portfolio managers, who must strike a balance between the granularity of their data and the accuracy of their forecasts. While higher-frequency data may be necessary for real-time trading, the results suggest that integrating attention mechanisms, as seen in LSTM with Attention, could improve short-term predictive power by focusing on crucial market movements.

From a policy perspective, the demonstrated forecasting improvements using sophisticated machine learning models hold substantial promise for regulatory bodies tasked with overseeing cryptocurrency markets. More accurate prediction of price volatility and market swings could enable regulators to identify potential systemic risks earlier and implement measures designed to enhance market stability, such as circuit breakers or capital reserve requirements. Moreover, models like LSTM with Attention that provide interpretability offer regulators a transparent framework to better understand market dynamics, helping to detect price manipulation or irregular trading behavior and thereby strengthen market integrity.

Additionally, these findings underscore the growing role of artificial intelligence and machine learning in financial market infrastructure, suggesting that policymakers should prioritize fostering innovation in this domain. Supporting research and development in AI-driven forecasting tools could accelerate advancements in market analytics and improve the competitiveness of the fintech sector, particularly as digital assets continue to gain prominence. Finally, given the complexity and volatility demonstrated in cryptocurrency markets, these insights can inform investor education initiatives, helping to raise awareness about the risks and challenges of trading digital currencies. By highlighting the importance of advanced modeling techniques, regulators and educators can encourage more informed and cautious investment behaviors, contributing to healthier and more resilient markets.

In conclusion, this study highlights that while LSTM remains the most dependable model across various forecasting horizons, the choice of model should reflect the specific needs of the user, whether for short-term or long-term predictions. It also emphasizes the critical role of data granularity and model sophistication in navigating the volatile cryptocurrency market. The practical benefits for investors and traders, combined with the policy implications for regulators and market supervisors, illustrate how machine learning models can be strategically integrated into the evolving landscape of financial time series forecasting, ultimately supporting more stable and efficient digital asset markets.

CONCLUSIONS AND RECOMMENDATION

In conclusion, this study demonstrates that advanced machine learning models, particularly LSTM and its variants, offer significant advantages in forecasting Bitcoin prices across different time horizons. The LSTM model consistently outperformed other architectures, showcasing its ability to effectively capture both short-term fluctuations and long-term trends in highly volatile cryptocurrency data. While the LSTM with Attention model excels in short-term forecasting by highlighting key temporal features, Weighted LSTM provides an important improvement over simpler models like GRU by emphasizing critical data points through temporal weighting. These findings highlight the necessity of selecting forecasting models based on the specific characteristics of the data and the intended application, whether for high-frequency trading or longer-term investment analysis. Moreover, the study underscores the impact of data granularity on model performance, with monthly aggregated data offering smoother patterns that enhance generalization, whereas weekly data benefits from attention mechanisms that capture rapid market changes.

Given these insights, it is recommended that practitioners and financial analysts prioritize the use of LSTM-based models for Bitcoin price prediction, tailoring the choice of model to the forecasting horizon and data frequency. For short-term trading strategies, incorporating attention mechanisms can provide enhanced interpretability and predictive accuracy. Additionally, the integration of temporal weighting should be considered to better manage volatility and noise in financial time series data. Regulators and policymakers should encourage the adoption and development of such sophisticated forecasting tools to improve market transparency and stability, as these models can help anticipate market disruptions and inform timely regulatory interventions. Further research should explore hybrid and ensemble models that combine the strengths of different architectures to push predictive performance even higher. Overall, embracing machine learning innovations will be critical to navigating the complexities of cryptocurrency markets and ensuring more informed decision-making for investors, traders, and regulators alike.

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