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A new deep learning approach for predicting high-frequency short-term cryptocurrency price

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ABSTRACT

Cryptocurrencies are known for their volatility and instability, making them an attractive but risky investment for traders, analysts, and researchers. As the allure of Bitcoin (BTC) and other cryptocurrencies continues to grow, so does the interest in predicting their prices. To forecast the market rate and sustainability of cryptocurrencies, this study uses machine learning-based time series analysis. The study employs forecast periods ranging from 1 to 10-minutes to categorize the consistency of the market. High-frequency pricing of cryptocurrencies is anticipated with a timestep of up to 10 seconds using various deep learning (DL) models. A hybrid model combining long short-term memory (LSTM) and gated recurrent unit (GRU) is created and compared with standard LSTM and GRU models. Mean squared error (MSE) is the benchmark for estimating the models' performance. The study achieves better results than benchmark models, with MSE values for BTC, Cardano (ADA), and Cosmos (ATOM) in a 5-minute window size being 0.000192, 0.000414, and 0.000451, respectively, and for a 10-minute window size being 0.000212, 0.000197, and 0.000746. Compared to existing models, the suggested model offers a high price predicting accuracy. This study on crypto price prediction using machine learning applications is a preliminary investigation into the topic.

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1. INTRODUCTION

Cryptocurrencies have emerged as a novel and disruptive financial technology, challenging traditional notions of currency and investment. These digital assets, underpinned by blockchain technology, offer a decentralized alternative to conventional fiat currencies, making them immune to central authority interference or manipulation [1]. The allure of cryptocurrencies, such as bitcoin (BTC) and ethereum (ETH), lies not only in their technological innovation but also in their potential for speculative investment. Due to their inherent volatility, cryptocurrencies present a unique challenge for predictive modeling, attracting significant interest from researchers and investors alike.

Despite the growing body of research on cryptocurrency price prediction, there remains a substantial gap in accurately forecasting short-term price movements. The volatile nature of the cryptocurrency market, driven by factors such as market sentiment, regulatory news, and technological advancements, complicates the application of traditional financial models and time-series analysis. While models like autoregressive integrated moving average (ARIMA) have been applied to financial markets with varying degrees of success, they often fall short in the cryptocurrency context due to these markets' speculative and erratic behavior [2].

Recent advancements in machine learning, particularly deep learning (DL), have opened new avenues for predicting cryptocurrency prices. Long short-term memory (LSTM) networks, a type of recurrent neural network (RNN), have shown promise in modeling the temporal dependencies characteristic of time-series data, including financial markets. LSTMs have the advantage of capturing long-term patterns and relationships in data, which are crucial for understanding and forecasting the behavior of highly volatile assets like cryptocurrencies [3]. However, despite the potential of LSTM networks, there remains room for improvement, particularly in terms of model interpretability, generalization to different market conditions, and the need for large amounts of data to train effectively.

This study introduces a novel approach to predicting high-frequency, short-term cryptocurrency prices by proposing a hybrid DL model that combines the strengths of LSTM and gated recurrent unit (GRU) networks. This hybrid model aims to capture the complex dynamics of cryptocurrency markets more effectively than existing methods. By leveraging the unique features of both LSTM and GRU architectures, our model offers improved prediction accuracy, reduced training requirements, and enhanced interpretability, addressing some of the key limitations of current DL approaches.

Our contribution to the literature is threefold. First, we provide a comprehensive analysis of the cryptocurrency market's behavior, highlighting the factors that contribute to its volatility and the challenges they pose for predictive modeling. Second, we detail the development and implementation of our hybrid LSTM-GRU model, demonstrating its superiority over traditional models through rigorous empirical testing. Finally, we discuss the implications of our findings for traders, investors, and researchers, offering insights into the potential of DL for enhancing predictive accuracy in the volatile domain of cryptocurrency trading.

The remainder of the paper is organized as follows: section 2 outlines our method, detailing the related work, system model, proposed scheme, and performance evaluation methods. Section 3 presents our results, discussing the performance of our hybrid model across three cryptocurrencies: Cardano (ADA), BTC, and Cosmos (ATOM). Finally, section 4 concludes the paper by summarizing our contributions and suggesting directions for future research. At the end of this introduction, we provide Table 1, which serves as the table of acronyms to clarify the meaning of abbreviations used throughout the paper. This table is intended to aid readers in understanding the terminology employed in subsequent sections.

Table 1. Table of acronyms

Acronyms	Meaning
RNN	Recurrent neural network
ANN	Artificial neural networks
BPNN	Back-propagation neural network
LSTM	Long short-term memory
GRU	Gated recurrent unit
MSE	Mean squared error
MAE	Mean absolute error
RMSE	Root mean square error
XGB	Extreme gradient boosting
LR	Logistic regression
SVM	Support vector machine
LDA	Linear discriminant analysis
ARIMA	Autoregressive integrated moving average
DFFNN	Deep feedforward neural network
GARCH	Generalized autoregressive conditional heteroskedasticity

2. METHOD

2.1. Related work

The quest to accurately predict cryptocurrency prices has attracted significant attention from the research community, spurred by the digital currencies' notorious volatility and the growing interest from investors. Cryptocurrencies, unlike traditional financial assets, are subject to a wide range of influences, including but not limited to technological innovations, regulatory announcements, and shifts in market sentiment. This complex web of factors contributes to the market's unpredictable fluctuations, presenting a unique challenge for predictive modeling.

Initial research efforts, as elucidated by Vaidehi *et al.* [4], have demonstrated the potential of LSTM networks in forecasting BTC prices, shedding light on the critical impact of batch sizes and training lengths on model performance. This seminal work not only underscored the risks associated with overfitting but also prompted further investigation into the optimization of neural network hyperparameters and the exploration of GRU architectures for improved accuracy. Research by Chen *et al.* [5] comprehensive analysis contrasts the effectiveness of statistical methods against machine learning algorithms in predicting BTC price movements. This study revealed that while traditional statistical methods like LR could achieve substantial accuracy, machine learning models, particularly LSTM, excelled in capturing the nuances of short-term price dynamics. Such findings advocate for a broader adoption of machine learning techniques in the cryptocurrency forecasting realm, highlighting their superior adaptability to the market's volatile nature.

Demonstrated by the DFFNN's ability to generate forecasts close to observed values under various training algorithms [6], this marks a significant advancement in the field. The strategic inclusion of cryptocurrencies in diversified investment portfolios has been explored, with research [7] illustrating their potential to enhance portfolio performance by improving diversification and optimizing the risk-return profile. This insight is invaluable for investors aiming to leverage the unique characteristics of cryptocurrencies to maximize portfolio efficiency.

The comparative study of SVM, ANN, and DL techniques highlighted SVM's superior accuracy [8], while another research emphasized LR effectiveness over SVM and RF in predicting BTC and ETH prices with selected reliable predictors [9]. These studies underscore the diverse methodological approaches yielding promising results in cryptocurrency price forecasting. Ensemble methods have emerged as a powerful tool in the predictive arsenal, as evidenced by studies [10], [11], which demonstrate their efficacy in minimizing prediction errors across a spectrum of cryptocurrencies. By harnessing the collective capabilities of various algorithms, such as ANN, KNN, and gradient-boosted trees, these methods offer a more nuanced approach to price forecasting, accommodating the multifaceted drivers of market movements.

The evolution of DL technologies, especially through the implementation of RNNs like LSTM and GRU, signifies a pivotal shift in financial time series prediction. A novel two-stage model that integrates ANN and RF for feature selection, followed by LSTM for price forecasting [12], showcases the marked superiority of DL models over traditional approaches, such as ARIMA and SVM. Furthermore, hybrid models that blend LSTM and GRU architectures [13] have proven to be particularly adept at modeling the intricate temporal patterns inherent in cryptocurrency price data, offering promising avenues for future research. Integrating autoregressive (AR) features into LSTM networks has further improved daily BTC price predictions [14], and an ensemble learning method combining LSTM, Bi-LSTM, and CNN has led to accurate predictions for selected cryptocurrencies [15], underscoring the effectiveness of multi-model approaches in enhancing forecasting accuracy.

Recent advancements have introduced sophisticated models like the weighted and attentive memory convolutional neural network (WAMC) [16], which combines the predictive strengths of GRU, CNN, and advanced weighting mechanisms to achieve unprecedented accuracy levels. Such innovative approaches reflect the dynamic nature of the field, continuously pushing the boundaries of what is possible in cryptocurrency price prediction. Table 2 serves as a testament to the rapid advancements within this domain, providing a detailed comparison of various predictive models and their contributions to the field. This comprehensive overview not only highlights the incremental improvements achieved through DL techniques but also sets the stage for future explorations aimed at unraveling the complex dynamics of cryptocurrency markets.

The exploration of cryptocurrency price prediction is a testament to the intersection of finance and technology, where innovative computational methods meet the ever-changing landscape of digital currencies. As this field evolves, the continuous refinement of predictive models, coupled with the integration of diverse data sources and computational techniques, will undoubtedly enhance our understanding of market dynamics, offering valuable insights for both theoretical research and practical investment strategies.

Table 2. The state-of-the-art of various methodologies and approaches for predicting cryptocurrency prices

Ref	Year	Solution	Result
[17]	2017	Explored four distinct ANN techniques for optimal BTC price prediction.	Identified BPNN as the superior method among the evaluated techniques.
[18]	2019	Applied LSTM-RNN for cryptocurrency price prediction, incorporating 10-fold cross-validation to enhance validation.	Demonstrated that integrating cross-validation with LSTM-RNN significantly improves prediction accuracy. Reported MAE=0.0043.
[19]	2020	Implemented a stochastic neural network model for forecasting cryptocurrency prices.	Successfully decoded market volatility, indicating the model's capability to interpret complex market dynamics.
[20]	2021	Combined LSTM and random walk models for predicting BTC and ETH prices.	Achieved an optimal balance of practical application and accuracy. MAE loss=0.0037, showcasing the model's effectiveness.
[21]	2021	Utilized an LSTM-GRU hybrid model considering the interdependent properties of cryptocurrencies like Litecoin and Zcash with BTC.	The model accurately predicts Litecoin and Zcash prices with minimal losses, emphasizing the importance of considering parent coin trends.

2.2. System model and problem formulation

As we explore the system model, a visual representation is crucial for a comprehensive understanding. Figure 1 depicts the architecture of our hybrid model, outlining the essential components and their interactions for effective cryptocurrency price prediction. System model: our research introduces a cutting-edge hybrid LSTM-GRU neural network model, specifically engineered to predict the short-term price movements of cryptocurrencies such as BTC, ADA, and ATOM. The model's architecture is meticulously designed to process high-frequency trading data, capturing the minute-to-minute volatility inherent in cryptocurrency markets.

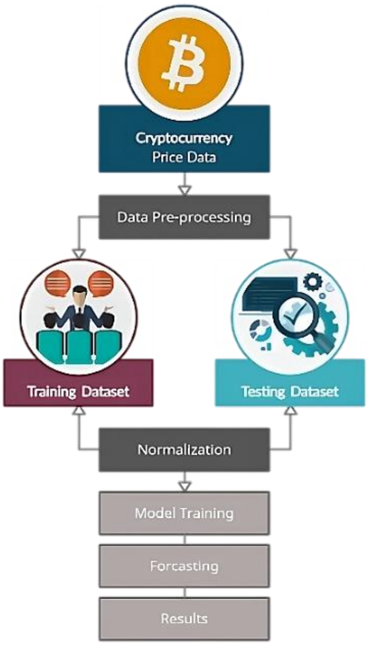

Figure 1. The system model used in the proposed approach

The initial phase of our model's operation involves the comprehensive collection of historical price data, which is subsequently segregated into training and testing datasets. This bifurcation is pivotal for the model's learning and validation phases, ensuring that the predictive accuracy is rigorously tested against unseen data. In the preprocessing stage, the raw data undergoes a series of transformations, including normalization and reshaping. This process is vital for aligning the data with the neural network's requirements, thereby optimizing the input for enhanced model performance.

A distinctive feature of our model is its adaptive window size mechanism. The window size concept is crucial for delineating the quantity of historical data utilized in forecasting future cryptocurrency prices [22]. By dynamically adjusting the window size based on the dataset's temporal resolution, our model achieves unparalleled flexibility. For datasets with a 1-minute timestep, the window extends to encapsulate a 10-minute historical span, while for data recorded every 10 seconds, the window compresses to a 5-minute span. This adaptability allows for precise tuning of the model to different data frequencies, enhancing the predictive accuracy across various market conditions.

Problem formulation: central to our predictive model is a sophisticated problem formulation strategy that intricately analyzes the relationships between multiple cryptocurrency price indicators open, close, high, low, last prices and trading volume. These indicators are amalgamated into a dataset P, with P_i denoting the set of indicators at any given time instance i. This comprehensive dataset serves as the foundation for our model's input.

The predictive model is formulated to leverage sequences of historical price data [P_{i-w+1}, P_{i-w+2}, P_{i-w+3}, ..., P_{i-1}, P_i], where w represents the window size, to forecast the next price point P_{i+1}. This approach not only encapsulates the temporal dynamics of cryptocurrency prices but also underscores the model's capability to infer future price movements from past trends. The selection of window size, a critical parameter in our model, is determined through extensive experimentation, ensuring that the model's predictions are both accurate and relevant to the market's current state.

2.3. The proposed scheme

In this section, we introduce the architecture of our innovative hybrid LSTM-GRU model, meticulously crafted to predict cryptocurrency prices with high precision. Figure 2 illustrates the detailed workflow of our proposed model, highlighting the predictive mechanisms within the hybrid LSTM and GRU layers. This model leverages the strengths of both LSTM and GRU networks to effectively process and analyze high-frequency data for BTC, ADA, and ATOM.

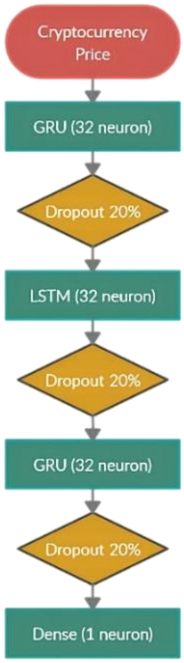

Figure 2. Contents of the proposed model

The equations outlined form the backbone of our predictive model, encapsulating the intricate process of transforming historical cryptocurrency price data into actionable insights. In (1) represents the comprehensive dataset, capturing the price dynamics of targeted cryptocurrencies over a specified period. Subsequent equations, from (2) to (7), meticulously define the input-output relationship essential for our model's training and prediction phases. These relationships facilitate the model's ability to understand and interpret the temporal patterns inherent in the cryptocurrency market, leveraging past price movements to forecast future values. The input sequences, denoted by $inputP_i$ in (2), (4), and (6), are carefully selected slices of historical price data, designed to provide a contextual foundation for each prediction. The corresponding output, $outputP_i$, as detailed in (3), (5), and (7), represents the model's predicted price point, showcasing the direct application of learned patterns to future price estimation. This systematic approach to data structuring not only enhances the model's predictive accuracy but also underscores the adaptability of our hybrid LSTM-GRU architecture in capturing and analyzing the volatile nature of cryptocurrency prices.

$$price_{data}=[P_1, P_2, P_3, \ldots, P_{k-1}, P_k] \tag{1}$$

$$inputP_1=[P_1, P_2, P_3, \ldots P_{n-1}] \tag{2}$$

$$outputP_1=[P_{n+i}] \tag{3}$$

$$inputP_2=[P_1, P_2, P_3, \ldots P_n] \tag{4}$$

$$outputP_2=[P_{n+i+1}] \tag{5}$$

$$inputP_r=[P_{r-1}, P_r, P_{r+1}, \ldots P_{k-1}] \tag{6}$$

$$outputP_r=[P_{k+i+1}] \tag{7}$$

Our hybrid model is a sophisticated solution to the short-term memory limitations inherent in traditional RNNs. By integrating LSTM and GRU layers, we enhance the model's ability to retain information over longer sequences, thereby improving prediction accuracy for cryptocurrency market prices. The LSTM-GRU hybrid model is adept at mitigating the vanishing gradient problem, a significant challenge identified in [23]. This ensures that our model learns effectively from the historical data, capturing both short-term fluctuations and long-term trends in cryptocurrency prices. After processing the input data through the LSTM and GRU layers, the model outputs predictions for future prices. The architecture includes a dropout layer to prevent overfitting, ensuring that the model generalizes well to unseen data. The model is evaluated across two window lengths, demonstrating its capability to produce highly accurate predictions.

Our proposed model architecture integrates LSTM and GRU layers to optimally capture both short- and long-term dependencies in price data. To address the challenge of overfitting, the model includes a dropout layer with a 20% dropout rate, positioned strategically after a 32-neuron GRU layer. This setup precedes a 32-neuron LSTM layer, further enhancing the model's robustness and predictive accuracy. The final output is generated through a dense layer with a single neuron, which encapsulates the predicted future price.

The model undergoes training over 100 epochs, incorporating an early stopping callback from Keras to optimize the learning process. This approach ensures efficiency and prevents overtraining, allowing the model to generalize effectively to unseen data. The evaluation of the model across two distinct window lengths demonstrates its exceptional capability in accurately predicting cryptocurrency prices, confirming the viability of our proposed hybrid LSTM-GRU approach for high-frequency, short-term price forecasting.

2.4. Performance evaluation

The suggested model's performance is evaluated in this section, and the findings are compared to those of the LSTM and GRU models. We implemented the recommended models using a 5-minute and 10-minute window size. TensorFlow APIs were used to train the DL models on the Python platform. As seen in the figure presented later in the results section, the predicted Cardano data for a 5-minute timeframe is shown. Models were trained for various epochs using Adam as the optimizer and different batch sizes. Table 3 contains data on several parameters and their values, including the programming language, datasets used, optimizer, and other relevant parameters.

Table 3. The used parameters of the performance in our models

Parameters	Values
Programming language	Python
Platform	Jupyter
Data	Bitcoin
	Cardano
	Cosmos
Window sizes	10-minute
	5-minute
Batch sizes	16
Epochs	Variable
Optimizer	Adam
Metrics	MSE

Dataset description: this research employs a dataset provided by the CCXT [24] library. The dataset facilitates connectivity and trading with cryptocurrency exchanges and payment processing services worldwide. The data was collected at a high frequency, with up to 10-second timesteps for three cryptocurrencies: BTC, ADA, and ATOM. The dataset comprises five essential features: i) LastPrice: closing price of the respective cryptocurrency; ii) OpenPrice: opening price of the respective cryptocurrency; iii) HighPrice: highest price of the respective cryptocurrency; iv) LowPrice: lowest price of the respective cryptocurrency; and v) volume: traded volume of the respective cryptocurrency.

We have chosen the closing price as the primary metric, as it effectively reflects both the currency's trend and its overall value. Our proposed methodology was rigorously tested for forecasting BTC, ADA, and ATOM prices over two distinct time frames: 1-minute and 10 seconds. The dataset has been partitioned, and data points for all currencies have been allocated to train the proposed model:

- BTC contains 816,873 data points spanning from August 10th, 2021, to February 15th, 2022. 1-minute data: train dataset: 478,727 data points, test dataset: 119,682 data points. 10 seconds data: train dataset: 621,200 data points, test dataset: 195,673 data points.

- Cardano contains 595,141 data points from November 3rd, 2021, to February 10th, 2022. 1-minute data: train dataset: 350,728 data points, test dataset: 53,129 data points. 10 seconds data: train dataset: 496,066 data points, test dataset: 99,075 data points.
- Cosmos contains 499,499 data points from August 14th, 2021, to January 6th, 2022. 1-minute data: train dataset: 161,344 data points, test dataset: 40,336 data points. 10 seconds data: train dataset: 399,552 data points, test dataset: 99,888 data points.

This dataset and its partitioning provide a comprehensive basis for training and evaluating the proposed model's performance in cryptocurrency price forecasting. The chosen features and time frames are expected to yield valuable insights for the specific cryptocurrencies under study.

Data preprocessing: because of outliers and fluctuations, the suggested model cannot use the original data values directly. To reduce noisy data and enhance accuracy, normalization is performed during the preprocessing step. The Min-Max scaling normalization approach was applied as (8):

$$X_{sc} \frac{X-X_{min}}{X_{max}-X_{min}} \tag{8}$$

where the minimum and maximum values pertain to the value x being normalized. Sample value that will be normalized between 0 and 1. When the input data has a huge standard deviation, this strategy is particularly efficient. After normalization, since our challenge is a time series problem, we needed to construct a function to reshape our training data so that we could feed historical data into our model and forecast the future.

Evaluation metrics: we employed the MSE [25] as our primary metric, providing a quantifiable measure of the model's forecasting error and overall accuracy. The MSE is calculated as follows, offering a direct insight into the precision of our predictions:

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(\widehat{P_i} - P_i) \tag{9}$$

where $\widehat{P_i}$ indicates the anticipated price, P_i is the actual price, n signifies the total number of instances.

3. RESULTS

The assessment of our hybrid LSTM-GRU model reveals its superior predictive prowess over traditional LSTM and GRU models across several cryptocurrencies. This section delves into the outcomes for ADA, BTC, and ATOM, offering a nuanced discussion on the model's accuracy and implications.

3.1. Results for Cardano

The ADA analysis encompassed over 595,141 data points from November 3, 2021, to February 10, 2022. The hybrid model's performance, particularly with a 5-minute window size, resulted in an MSE loss of 0.000414, showcasing exceptional predictive accuracy. When expanded to a 10-minute window, the model further refined its precision, evidenced by an even lower MSE loss of 0.000197. This indicates the model's adaptability and effectiveness in capturing ADA's price movements over varying time frames. Figures 3 and 4 graphically juxtapose the model's predictions against actual market prices, highlighting the close alignment and the model's capability to anticipate short-term fluctuations accurately.

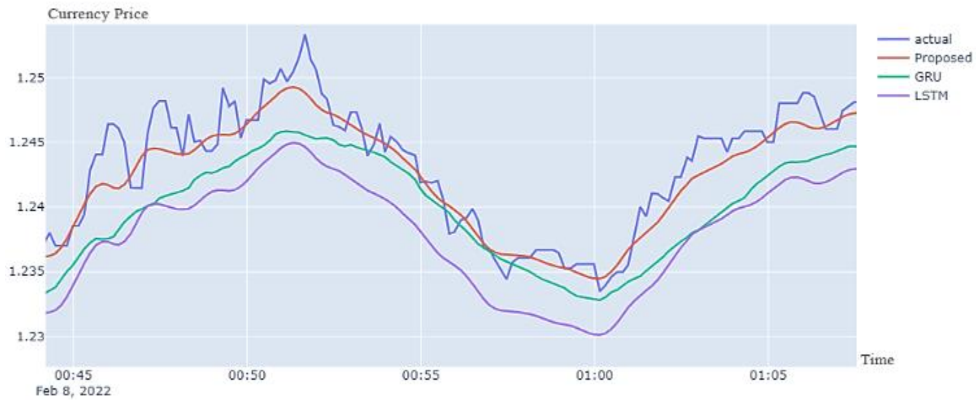

Figure 3. Cardano actual data compared with the obtained forecasts for 10-minutes window

Figure 4. Cardano actual data compared with the obtained forecasts for 5-minutes window

3.2. Results for bitcoin

For BTC, our dataset spanned 816,873 data points between August 10, 2021, and February 15, 2022. In the 10-minute window setting, the proposed model achieved an MSE loss of 0.000212, while the 5-minute window recorded an even tighter MSE loss of 0.000192. These results underscore the model's remarkable accuracy in forecasting BTC prices, surpassing traditional LSTM and GRU models. Figures 5 and 6 visually represent this accuracy, showcasing the model's consistent alignment with BTC's actual price trends, thereby affirming its utility in navigating the market's inherent volatility.

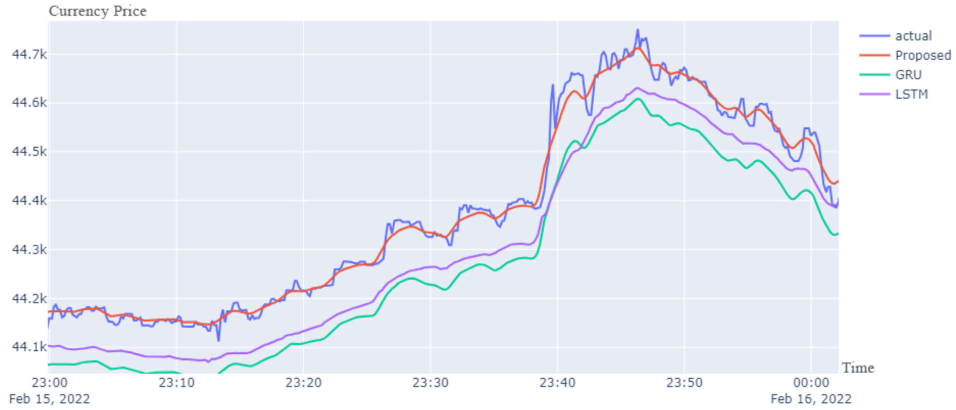

Figure 5. BTC actual data compared with the obtained forecasts for 10-minutes window

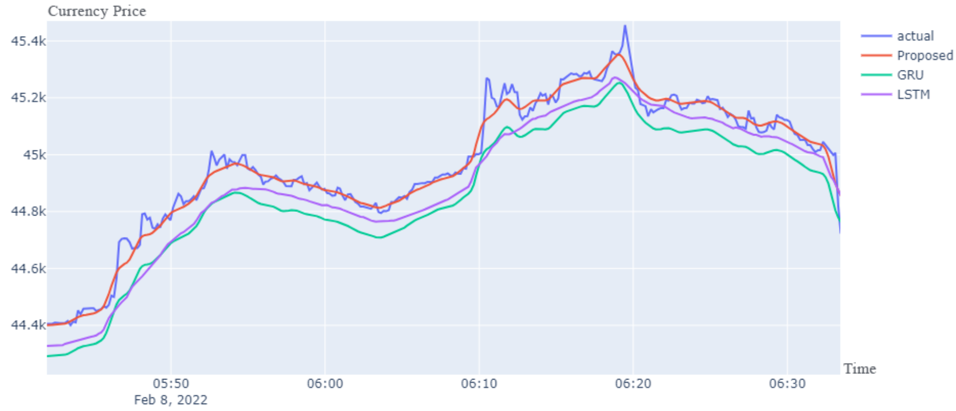

Figure 6. BTC actual data compared with the obtained forecasts for 5-minutes window

3.3. Results for Cosmos

The performance evaluation for ATOM, incorporating 499,499 data points from August 14, 2021, to January 6, 2022, revealed the hybrid model's MSE losses of 0.000746 for a 10-minute window and 0.000451 for a 5-minute window. These metrics highlight the model's superior predictive performance, especially in capturing ATOM's short-term price dynamics. Figures 7 and 8 depict the predictive accuracy visually, comparing the model's forecasts with actual prices and demonstrating its effectiveness in predicting price trends.

The comparative analysis across ADA, BTC, and ATOM accentuates the hybrid model's enhanced accuracy in predicting cryptocurrency prices. This is particularly evident in the context of MSE losses, where the proposed model consistently achieves lower values compared to LSTM and GRU models, as detailed in Tables 4 to 6. These findings not only validate the hybrid model's effectiveness but also highlight its potential as a robust tool for high-frequency, short-term price forecasting in the volatile cryptocurrency market.

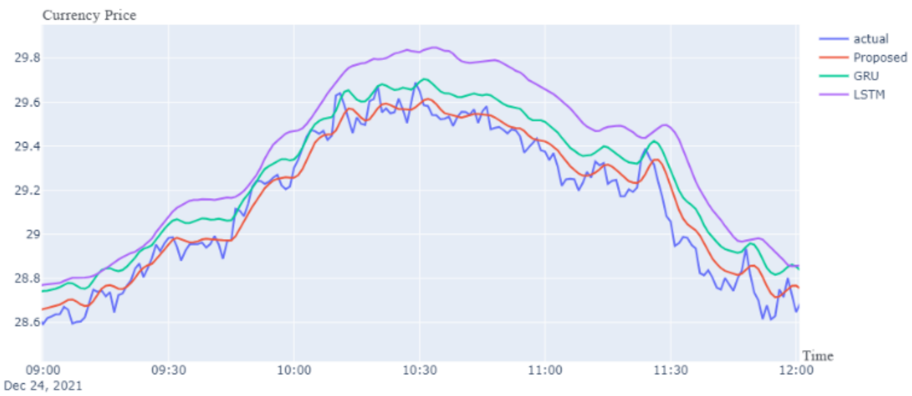

Figure 7. Cosmos actual data compared with the obtained forecasts for 10-minutes window

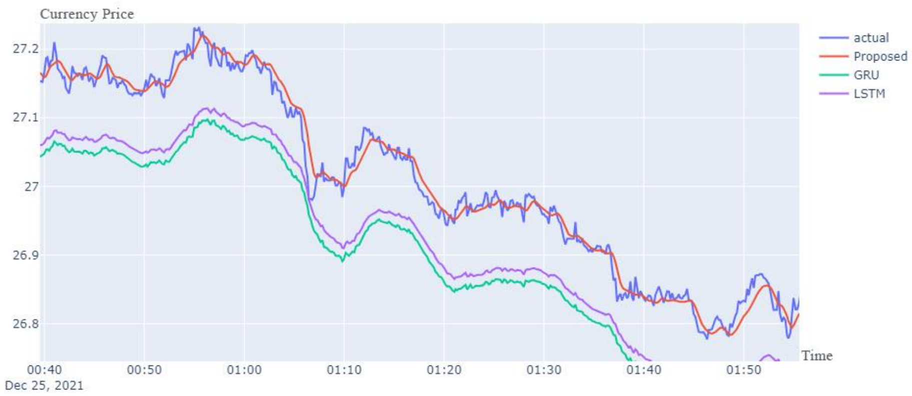

Figure 8. Cosmos actual data compared with the obtained forecasts for 5-minutes window

Table 4. BTC model-loss comparison

Model	MSE 10-minute	MSE 5-minutes
LSTM	0.000445	0.000331
GRU	0.000399	0.000274
Proposed	0.000212	0.000192

Table 5. ADA model-loss comparison

Model	MSE 10-minute	MSE 5-minutes
LSTM	0.000505	0.000743
GRU	0.000496	0.000629
Proposed	0.000197	0.000414

Table 6. ATOM model-loss comparison

Model	MSE 10-minute	MSE 5-minutes
LSTM	0.000891	0.000748
GRU	0.000807	0.000632
Proposed	0.000746	0.000451

The hybrid LSTM-GRU model's success can be attributed to its ability to leverage the strengths of both LSTM and GRU architectures, providing a balanced approach to capturing both short-term and long-term dependencies in price data. This adaptability is crucial in navigating the complexities of cryptocurrency markets, offering valuable insights for traders and researchers aiming to forecast price movements with higher precision. The results affirm the proposed hybrid model's superior capability to enhance cryptocurrency price prediction accuracy. This advancement opens avenues for further research, including the exploration of additional data features and the integration of more complex machine learning techniques to further improve predictive performance.

4. CONCLUSION

In this study, we embarked on a journey to refine cryptocurrency price prediction models by integrating DL techniques, specifically through a hybrid LSTM-GRU model. This innovative approach was meticulously designed to forecast the prices of BTC, Cardano, and Cosmos across different time windows, demonstrating a notable improvement in predictive accuracy as reflected in the MSE losses for various cryptocurrencies. Cryptocurrency markets, known for their volatility and unpredictability, pose a significant challenge for predictive modeling. Traditional time series models like vector autoregressive integrated moving average (VARIMA), ARIMA, and GARCH, while commonly used in financial forecasting, often fall short when applied to the dynamic cryptocurrency market due to their limitations in handling non-uniform data. To overcome these challenges, we explored DL algorithms, which have shown promising results in various financial markets. Our research contributes to this growing body of knowledge by proposing a model that leverages the strengths of both GRU and LSTM networks.

Key findings: i) the proposed hybrid model achieved MSE losses of 0.000212 and 0.000192 for BTC, 0.000197 and 0.000414 for Cardano, and 0.000746 and 0.000451 for Cosmos, for 5-minute and 10-minute windows respectively. These results underscore the model's capability to capture and predict short-term price movements with high accuracy and ii) compared to standalone LSTM and GRU models, our hybrid approach demonstrated superior performance, validating the effectiveness of combining these two neural network architectures. Future directions: i) expanding the dataset to include more correlated variables and exploring interdependencies between different cryptocurrencies could further enhance the model's accuracy. Incorporating technical indicators, sentimental analysis, and traditional commodities into the predictive framework offers promising avenues for research and ii) continuous refinement of the model by experimenting with additional DL architectures and tuning hyperparameters will be crucial in adapting to the evolving cryptocurrency market.

In conclusion, our study highlights the potential of hybrid DL models in advancing the field of cryptocurrency price prediction. By addressing the limitations of traditional models and leveraging the computational power of LSTM and GRU networks, we present a robust tool for traders and investors seeking to navigate the complexities of the cryptocurrency market. As we look to the future, the integration of more sophisticated machine learning techniques and diverse data sources stands to further revolutionize cryptocurrency forecasting, opening new opportunities for research and investment strategies.

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