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Cryptocurrency Price Prediction using Machine Learning

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Abstract: *Cryptocurrency price prediction is a complex task due to the volatile and dynamic nature of the market. To tackle this challenge, a study was conducted to compare the effectiveness of two popular machine learning models: Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). These models are designed to capture temporal dependencies in sequential data, making them suitable for predicting price movements based on historical trends. The study utilized historical price data, specifically focusing on the closing prices of various cryptocurrencies. The data was collected using the yfinance library, a tool that provides easy access to financial data fromYahoo Finance. By concentrating on closing prices, the study aimed to simplify the prediction taskand improve the accuracy of the models.*

Keywords: Cryptocurrency, GRU, LSTM, Machine Learning, Price Prediction

I. INTRODUCTION

Over the last ten years, the cryptocurrency market has grown at an unprecedented rate, attracting many investors and traders due to its high volatility. The decentralized nature of cryptocurrencies,coupled with susceptibility to speculative trading and external factors such as regulatory news, leads to significant price fluctuations, making accurate price prediction both challenging and essential for investors seeking to maximize returns and mitigate risks.

The development of machine learning led to the investigation of increasingly complex methods byresearchers. For time series forecasting, recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have gained widespread traction. Long short-term dependencies can be captured using LSTMs, which have demonstrated superior performance compared to standard models [7]. Several studies have shown that by identifying temporal patterns in cryptocurrency data, they are useful in forecasting the price of bitcoin [3].

Price prediction has also made use of the Gated Recurrent Unit (GRU), an additional RNN version.GRUs are a prominent option in recent research since they have simpler architecture than LSTMs while still performing comparably [1]. Research has demonstrated that GRUs are capable of accurately modeling cryptocurrency prices and generating short-term forecasts [2].

II. LITERATURE REVIEW

Early research on predicting cryptocurrency prices used econometric models, namely autoregressive integrated moving average ARIMA models, to capture the dynamics of Bitcoin's price. Despite their relative performance, these models were unable to cope with the extreme volatility seen in bitcoin markets [4].

Neural networks are not the only method used in machine learning applications. Because support vector machines (SVMs) can handle non-linear correlations in data, they have been used to predict bitcoin values [6]. But SVMs frequently need a lot of feature engineering, and They may not be ascapable of capturing complicated patterns as deep learning algorithms [5].

GRU and LSTM networks address the vanishing gradient problem common in traditional RNNs by maintaining long-term dependencies and selectively remembering or forgetting information. The effectiveness of LSTM and GRU models in forecasting cryptocurrency prices is compared inthis study, focusing on accuracy, computational efficiency, and generalization across different cryptocurrencies.

III. METHODOLOGY

Data Collection and Preprocessing

Historical price data for selected cryptocurrencies was collected using the yfinance library, which provides real-time access to financial data from Yahoo Finance. For this study, we focused on theclose prices, as they reflect the final price of cryptocurrency at the end of a trading day and are widely used in financial analysis.

To enhance the performance of the neural network models, the gathered data was normalized. Normalization ensures that the data falls within a specific range, typically between 0 and 1, whichhelps in accelerating the process for training and improving the model's convergence. Thefollowing normalization formula was used:

$$normalized\_value = value - mean \, / \, standard \ deviation$$

Model Architecture

We implemented two models for this study: LSTM and GRU, using the PyTorch library. Both models share a similar architecture, comprising a fully connected (linear) layer after an RNN layer.

LSTM Model

The LSTM model consists of an LSTM layer that captures the temporal dependencies in the data. The output of the LSTM layer is passed to a fully connected layer, which maps the output to the desired prediction

GRU Model

The GRU model has a similar structure to the LSTM model but uses GRU cells instead of LSTMcells. GRU cells are known for their simpler architecture, which often results in faster training times while maintaining effective performance in capturing temporal dependencies.

Training Procedure

The sequence length was set to 10 days, meaning that the models use the previous 10 days of datato predict the price for the following day. The data was divided into training and testing sets, withthe training set being used to train the models and the testing set being used for evaluation.

The following steps are involved in the training process:

Data Preparation: The target price on the eleventh day corresponded to the segmentation of the normalized data into sequences of ten days. The training dataset was created by repeating this procedure.

Model Initialization: Both LSTM and GRU models were initialized with the following parameters:

- Input Dimension: 1 (since we are using only close price)
- Hidden Dimension: 64
- Layer Dimension: 1
- Output Dimension: 1 (predicting the next day's close price)

Loss Function and Optimizer: The Mean Squared Error (MSE) was used as the loss function, and the Adam optimizer was chosen for its adaptive learning rate capabilities.

Training Loop: The models were trained for 75 epochs with a batch size of 64. During each epoch, the optimizer minimized the loss by adjusting the model parameters.

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IV. RESULT AND DISCUSSIONS

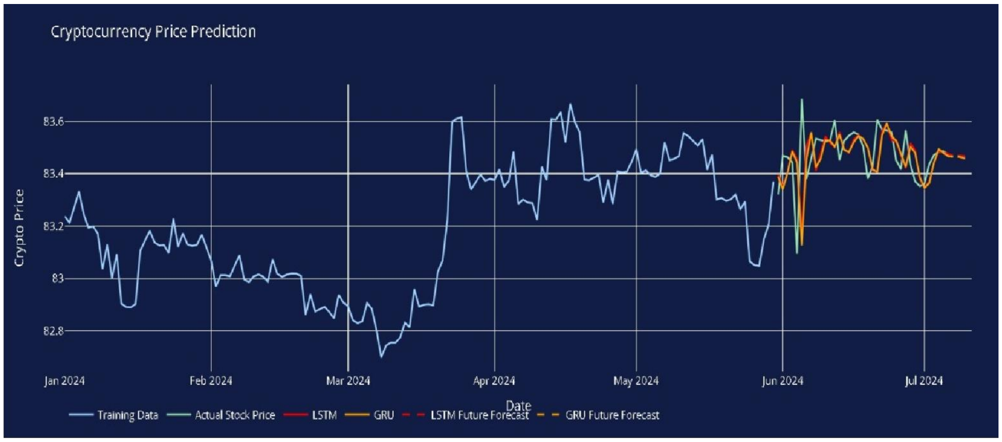

Fig 1: USDC-INR price prediction (MSE: LSTM-0.01724, GRU-0.01720)

[Fig 1] describes the prediction of cryptocurrency prices from January to July 2024. It includes training data (blue), actual stock price (green), LSTM predictions (red), GRU predictions (orange), and their future forecasts (dotted lines). Both models follow actual prices closely, with LSTM slightly more accurate.

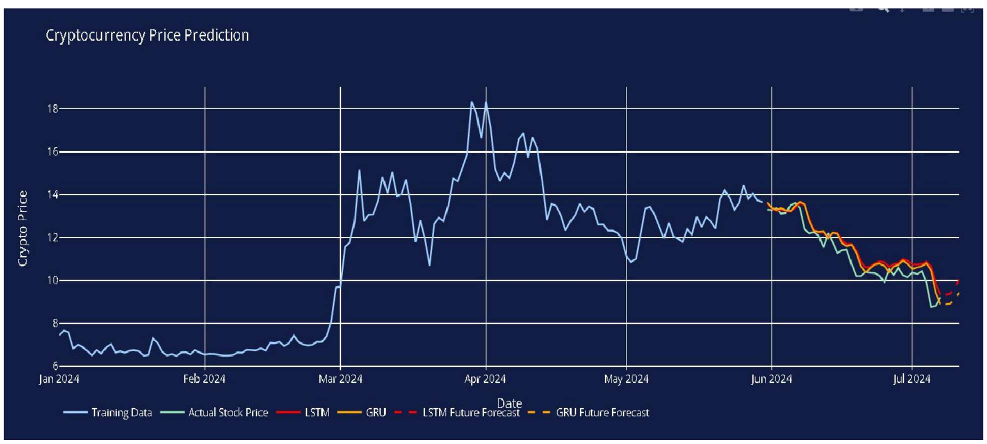

Fig 2: DOGE-INR price prediction (MSE: LSTM-0.42238, GRU-0.33071)

[Fig 2] depicts cryptocurrency price predictions from January to July 2024, showing training data (blue), actual stock price (green), LSTM predictions (red), GRU predictions (orange), and their future forecasts (dotted lines). Both models closely track actual prices, with LSTM providing slightly more accurate predictions, especially noticeable in future forecasts.

Comparison between LSTM and GRU models

Feature	LSTM	GRU
Architecture	Uses separate memory cellsand gates	Combines memory cell andgates
Parameters	More parameters due tomultiple gates	Fewer parameters due tocombined gates
Training Time	Generally slower to train	Generally faster to train
Memory Usage	Higher memory usage	Lower memory usage
Performance	Can capture long-termdependencies well	Efficient for both short and long-term dependencies
Ease of Implementation	More complex	Simpler implementation
Applications	Time series forecasting, NLP, speech recognition	Time series forecasting, NLP,speech recognition

Table 1: Comparison of Models for Cryptocurrency price prediction

[Table 1] The table compares both models in predicting cryptocurrency prices, highlighting LSTM's slightly higher accuracy and stability, while GRU offers good performance with better computational efficiency and faster predictions.

V. CONCLUSION

The study presented a comparative analysis of both models for predicting cryptocurrency prices using historical close prices obtained via the yfinance library. Both models demonstrated a strong ability to capture temporal dependencies and predict future prices with reasonable accuracy, showcasing their suitability for time series forecasting in the volatile cryptocurrency market. The LSTM model, known for its robust handling of long-term dependencies, performed well but required more computational resources. Conversely, the GRU model, with its simpler architecture, exhibited slightly better computational efficiency while maintaining comparable prediction accuracy. These findings suggest that both LSTM and GRU models are viable options for cryptocurrency price prediction, with the choice between them depending on specific application requirements and available computational resources. The GRU model's efficiency may be particularly advantageous in scenarios with limited processing power. Future work could explore the integration of additional features, such as trading volume, market sentiment, and external economic indicators, to further enhance prediction accuracy and robustness. Incorporating these additional data points could provide a more comprehensive understanding of market dynamics, potentially leading to even more accurate and reliable cryptocurrency price forecasts.

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