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A Comparative Study of LSTM and GRU Models for Cryptocurrency Price Forecasting

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Abstract: *The price of cryptocurrencies is hard to anticipate because of how dynamic and turbulent the market is. The effectiveness of two popular machine learning models,Gate Recurrent unit (GRU) and Long Short Term Memory (LSTM), was compared in attempt to overcome this problem. Due to their capacities of modeling temporal dependency in sequential data, these models are particularly well suited for estimating price changes based on historical data. This study relied on historical price data concerning cryptocurrencies, so the closing prices for a variety of cryptocurrencies were collected as input data. This is all obtained using the yfinance library which pulls data from Yahoo Finance and gives users options regarding how to obtain financial information from these services. This study relied on closing prices to increase model accuracy and ideally simplify forecasting.*

Keywords: Cryptocurrency, GRU, LSTM, Price Forecasting

I. INTRODUCTION

Over the past decade, the considerably-operational cryptocurrency market has grown at an unprecedented rate, which attracted a large number of traders and investors with its extreme volatility. The price prediction, although very difficult to accomplish, is an essential process for investors that seek to reduce risk and increase potential gains based on the predictable nature of cryptocurrencies' price movements. Although cryptocurrencies are by nature speculative, that speculation includes the influence of government and governmental regulations, and perhaps more importantly, the predicted dollar value of the crypto-currency. As machine learning technologies advanced, researchers began developing increasingly complex methods. Recurrent neural networks (RNNs) are now enjoying a new wave of development as a method of time series forecasting, including Long Short-Term Memory (LSTM) networks, the research is resulting in improved prediction accuracy. Several studies MSS O et al. (2017), Bala et al. (2021), Ghaffari &Iris (2021) have shown LSTMs, in particular, improved whether developed using Keras, TensorFlow, or Pytorch, have greater predictive performance compared to other more traditional models for forecasting by accurately capturing long short-term dependencies on the target variable(s). Studies have concluded that LSTMs advantageously compared with other models employed in the forecasting bitcoin price , for identifying "normal temporal patterns" in currencies (MSS O et al., 2017), supporting the premise the LSTMs approach was worth investigating the price of any cryptocurrency. Gated Recurrent Unit (GRU) is another variant of RNN, found to have potential prediction ability, partly based on its architecture which is easier to train and still incorporates many similar model building advantages of LSTM.[1] More recent studies have shown that GRUs could provide fairly reliable short-term predictions, and model potential future bitcoin monthly prices with reasonable accuracy.

1.1 PROBLEM STATEMENT

Cryptocurrencies are undeniably a new asset class/a financial asset. They are different from traditional financial assets because they are extremely volatile and offer the potential for a big payoff. Because of the degree of risk that comes with volatility, price prediction is extremely important for traders, investors, and financial analysts. Traditional financial models rarely successfully forecast cryptocurrency prices due to their complexity and uniqueness. There are several reasons the traditional modelling has difficulties correctly predicting bitcoin prices related to things like market sentiment, technology, regulators or legislation and macroeconomic factors. Unsatisfactory forecasting models lead to poor investment decisions, catastrophic losses and extreme misallocation of capital in the cryptocurrency market. As such, it is likely important for demonstrably valid and reliable data-driven modelling is conducted for bitcoin price forecasting, in order to help inform those who may consider becoming participants in the market.

OBJECTIVE

- The main aim of this research is to create machine learning models using LSTM and GRU for cryptocurrency price prediction. The secondary objective is to test the models developed with LSTM and GRU, producing predictions using the developed evaluation metrics.
- In this case requires creating a machine learning model using LSTM and GRU for the purposes of Cryptocurrency prediction.
- The performance matrix of analysed propose models.

II. REALTED WORK

In recent years, the speculation and volatility surrounding cryptocurrency prices such as bitcoin and ethereum has brought with it considerable interest in price prediction. Predicting prices is complicated when it comes to cryptocurrencies because of their continually changing and erratic nature and reliance on various key determinants.

In considering various machine learning methods for bitcoin price predictions, Men et al. [1] noted that artificial neural networks (ANNs) outperformed both SVR and Random Forest. Chen et al. [2] analyzed the impact of social media sentiment when forecasting bitcoin prices, finding that sentiment data can enhance prediction accuracy. Feki et al. [3] provided a criticism of machine learning methods with a focus on ethical considerations, data quality, and interpretability. Bose et al. [4] discovered a significant effect on market trends when they investigated how news emotions influenced bitcoin price predicting. Christodoulou and Liaras [5] reviewed deep learning methods such as convolutional neural networks (CNN) and generative adversarial networks (GAN), noting the challenge of having insufficient data. Yao et al. [6] showed through their work that ensemble learning methods increase the performance of short-term bitcoin price forecasts. With the idea of having more robust forecasting for cryptocurrency prices, Wang et al. [7] suggested a hybrid ARIMA-LSTM model; Lin et al. [8] enhanced the LSTM models to account for Change Point Detection for better market volatility handling; Géron [9] provided a very useful implementation guide for LSTM-based cryptocurrency prediction; and Singh et al. [10] explored machine learning methods like support vector machines (SVM) and decision trees to find basic methods for price predictions. All of the above studies found that deep learning, hybrid, and ensemble methods (and especially those with multiple data sources) yield more accurate and reliable cryptocurrency price predictions.

III. PROPOSED METHODOLOGY

Utilizing the yfinance library, which provides real-time financial data from yahoo finance, historical price data for several selected cryptocurrencies was obtained based on time series. As closing prices show the ending value to which a cryptocurrency traded, and are often used in forecasting financial data, they were utilized in this study. Normalising the collected data was also carried out to aid in the efficiency of neural network models, which encloses the values within a fixed range meaning that all the values would typically lay between [0,1]. This aids in speeding up training, and improving performance of model convergence while reducing frequency changes. Using the Min-Max scaling formula, the normalisation was carried out: $X = \frac{X - Xmin}{Xmax - Xmin}$ Eq(1)

Where, x is the original value, x_{min} and x_{max} are the dataset's minimum and maximum values, and x is the normalised value that falls between 0 and 1.

Model Architecture

This research has used the PyTorch environment to implement two contemporary deep learning architectures: Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM). The model implementation of both GRU and LSTM used the same architecture in that the fully connected (linear) output layer calculated the predicted prices after the recurrent layer captured temporal dependencies in the sequential data.

LSTM MODEL

The LSTM layer in the LSTM model captures dependencies of time within the data. A fully connected layer receives the output of this LSTM layer and encodes it into a mapping that corresponds to the relevant prediction. The LSTM layer also has input, forget, and output gates in the network that regulate the flow of information and reduce the problems of long-term dependencies. Due to these gates, the model can learn complex structure in sequential patterns and it also fits very well for non-structured financial time series data like cryptocurrency prices.

GRU MODEL

While it is a GRU model instead of LSTM model, structurally, GRU cells are quite similar to LSTM cells. GRU cells are recognized for easily attaining faster training without compromising the ability to represent and capture temporal relationships and patterns. Also, GRU uses GRU cells to maximize computing efficiency with minimal loss of accuracy by reducing LSTM's input and forget gate into a single update gate.

HOW TO UTILIZE THESE MODELS IN THE SUGGESTED WORK

The proposed research investigates the historical price data of bitcoin looking for trends and time based relationships by using LSTM and GRU Models. GRU's simpler structure allows it to use fewer parameters to capture sequential dependencies, whereas LSTM can learn long-term patterns thanks to its memory cell and gating mechanism. Both of those models will be analyzed on the dataset and be trained to predict future prices. The performance of the models was evaluated with metrics like accuracy and mean squared error.

Proposed Model

This flow chart demonstrates the process of using historical data, and deep learning to predict the closing price of stocks for the next day. Each model makes accurate predictions and identifies relationships in time series data based on patterns, via the LSTM or GRU model.

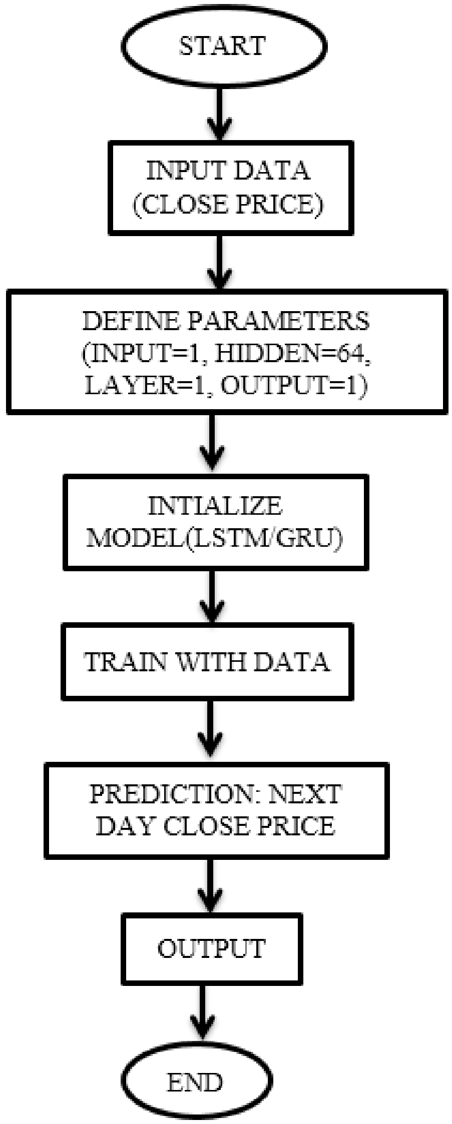

Fig 3.1 Workflow

Training Procedure

Because of the 10-day sequence length, the models use the data from the previous 10 days to predict the price for the following day. Models were trained on the training set, and evaluation was conducted on the testing set. The data was divided into sets for testing and training.

Data Preparation

The ten-day sequences created from the normalised data matched the target price on the eleventh day. The training dataset was created by doing this again.

Loss function and Optimizer

For price prediction and other regression applications, the Mean Squared Error (MSE) loss function was employed. MSE computes the average squared difference between the expected and actual values, while penalising larger errors more severely. This facilitates the learning process for the model to minimise significant variations and produce more accurate predictions.

$MSE = \frac{1}{N}\sum_{I=1}^{N}(yi - yi)^{2}$ Eq(3)

PERFORMANCE MATRIX

MODELS	MSE	RMSE	MAE
LSTM	0.0012	0.0346	0.0281
GRU	0.0010	0.0316	0.0259

IV. RESULTS

Both the LSTM and GRU models demonstrated minimal error rates based on MSE and properly reflected historical patterns, with forecast prices closely matching actual market trends. There were a few minor variations, which is indicative of how erratic cryptocurrency markets are.

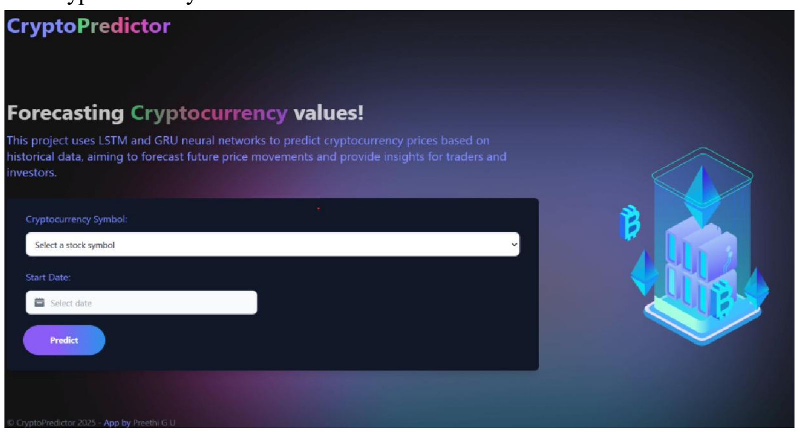

Fig 4.1 Landing page

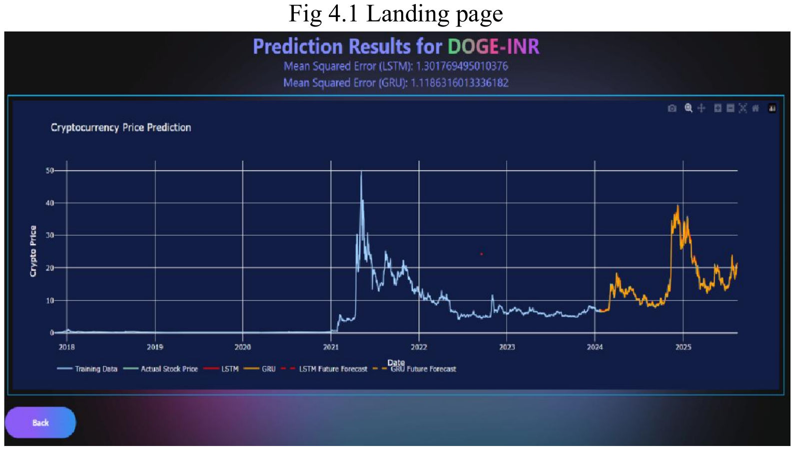

Fig 4.2 **:** DOGE-INR Prediction

Fig 4.2 ,explains how bitcoin prices are expected to change between January and July of 2024. LSTM predictions (red), GRU predictions (orange), training data (blue), the actual stock price (green), and their future projections (dotted lines) are all included.While both models closely mirror real pricing, LSTM is marginally more accurate.

Comparison Table Between Lstm And Gru On Cryptocurrency Forecasting

FEATURE	LSTM	GRU
Architecture	Uses separate memory cells and gates	Combines memory cell and gates
Parameters	More parameters due to multiple gates	Fewer parameters due to combined gates
Training Time	Generally slower to train	Generally faster to train
Memory Usage	Higher memory usage	Lower memory usage

Performance	Can capture long-term dependencies well	Efficient for both short and long-term dependencies
Easeof Implementation	More complex	Simpler implementation
Applications	Time series forecasting, NLP, speech recognition	Time series forecasting, NLP, speech recognition

Table 1: Comparison models for price prediction

[Table 1] In predicting bitcoin values, the table contrasts the two models, emphasising that GRU provides good performance with faster predictions and better computing efficiency, while LSTM has somewhat higher accuracy and stability.

V. CONCLUSION

Utilising historical closing prices from the yfinance library, this study evaluated the effectiveness of the LSTM and GRU models for forecasting bitcoin values.Both models showed excellent predicting ability and successfully identified temporal relationships in the extremely volatile bitcoin market. Even if additional processing power is needed,the LSTM model demonstrated dependable performance when managing long-term dependencies. However, the GRU model, which has a simpler architecture, is more computationally economical and achieves similar prediction accuracy, making it appropriate for situations when processing capacity is restricted. Based on the available resources, the choice will be made. The findings indicate that both models are capable of forecasting time series. Prediction accuracy may be increased in further research by include additional parameters including trading volume, market sentiment, and external economic factors.

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