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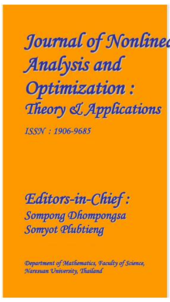

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CRYPTOCURRENCY FORECAST USING LSTM AND GRU ALGORITHM

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Abstract: The unparalleled volatility of cryptocurrency markets creates a unique challenge for investors and speculators wanting to make well-informed decisions. This program uses deep learning approaches, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks, to estimate future Bitcoin price changes. Because of their ability to capture and interpret the subtle patterns contained in time-series data, LSTM and GRU architectures are particularly successful in modeling the complex dynamics of cryptocurrency markets. Our goal is to create accurate projected models that can forecast future price movements using a combination of historical Bitcoin price data, relevant technical indicators, and market sentiment analysis. Our project's major goal is to develop a forecasting instrument that considers past price trends as well as current changes in the bitcoin market. By combining LSTM and GRU networks, we improve the model's temporal learning capabilities, allowing it to understand both transient fluctuations and long-term patterns. Furthermore, we look into ensemble approaches to supplement the benefits of LSTM and GRU models with greater precision and reliability in our forecasts.

Keywords: *Gated Recurrent Unit(GRU), Long Short Term Memory (LSTM), blockchain, cryptocurrency, deep learning, predictive model, time series analysis.*

INTRODUCTION

Bitcoin dominates the digital currency market, accounting for 58% of all exchanges, $4.9 billion in exchange volume, and over 5.8 million active users. Satoshi Nakamoto originally launched Bitcoin in October 2008 with his white paper "Bitcoin: peer-to-peer Electronic Cash System." Bitcoin, the first decentralized cryptographic money, serves as a template for alternative virtual currencies (Altcoins) and other sophisticated monetary forms (made by reproducing or changing Bitcoin).

All cryptographic transactions are secure, authorized, and stored in a decentralized ledger known as a "blockchain." Because the concept is based on the new electronic money

Under this system, online installment transactions between two consenting individuals should be possible directly, without the requirement for a trusted third party, such as a financial institution. In March 2017,

Bitcoin emerged as the dominant and well recognized digital currency marketplace, as assessed by market capitalization. Bitcoin accounts advertised 72% of all cryptographic currencies, and there were 286,419 exchanges from January to February 2017, more than all other digital currencies combined. Bitcoin's price rose from $1,000 USD in 2013 to $16,000 USD in December 2017. This makes predicting Bitcoin's prices extremely difficult.
Bitcoin's value fluctuates similarly to stock prices, albeit in an unpredictable manner. A wide range of calculations are used to estimate value from stock market data. Nonetheless, the forces affecting Bitcoin are distinct. As a result, forecasting the future of Bitcoin is crucial for making informed investment decisions. Unlike the stock market, Bitcoin's prognosis is unaffected by corporate events or governmental organizations. Within the
The graphic below depicts the current bitcoin price, while the prediction represents the expected price.

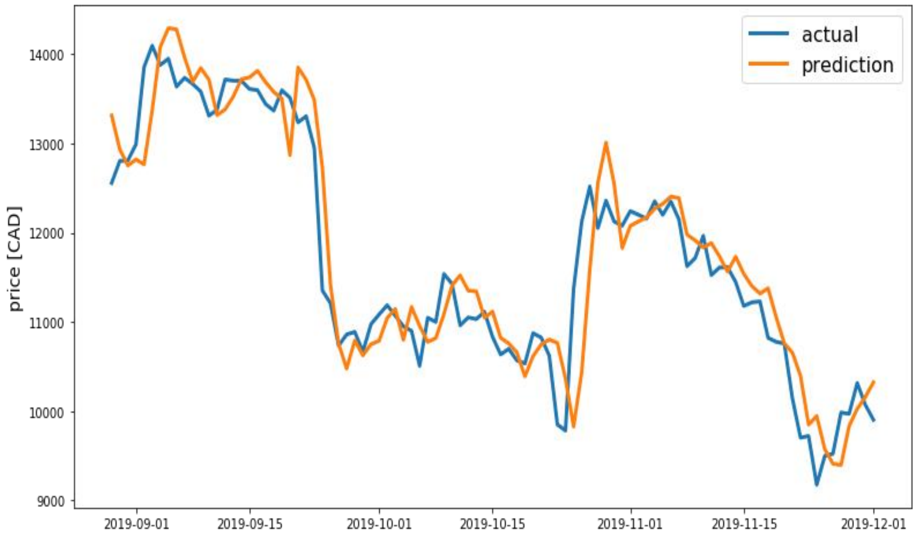

Fig1 :bitcoin prediction[1]

Analysis of forecasts for global financial markets, particularly the stock market, has taken a significant amount of time. This is a prognostic concern for time series in a market in transition; Bitcoin provides an intriguing parallel. Current prediction approaches for time series, such as Holt-Winters, are generally focused on static expectations, which include data that can be broken down into seasonal models, averages, and sound to be precise. This technique is more suited for revenue forecasting in scenarios with seasonal impacts.

Existing systems

Samikshamarne et al. described the use of a deep learning technology called LSTM to forecast cryptocurrency values.The user discussed data visualization, process flow, and the deployment of recurrent neural networks.Several categorization techniques are described, including GLM, SVM, and Random Forest.In addition, the document explores the use of multivariate linear regression to anticipate bitcoin's maximum and minimum values.
Akhila et al. proposed a model for predicting cryptocurrency values that combines Deep Learning, notably Long Short-Term Memory (LSTM) networks, with technical indications and historical data. Change Point Detection (CPD) is included in the model using the Pruned Exact Linear Time (PELT) method to detect significant fluctuations in bitcoin prices and improve forecasting capabilities.
Minakhi Rout et al. focused their research on the use of deep learning models, LSTM and GRU, to predict Bitcoin prices. Historical Bitcoin data is being used for training and evaluation. The performance of the two models is compared using measures like MSE, MAE, and RMSE. The study demonstrates the usefulness of LSTM and GRU in detecting subtle patterns in Bitcoin price movements, thereby providing a substantial

addition to the field of cryptocurrency analytics. In the future, researchers may look at the viability of using hybrid models and supplemental features to improve prediction accuracy.

Rasheed et al. (5) used a Long Short-Term Memory (LSTM) Recurrent Neural Network to estimate Bitcoin prices, effectively addressing the complex and unpredictable nature of cryptocurrency dynamics. Using real-time data collected over a five-year period and effective pre-processing procedures, the LSTM model achieves an extraordinary accuracy of 95.7% and a minimal root mean square error (RMSE) of 0.05. The study emphasizes the effectiveness of LSTM in forecasting cryptocurrency values, highlighting its potential to support well-informed investing decisions.

Yuzi Li et al. [6] suggested a novel data decomposition-based hybrid bidirectional deep-learning model for algorithmic trading and forecasting daily price variations in the Bitcoin market. The methodology consists of two basic phases: data decomposition using variational mode decomposition (VMD) to identify inner factors and bidirectional deep learning using a Long Short-Term Memory neural network (BiLSTM) for price forecasting. In terms of accuracy and investment returns, the results show that the suggested model outperforms benchmark models such as econometric, machine learning, and deep learning. The model's robustness is proven by extended testing and predicting intervals.

Proposed system

Long Short-Term Memory (LSTM) is an architectural version of recurrent neural networks (RNNs) designed to solve the inadequacies of traditional RNNs in terms of learning knowledge about and capturing long-term dependencies within sequential input. Long Short-Term Memory (LSTM) models are particularly effective in domains such as natural language processing, time-series data, and other applications that require temporal and contextual links.The primary function of LSTM is to selectively retrieve, update, and store information across long sequences. Traditional recurrent neural networks (RNNs) are limited in their ability to learn from distant relationships due to the vanishing gradient problem. To address this issue, LSTMs use a memory cell with three fundamental components: an input gate, a neglect gate, and an output gate.

Memory Cell: The memory cell, like a conveyor belt, carries data throughout time steps. It helps to retain knowledge from prior inputs in the long run. The cell state is critical to the long-term retention of information. Input Gate: The input gate determines which data should be saved in the memory cell based on the current input. It regulates the flow of novel information into the cellular environment. The forget gate determines which information from the memory cell is to be discarded. It aids in the process of removing unneeded information, protecting the model from being overburdened with unnecessary details. The output gate regulates the data transferred to the next time phase. The ultimate output of the LSTM unit is calculated by comparing the current input to the state of the memory cell. LSTMs excel in capturing and learning dependencies in data sequences because they allow relevant information to be included.

The process of allowing data to travel across the network while removing unnecessary information. Their architectural design allows for the effective display and comprehension of complicated patterns and relationships.

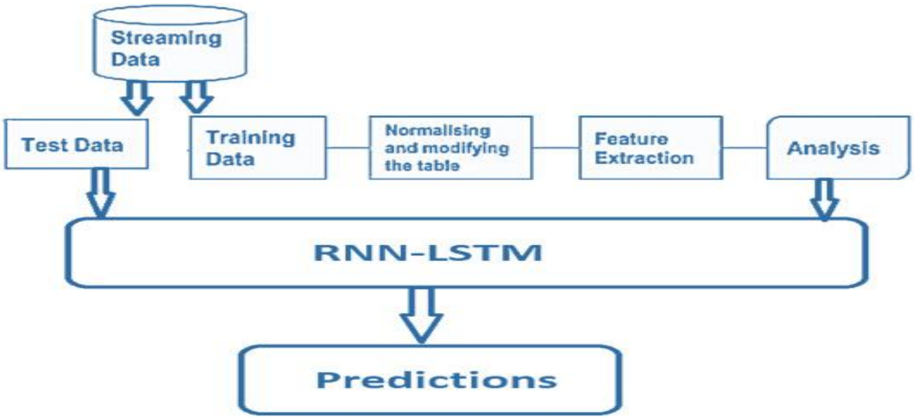

Fig2:LSTMarchitecture

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)(1)\ [7]$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)(2)\ [7]$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)(3)\ [7]$$

In equation→[1]:

i_t →represents input gate

σ→represent sigmoid function

w_i →weight for the respective gate(i) neurons.

h_{t-1} →output of the previous lstm block

x_t →input of current timestamp

b_i →biases for the gate

In equation→[2]:

f_t →represents forget gate

σ→represent sigmoid function

w_f →weight for the respective gate(f) neurons.

h_{t-1} →output of the previous lstm block

x_t →input of current timestamp

b_f →biases for the gate

In equation→[3]:

o_t →represents output gate

σ→represent sigmoid function

w_o →weight for the respective gate(o) neurons.

h_{t-1} →output of the previous lstm block

x_t →input of current timestamp

b_o →biases for the gate

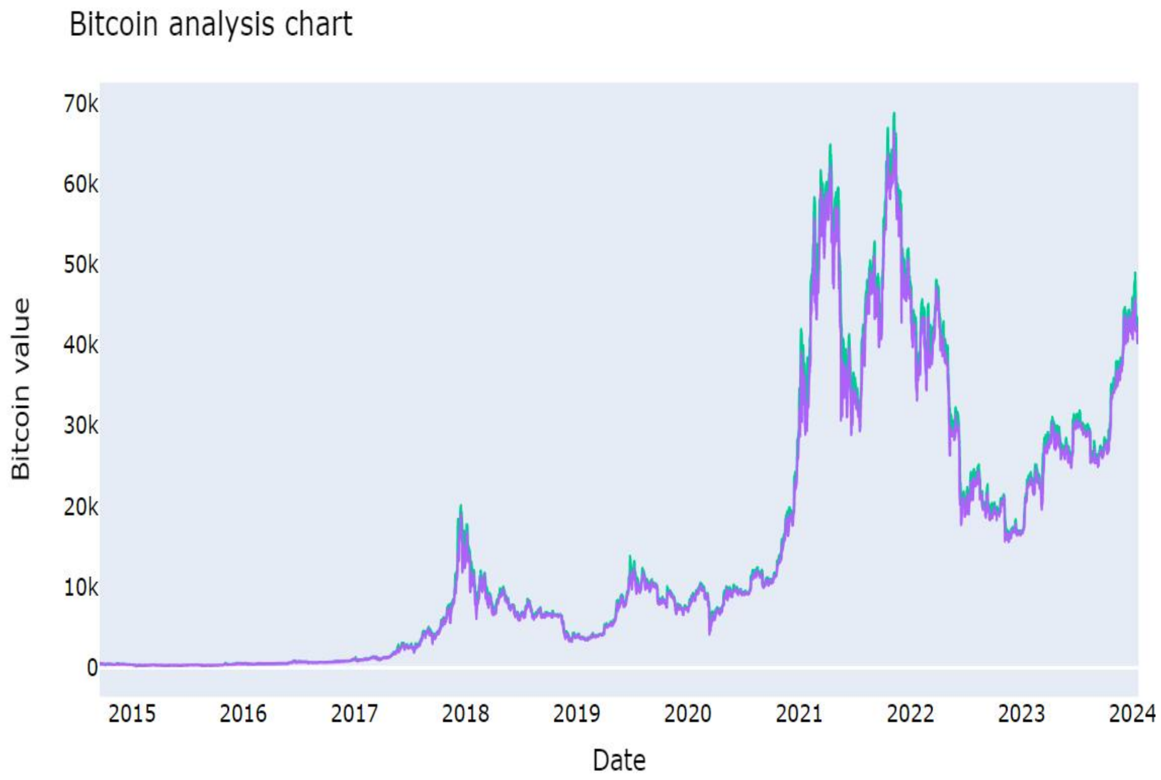

Fig.4Train andvalidation accuracy oftheoriginal imagedatasets

Emphasis on definition Conclude the latest exchange. Open exchange for opening. Highest exchange rate of the day Minimum exchange rate during the day. Weighted value represents Bitcoin's worth. Bitcoin's entire exchange volume.USD daily volume of all exchange transactions. Time data with a timestamp The scikit-learn toolkit is used in this study to create models that only include highlights. Predict the values for Close, Open, High, and Low for the Weightedvalue. Regression AI was used in this study because the Bitcoin price was constantly estimated. The scikit-learn library generates the two most efficient regression models. Recurrent Short Term Memory (RNN) and Long Short Term Memory (LST). LSTM and GRU models for profound learning-based relapse models were created with the Keras library.
Our implementation was carried out using Google Collaboratory (version 3.10). Pandas, NumPy, Math, Matplotlib, PyPlot, Sklearn, TensorFlow, and more modules have been implemented.

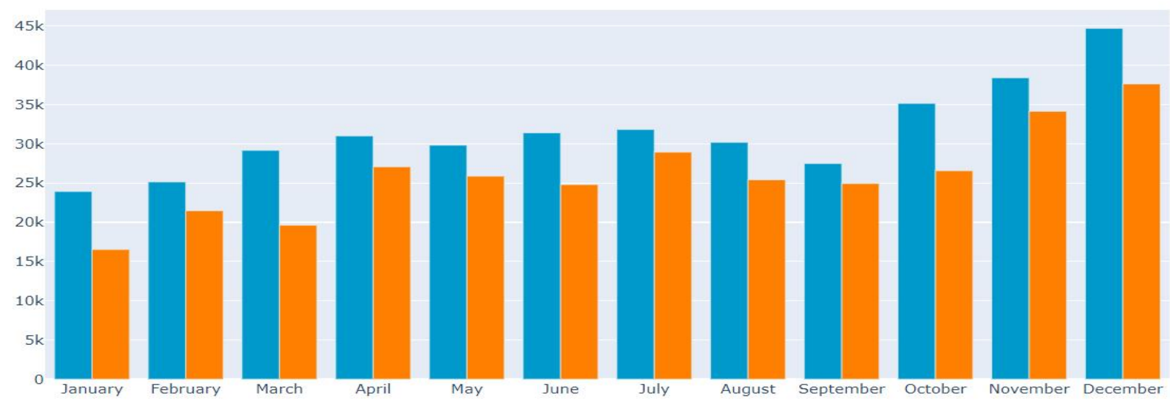

Fig 5: Monthly wise close and open price

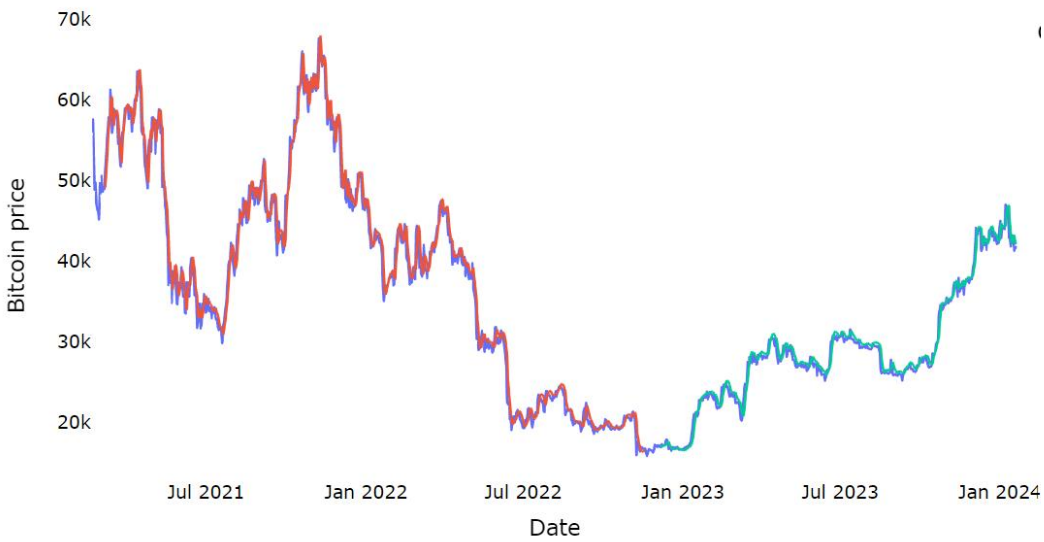

Fig 6: Prediction of Bitcoin.

CONCLUSION

Our research goal is to create a deep learning-based model that can predict the price of bitcoin. Deep learning is used to determine which factors produce sequential results during model building. After implementing the aforementioned models (RNN, LSTM, and GRU), we noticed that the overall number of parameters and dataset size can influence the output. The prior model, which included RNN and LSTM, had a prediction accuracy of about 52%. In contrast, our study showed that the GRU model outperformed the LSTM model. The optimum model for GRU outcomes has an accuracy of 94.70%. The proposed model improves accuracy by around 42.3%. Testing each of our GRUs produces the most complete and time-consuming results. Furthermore, certain indicators—Los, High, Close, and Open—do not suffice to forecast the value of Bitcoin, as price fluctuations are influenced by a variety of factors, including social media reactions, legislation, and the regulations that each country promotes for the management of this digital currency.

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