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A Method Which Uses GRU-ALR Model With Marine Predator Optimization Algorithm To Predict The Trend Of Cryptocurrencies.

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Abstract:
Cryptocurrencies have become a popular and volatile investment asset class, where accurate price prediction is crucial for informed decision-making by investors and traders. Cryptocurrency price fluctuations are influenced by various factors such as news, tax policy changes, technical changes, and external factors. To predict the price trend of cryptocurrencies, individuals and analytical organizations use various tools such as technical analysis, fundamental analysis, and machine learning models. This study introduces an efficient model using the GRU-ALR recurrent neural network, optimized with the Sea Hunter algorithm, for cryptocurrency price prediction. The GRU-ALR network architecture enables modeling long-term dependencies and capturing complex patterns in time series data. By learning from historical price movements, the network aims to predict future prices. In the proposed method, the ADAM optimizer function is used to adjust the weights of the GRU network. Adaptive adjustment of the learning rate in the network increases the prediction accuracy compared to the standard GRU algorithm. In addition, fine-tuning the parameters of the deep recurrent neural network GRU-ALR with the marine predator optimization algorithm has improved the efficiency of the proposed method. According to the simulations, the RMSE and MAE metrics for the proposed method are 33 and 26.
Keyword: *Cryptocurrency price prediction, GRU-ALR, Bitcoin*

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I. Introduction

A distinctive feature of the contemporary era is its continuous evolution. Every day we witness the emergence of new developments and advances, from the spread of computers and telecommunication satellites to the integration of intelligent information systems in human societies. The modern landscape is characterized by the adoption of advanced production technologies, the widespread use of robotics in factories and organizations, and the creation of complex telecommunication networks. These developments, along with industrial innovations, are intricately woven into the fabric of the national economy and have complicated and strengthened its operations and responsibilities (Fang et al., 2025).

At the same time, the exchange rate and its fluctuations stand out as determining factors in the cost dynamics of industrial units. Such deviations, which often lead to deprivation of the ability of units to plan, especially concerning export activities, can cause higher production costs and, thus, lower their competitiveness. Contrary to other markets, foreign exchange market functions all day long because of the worldwide character of its rates and continuous fluctuations in foreign exchange rates. The development of foreign trade operations' sphere is accompanied by the emergence of the international financial market, and, therefore, it is necessary for traders, producers, exporters and importers to possess foreign exchange. It proves the necessity of the correct forecast of foreign exchange rates, which facilitates the managers' decision making(Almeida& Gonçalves, 2023).

Companies dealing with heavy investments into assets valued in higher currency have always faced high risks connected with sudden exchange rate fluctuations. Therefore, the influence of such fluctuations on balance sheets of individuals or entities can be huge because of people trying to maximize returns on investment portfolio. However, the lack of sufficient scientific insight on exchange rates may prove a burden for manufactures and small businesses (Almeida& Gonçalves, 2022).

Recently, many world-wide problems have emphasized the importance of effective systems for the evaluation of market risk for the company. Especially for large companies that are struggling with increasing exchange rate fluctuations, adopting effective forecasting models has become crucial. In fact, a fully informed forecast acts as a harbinger of sound decision-making.

II. Research Problem And Objectives

Problem Statement

Digital currencies and cryptocurrency price prediction are two important topics in the world of finance and technology. Digital currencies are units of currency based on cryptographic technology that are used to transfer and store various currencies. These currencies are different from traditional currencies and usually work on blockchain technology that allows for secure and intermediary-free transfer of currencies (Akyildirim et al., 2023).

Predicting the price trend of digital currencies is a challenging issue. Digital currencies often experience extreme price fluctuations that are influenced by various factors such as news, changes in tax plans, technical changes, and cross-sectional factors. To predict the price trend of digital currencies, individuals and analytical communities use various tools such as technical analysis, fundamental analysis, and machine learning models (Alonso-Monsalve et al., 2020).

Technical analysis examines past price patterns and charts to provide predictions about the future of currencies based on history. Fundamental analysis examines economic, technological, and news factors related to projects and currencies. Machine learning models can also make predictions based on historical data and various parameters (Almeida & Gonçalves, 2023).

In this study, a deep recurrent GRU-ALR neural network improved with the marine predator optimization algorithm was used to predict the price trend of digital currencies.

Objectives of the study

1. To provide an effective method for predicting cryptocurrency price trends using neural networks.
2. To improve and develop the current study compared to previous studies.

III. Digital Currency

The basic concept behind digital currencies is to increase security, eliminate intermediaries, and ensure complete transparency of transactions (Navamani, 2023). To protect against hacking and interception during internet transactions, digital currencies are encrypted. Encryption technology, which was originally used for military communications during World War II, now uses mathematics and computer science in the field of electronic commerce to secure communications, information, and monetary transfers. Digital currencies help to provide security and anonymity in transactions. Due to their decentralized and ownership-free nature, digital currency transactions are immune to fraud and manipulation, eliminating the need for intermediaries. Individuals can use digital currencies without the need for special licenses or registration, while mining digital currencies and making a profit only requires the appropriate hardware. The increasing use emphasizes the necessity of rules and guidelines governing the cryptocurrency market, just as in the case of other markets. Regulation of the market by the government is necessary to create trust among consumers, to maintain stability, and to make the process sustainable (Atsalakis et al., 2019). Although currency can be expressed in terms of dollars, cryptocurrencies have their value determined based on the value of the currency such as dollars, euros, or even rials.

Information Security is one of the most important security threats when it comes to information dissemination via the internet. Encryption of information refers to the process whereby information is encoded in order to secure it from any form of unauthorized decryption. Data encryption has been used for years as a mechanism of ensuring information security. Cryptographers have distinguished between ciphers and codes, noting that encryption entails encoding information using different forms of mathematical manipulations (Shin & Rice, 2022).

Types of Digital Currencies

Bitcoin

The operation of Bitcoin as a payment system is not regulated; it does not depend on any form of governance and regulation, whether it be central bank control or otherwise (Almeida & Gonçalves, 2024). All users of Bitcoin can observe each other's behavior to make sure that transactions are legitimate and that nothing disrupts the system. To remain anonymous in their transactions, users utilize pseudonyms in the form of strings of figures called Bitcoin addresses. Also, anyone can check out what other people pay with Bitcoin.

Being a virtual currency as well as a sophisticated payment method, Bitcoin enables its users to conduct money transactions over the Internet. In general, Bitcoin is similar to traditional methods like Visa, MasterCard, PayPal, or any other bank cards, as well as online bank transfers. Still, Bitcoin has two major distinctions compared with conventional payment techniques.

First of all, Bitcoin functions in a decentralized way. Contrary to payment networks which work for companies, organizations, and banks, Bitcoin lacks any central management or ownership. Bitcoin uses the principle of peer-to-peer network which includes several hundred computers connected over the Internet and cyberspace. Thus, Bitcoin becomes the first-ever open payment system in history (Choithani et al., 2024).

Figure 2-1 Bitcoin

Litecoin

Litecoin, launched in the market in 2011, has been identified as one of the significant and most valuable cryptocurrencies. Having evolved from an open-source worldwide payment system, Litecoin serves as a successor to Bitcoin. This cryptocurrency is not controlled by any entity; hence, it stands out as one of the leading cryptocurrencies available today. Based on the proof-of-work protocol scripting approach, Litecoin allows for mining of the currency through normal PCs. Despite having similarities with Bitcoin, one major factor differentiates Litecoin from its counterpart, which is block generation at a very fast speed (De Vries, 2023).

Figure 2-2 Litecoin

Ethereum

In 2015, Ethereum emerged as a pioneering digital currency. Operating as a decentralized software platform, Ethereum facilitates the creation and execution of distributed applications and smart contracts without the need for fraud, control, or external interference. Ethereum's versatility enables the encryption, decentralization, security, and trading of a wide range of assets and applications, making it a powerful tool for innovation and financial transactions.

Figure 2-3 Ethereum

Artificial Intelligence Techniques

The methods of artificial intelligence encompass a vast array of functions such as the knowledge of human beings, intelligence, and reasoning. Artificial intelligence improves the problem-solving process by using the experience gained in the past. The development of technology has resulted in the development of artificial intelligence, and computer technology has played a pivotal part in this regard. Some of the intelligent techniques involved in artificial intelligence are as follows: Neural Networks – Probabilistic Neural Network, Multilayer Perceptron, Self-organizing Models, Attributional Neural Network, Training Vector Quantification, Cascade Neural Networks Topic-Based Reasoning Decision Trees Genetic Algorithms Support Vector Machines Hard Sets Fuzzy Logic. Given the significant importance of these methods and their application in research, they are subject to thorough review (De Vries, 2023).

Cryptocurrency Security

Security concerns have emerged as a fundamental and pressing issue both internally and externally within the banking industry. The widespread adoption of cryptocurrencies has increased security risks and exposed closed systems to potential vulnerabilities. Authentication, authenticity, and privacy have become top priorities for all types of cryptocurrencies due to weaknesses in existing retail payment systems. Security breaches can occur during customer interactions with cryptocurrency sellers or issuers, including attempts to gain access to digital tools and equipment for counterfeiting purposes. These actions can include altering the product software or design, or tampering with messages sent during transactions. Understanding the extent of system penetration and the security of services provided over internet networks is crucial, as security breaches are carried out with the aim of exploiting financial and material benefits by compromising and disrupting systems (Murugesan et al., 2022).

Related works

Paper (Critien et al., 2022) aims to investigate global cryptocurrency price movement trends using social media communication data. The study focuses on analyzing thematic discussions within online communities and social media platforms to extract insights that can be used to predict cryptocurrency price fluctuations. It is based on the hypothesis that there is an empirical relationship between price changes and social media activity. Such models contribute to a better understanding of cryptocurrency ecosystems in the context of social media behavior and support the development of real-time trading systems.

In paper (Awotunde et al., 2021) the authors attempt to predict not only the direction of price movement but also the magnitude of increase or decrease using advanced technologies. The study relies on both the sentiment extracted from tweets and the volume of tweets. Experiments are conducted to examine the relationship between sentiment and future prices across different time scales in order to determine the optimal time interval at which sentiment becomes a reliable indicator of price changes. Two neural network models are evaluated: one based on recurrent networks and the other on convolutional networks. An additional model is proposed to predict the amount of price change as a multi-class classification problem. Results show that combining this model with a price trend forecasting model produces more reliable predictions, achieving an accuracy of 63%.

Paper (Biswas et al., 2021) focuses on implementing machine learning algorithms in order to create a predictive model for the prediction of stock and cryptocurrency prices through the use of technical indicators associated with market trends. In particular, the LSTM network is adapted based on a number of factors like open price, close price, high price, low price, trading volume, market capitalization, and other interdependent cryptocurrencies. Although there are no robust regulatory frameworks as well as cryptocurrency markets have high volatility, it can be stated that the application of machine learning provides enhanced prediction capability. Specifically, the LSTM network proves to predict Bitcoin, Ether, and Litecoin values better than any other models, with an accuracy of 67.43%.

Paper (Gupta & Nain,2020) presents a novel approach for the prediction of digital currency value based on a number of factors including stock market value, trading volume, distribution, and high delivery indicators. In particular, the implementation of LSTM networks together with a long-term trend-based framework is used for benchmark evaluation purposes.

The paper (Shahbazi & Byun, 2021) tries to forecast Bitcoin prices based on some important factors, like the supply of cryptocurrency, daily trade volume, and demand for the market. Time series methods are used to make predictions, including Moving Average, and ARIMA, and some machine learning models such as SVM, linear regression, LSTM, and GRU.

IV. Mythology

The GRU network, which is famous for its skill in learning feature sequences, is predicted to exhibit exceptional recognition accuracy even in the presence of nonlinear patterns. Consequently, the optimal configuration of network parameters is of significant importance in enhancing its performance. In this research, we use the Marine Predator Optimization Algorithm (MPA) to fine-tune the hidden layer size parameter in the GRU-ALR network. The following sections describe the proposed method in detail.

In this study, we aim to use the deep recurrent GRU-ALR network to predict the price trend of cryptocurrencies. The GRU network, known for its skill in learning feature sequences, is expected to exhibit remarkable detection accuracy even among nonlinear patterns. We will use the GRU network with the adaptive learning rate of GRU-ALR to predict the price trend of cryptocurrencies. As part of our suggested method, the weight parameters of the GRU neural network will be modified by applying the ADAM optimizer function. By modifying the learning rate adaptively in the network, the accuracy level of the prediction is improved relative to the standard GRU model. For increasing the system efficiency, the Sea Hunter Optimization technique is used for finding the optimal number of layers in the GRU-ALR model. It is possible to select the optimal number of layers in the GRU-ALR model by using the Sea Hunter Optimization technique.

Preprocessing

The process of normalizing data is considered a significant part of data preprocessing, which aims at transforming the input to a certain range, typically [0, 1], such that their influence is made consistent. The need for normalization becomes particularly significant when inputs fall within various ranges. In one of the approaches, normalization is achieved by dividing all the values of a parameter by the maximum of the parameter.

$$x_N = \frac{x_i}{x_{max}} \qquad (3-1)$$

GRU Neural Network Model

The GRU neural network, used in the current research to forecast prices of cryptocurrencies, is considered to be one of the types of recurrent neural networks (RNNs). The architecture of GRU network can be observed in Figure (3-1).

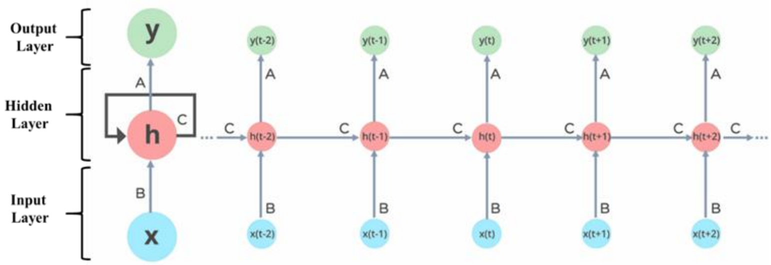

Figure 3-1- GRU neural network architecture

The GRU network is deliberately designed to work effectively with sequence data as it retains and updates its temporal memory at each step. There are three primary layers in the GRU network architecture: input, hidden, and output layers. According to Figure (3-1), the input layer accepts input data denoted as x(t-i), which has been preprocessed before, and produces hidden output as h(t-i). The hidden output data are added with the next input data x(t-i+1), making it possible for the next step to accept new inputs. The procedure keeps continuing, such that output data h(t-i+1)are used together with input x(t-i+2), and so forth.

Optimization of GRU-ALR Network by MPA Optimization Algorithm

The Marine Predator Algorithm (MPA) is used in this study to optimize the hidden layer size parameter of the GRU-ALR network.

The MPA algorithm is a population-based metaheuristic method inspired by the hunting behavior of marine predators. It consists of three main stages: stationary, Brownian motion, and Löwy strategy. In the stationary stage, the predator remains stationary, while in the Brownian motion stage, it exhibits random movements. In the final stage, known as the Löwy strategy, the predator follows a specific hunting strategy.

Similarly, prey species also undergo three corresponding phases that reflect the behavior of potential prey in marine ecosystems. Prey species may include organisms such as sharks and tuna, with sharks acting as predators of tuna while also being prey to other marine predators.

1. **Initial Population Generation:** In population-based algorithms such as the Marine Predator Algorithm (MPA), the initial population consists of a set of potential solutions to the optimization problem. These solutions, also known as search agents, are randomly generated and represent high-quality solutions to the problem at hand. In the context of optimizing the hidden layer size parameter of a GRU-ALR network, the position of each search agent corresponds to a set of values for this parameter.

During the initial stage of the MPA algorithm, the initial population is uniformly distributed across the search space. This means that the values of the hidden layer size parameter are randomly selected from a predefined range. The uniform distribution ensures that the initial population covers a wide range of potential solutions and allows the algorithm to explore the search space efficiently.

2. **Calculating Prey and Elite Matrices:** The prey matrix represents the current position of the search agents in the optimization process. Each row of this matrix corresponds to the current position of a specific search agent, indexed by i.
3. **Updating positions:** Once the initial population is generated and the prey matrix and elite matrix are obtained, the position of the search agents must be updated. The MPA uses an intelligent approach in order to achieve a trade-off between the exploration and exploitation stages. Three different approaches are used for updating the position of the search agents, which results in three stages for balancing exploration and exploitation.

V. Result

In this study, we used a GRU-ALR recurrent neural network, optimized with the sea predator algorithm, to forecast the prices of cryptocurrencies. This chapter evaluates the effectiveness of the strategy mentioned in the previous chapter. We discuss the database used in the simulation and the performance evaluation criteria of our proposed method in the following sections. Finally, we present the forecasting results obtained using our proposed approach and compare them with the results of previous works. It is worth noting that MATLAB software was used as the simulation program for this study.

Dataset

In this study, we used Bitcoin/US Dollar price data over six years, from 2013 to 2023. The data included daily Bitcoin prices, sourced from the internationally recognized website https://coinmarketcap.com/currencies.

Evaluation Criteria

In this research, we will use RMSE and MAE criteria to evaluate the results of the proposed method. The calculation method of this criterion is as follows (4-1) and (4-2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(X_{obs.i} - X_{model.i})^2} \quad (4\text{-}1)$$

$$MAE = \frac{\sum_{i=1}^{n}(X_{obs.i} - X_{model.i})^2}{N} \quad (4-2)$$

Data splitting

In this study, the GRU-ALR neural network undergoes a supervised learning process for prediction. This involves training the network on a portion of the data and then evaluating its performance on another portion. Specifically, 70% of the data set examples are allocated to train the GRU-ALR network and optimize the hidden layer size parameter, while the remaining 30% of the data is reserved for evaluating the model performance.

Forecasting Results with the Proposed Model

In this section, simulation results that show the forecast of the cryptocurrency price trend are presented through regression plots and graphs that show the actual values alongside the forecast errors. These results are displayed for three forecasting periods: 1-month, 2-month, and 3-month forecasts.

Figure 4-1 shows the actual and predicted prices of the cryptocurrency Bitcoin over a one-month period. The blue curve represents the actual price data, while the green curve represents the predicted prices generated by the proposed method. The close alignment between the predicted and actual price values demonstrates the accuracy of the proposed approach. In addition, the error curve is shown in this figure to provide further insight into the forecasting performance.

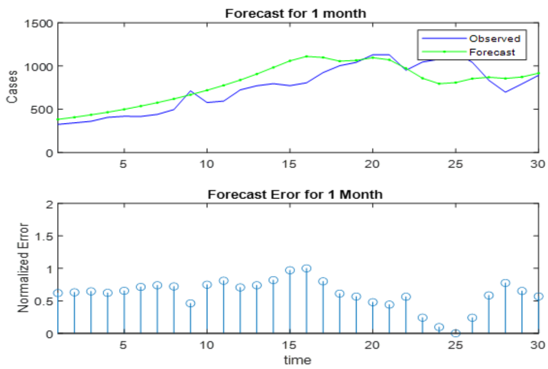

Figure 4-1 - Comparison of actual and predicted values over a one-month period for cryptocurrency price prediction

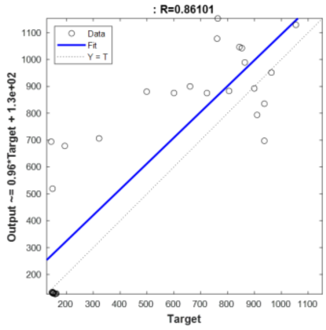

Figure 4-2- Regression curve for 1-month cryptocurrency price forecast

Figure 2-4 shows a regression plot that shows the prediction of cryptocurrency prices. In this plot, the predicted data points should align exactly with the fitted line, indicating a lower prediction error. The closer the alignment between the predicted data and the fitted line, the more accurate the prediction.

As can be seen in the figure, the regression line closely matches the data points, indicating the effective performance of the proposed method in predicting cryptocurrency prices. Furthermore, the regression coefficient for monthly cryptocurrency price prediction, which is calculated to be 0.86, emphasizes the effectiveness of the proposed approach.

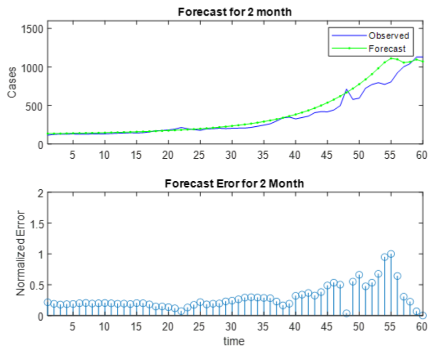

Figure 4-3 - Comparison of actual and predicted values over a two-month period for cryptocurrency price prediction

Figure 4-3 shows the actual and predicted prices of the digital currency Bitcoin over a two-month period. The blue curve represents the actual price, while the green curve represents the price predicted by the proposed method. A close inspection of the figure shows that the predicted price trend closely follows the actual price trend, indicating the accurate performance of the proposed method.

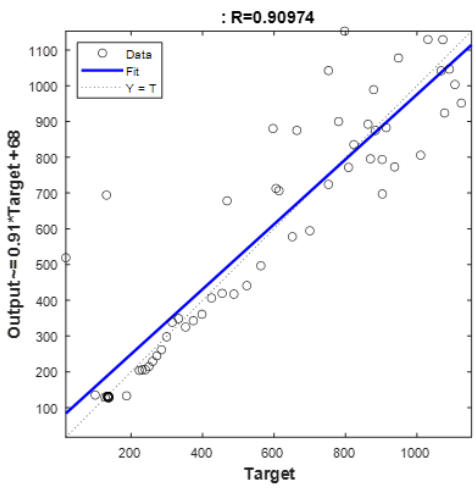

Figure 4-4 - Regression curve for two-month cryptocurrency price forecast

Figure 4-4 shows the regression plot for predicting cryptocurrency prices over a two-month period. The predicted data points are aligned with the fitted line on the regression plot. Analysis of the figure shows that the regression coefficient for predicting cryptocurrency prices over a two-month period is 0.90, indicating the high efficiency of the proposed method.

Comparison of Results

Table (2-1) shows the numerical values of RMSE and MAE for the price prediction of digital currency in this section. These error values are calculated based on the average of 30 simulation runs, which increases the reliability of the findings of the proposed method. In addition, the results of the proposed method are compared with the methods described in the reference paper. As can be seen in Table 4-1 , the RMSE and MAE metrics for the proposed method are 33 and 26, respectively, while these metrics for the RW method used in the reference paper, which has the best results after the proposed method, are 326 and 206.

Table 2.1: Performance Comparison of Digital Currency Price Prediction Models Using RMSE and MAE

Method	RMSE	MAE
RW (Maciel et al., 2022)	328	206
ARIMA (Shahbazi & Byun, 2021)	360	246
Preposed method (GRU-ALR-MLP)	33	26

VI. Conclusion

Bitcoin acts as both a consensus network and a new payment system that operates without intermediaries through peer-to-peer transactions. Its decentralization distinguishes it from traditional currencies, and its activities are recorded in a large decentralized database called the blockchain. Several techniques, including neural networks, logistic regression, support vector machines, and Bayesian methods, have been used to predict the price of Bitcoin, each of which helps to increase the accuracy of the prediction. Accurate estimation of the price of Bitcoin is very important given the growing trading volume of the currency, especially since the price trend of almost all other cryptocurrencies is correlated with the price of Bitcoin. In this study, the GRU-ALR recurrent neural network, optimized with the Sea Hunter optimization algorithm for its hidden layer size parameter, was used to predict the price trend. Simulation results show the effectiveness of the method in achieving accurate predictions with minimal error compared to other approaches. This superiority is due to the use of a powerful GRU-ALR recurrent neural network optimized through the marine predator algorithm.

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