A Hybrid Deep Learning-based Chaos Dynamic System for CryptoCurrency Prediction

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ABSTRACT

The financial market's price forecast for cryptocurrencies is of huge importance, particularly until the current global financial and economic crisis. Because of the nonlinear structure that involves the intrinsic fractality and chaoticity of cryptocurrencies, several studies found that a single method is not adequate to predict cryptocurrencies with quite greater resolution. While each framework used in cryptocurrency prediction has limitations and also the other capabilities, they may not provide the highest prediction performance for that duration in all scenarios. In the cryptocurrency time sequence, an efficient and modern prediction system was introduced to reduce this detrimental condition and maximize statistical performance. A new hybrid prediction model focused on long short-term memory (LSTM) neural network and Chaotic dynamic technique for cryptocurrency regression analysis is built in this research. While the Long short - term memory model's computing task is extremely high in nonlinear pattern classification as compared to brute force, deep learning rapidly proved extremely effective in predicting the underlying unpredictable nature of the cryptocurrency.

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1. INTRODUCTION

The transformation of currency used in the trading of products and services is evolving quickly from simple trade mechanisms to traditional currencies, non - ferrous metals, precious documents with gold, trusted money without precious metals and online/cryptocurrency, etc., [1]. The cryptocurrency, which is a sub-set of virtual currencies, is described as electronic money intended to serve as an encrypted means of interchange mechanism to monitor the process of generating foreign currencies, protect their payments and validate the exchange [2]. Performance in cryptocurrency, the overall stock price of which has exceeded lots of billions of dollars and impacts the financial and spending activity of individuals, has grown exponentially over the past several decades [3].

There is an increasing value in analyzing the specific structure of Bitcoin and cryptocurrency in particular in the emerging implementation of learning empirical research [4]. For example, long memory was evaluated to determine the economic growth of cryptocurrencies in [5], their stability was evaluated in [6], stability and surface morphology were studied in [7], vulnerability and investment factors were reviewed in [8] While trying to herd and efficient exchange were invested in [9]. While overall market prediction is an essential part of portfolio simulation and risk management, such a topic has been based on just a sufficient number of series, particularly for the value of bitcoin. For example, the authors in [10] used a list of specific factors as interfaces to profound learning objectives consisting of multiple modules to predict Bit coin's overall exchange pattern.'

To predict market demands and payments depending on customer views and feelings generated from online forums, a deep learning algorithm has been proposed [11]. Using nonlinearities as inputs [12] or including technological metrics, deep neural networks were commonly used to predict the capital sector [13].

Many studies assessed linguistic research and understanding metrics as predictors for stock market prediction. Nevertheless, creating precise predictions in a dynamic and rapid existing system also remains a difficult issue [14]. The objective of our following research is essentially important for two reasons; initially, researchers intend to evaluate the predictive power of most effective cryptocurrencies by analyzing their implicit dynamic behavior, like inherent chaoticity and fractality.

Furthermore, to plan to use deep learning as the basic dynamical device topology to efficiently remove unseen structures that conceal their process series' nonlinear dynamics. Correspondingly, researchers are responding in the two steps to the published studies: because exacting studies of the nonlinear parameter estimates of the most successful cryptocurrencies aren't current to the authors' knowledge in recent studies, researchers are attempting to look into every issue with an econophysics viewpoint.

The deep learning LSTM neural networks resolved issues with artificial neural networks (ANNs) correlated with backpropagation by combining ANN neurons with computer memory and activation function. In this way, it is an exciting deep learning neural network primarily due to its success in effectively analyzing long-term and short-term contextual information [15]. The structure of the LSTM is repetitive because links through modules create a common system/matrix that enables basic data packets to move both forward and backward throughout the network. The historical knowledge is then retained for potential retrieval. The Chaotic Method [16] is a memory-based linear framework that predicts the multivariate layer of a probability distribution thus enabling effective processing and interconnection to the ideal inference layer as the sample size was really large [17]. Because of these specific, unique advantages, LSTM and Chaos systems have been efficiently related to numerous statistical analysis and prediction problems [18].

This research is the only analysis of using the process of extraction and the technique of optimization in connection with deep learning to estimate the cost of cryptocurrencies. Often, as with other studies on this topic, it predicts a higher-performing crypto-currency cost than with research papers with the hybrid system, like LSTM and Chaos Theory Set (CTS) method of integrating.

The remaining of the study is summarized as follows. Chapter 2 describes the characteristic technique in general, such as the process of standardization, the evolutionary algorithm, and the hybrid approach established. Chapter 3 provides the research observations of the developed framework and other methods similar to the proposed system. The important and observable considerations are also discussed in the following Chapter 3, in addition, to also show the existence and consistency of the proposed system. Then, the outcomes of Chapter 4 are illuminated.

2. CHAOTIC SYSTEMS

Framework ease and dynamic chaotic nature of one-dimensional chaotic networks have provided others with a common resource for cryptographic techniques including neural networks. The logistic model is described by Equation (1) as those other maps. While this model has a broad variety for parameter r, it displays chaotic behavior only in scope including in this context, by certain metrics the model removes its chaotic behavior [19, 20].

$$C_{i+1} = H_s\,(C_i) = S.\,C_i\,(1 - C_i) \qquad (1)$$

Linear and tent models were some instances of one-dimensional chaotic models with large data set to logistic visualizations; particularly quadratic layouts have quite specific nonlinear patterns to logistic layouts, that have the same issue with their chaotic behavior. To solve these issues, Zhou et al. suggested a disorderly method of two one-dimensional maps as vectors to be defined as LS graphs for supply chain and coefficients pattern strategies in the discussion that follows. The method provided a probabilistic approach on the production chaotic sequence with α= β [21].

In cryptographic implementations, utilizing nonlinear attacks or their variations, attackers may use some kind of variation across a cryptographic hash function to crack the key or algorithm [22]. For binary functions of α= β, this could be far simpler to target the evaluation metrics because of the largest centralized parameters across the spectrum. To next LS method flaws, it could be even weaker to achieve performance from an amplitude model as opposed to linear regression. The LS device, therefore, has vectors with a specific pose a significant threat of composition that renders it somewhat susceptible to side-channel frequency attacks [23].

A very flexible approach is proposed in [24] to construct dynamic structures in each aspect of chaotic maps. This method results from several couplings of a chaotic system on various scales, which almost guarantees improved chaotic actions. However, throughout the instance of chaotic maps, variable field extension arises per r wherein the variable value of the basis function is significantly increased.

To satisfy values such as speed, ease of execution, an extension of test dataset, discrete behavior, and reliability, researchers are proposing chaos - based method defined during the next part and, in addition, a set of random key evaluations are implemented regarding the protection of the suggested method for cryptography algorithms.

3. LONG SHORT TERM MEMORY (LSTM) NEURAL NETWORK

The LSTM neural network, a specific kind of ANNs, that includes its performance in analyzing stochastic feature vectors has a good capacity to manage long-term and short-term dependence issues, also can retain associated ad-hoc information, and thereby monitor long-term information. The sensor node which covers the secret structures of traditional neurons is the origin of the LSTM neural network [25]. The LSTM may preserve specific knowledge which will greatly enhance its capacity to recognize frequency variations and non - linearity approach taken in it. Based on the inputs, the LSTM sensor node may recognize or ignore some activation function. The layer is protected by the security checkpoint of the entry, the cell of the output, and the security fence. The LSTM neural network will adjust memory cell condition knowledge from these gates [26]. Such arrangement helps the LSTM to predict that neurons will eliminate which layers will be stimulated similar to the previous condition, existing data, and existing storage. Thus the structure of the LSTM neural network as seen in Figure 1 accurately solves the gradient-fading issue ensuring that the artificial neural network can recognize long-range information [27].

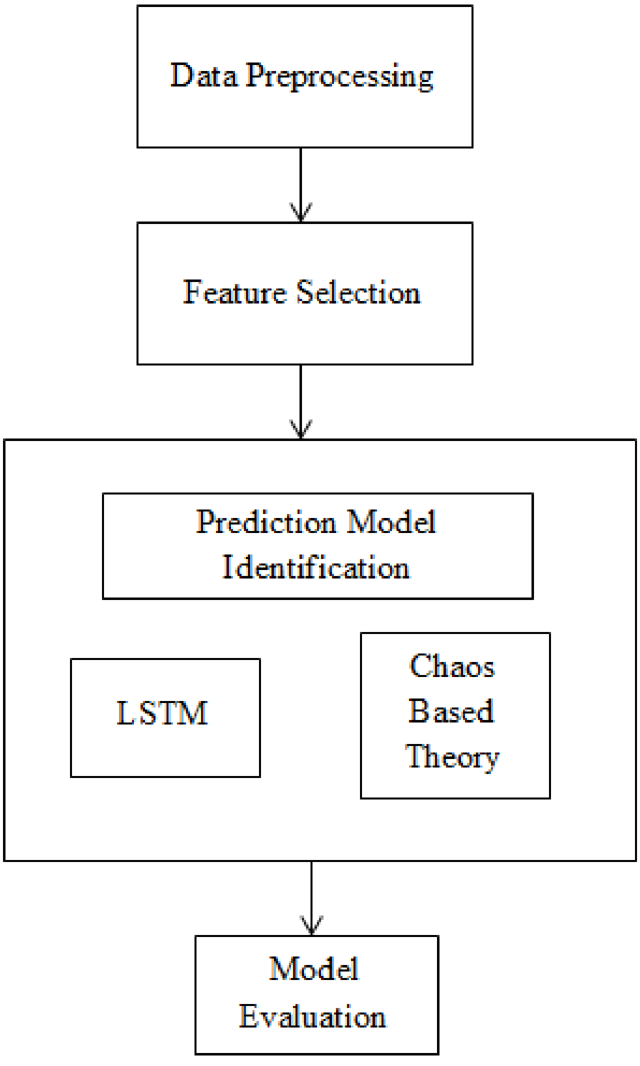

Figure 1. The Framework of Hybrid LSTM-Chaos-based Crypto Currency Prediction Model

In LSTM neural network design the input parameters are combined by the output of the activation function to classify existing knowledge that could be collected to the node. The test results for the system are compounded by the stimulation of the output neuron to determine the knowledge that could be transmitted to the device. To decide if the cell's final condition will be ignored the last period cell conditions are determined by the ignored gate activation [28]. The LSTM proceeding [29] is as follows:

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental studies with data from BTC, XRP, DASH, and LTC cryptocurrencies are being provided in this study to illustrate the predictive efficiency of the new hybrid LSTM-CTS cryptocurrency prediction models. The simulation results are being analyzed in this section in research with the outcomes of the various researches. The result of the CTS evolutionary algorithms on the prediction models for the cryptocurrency was also examined.

5. CRYPTOCURRENCY DATASETS

For this analysis data sets were used for BTC, XRP, DASH, and LTC cryptocurrencies representing real values in currency. The existence of software each including a million findings or strong visibility plays a significant factor in the collection of such basic cryptocurrencies. Consequently, such 3 cryptocurrencies were chosen to evaluate the research observations of the cryptocurrency prediction models that are often included in the existing literature. Data from 18th July 2010 to 28th March 2019 for the Bitcoin were used in the data series comprising industry stakeholders in Currencies, 22nd January 2015 to 28th March 2019 for the Ripple and 14th February 2014 to 28th March 2019 for Digital Cash.

Therefore, the duration of the logistic regression comprises 3000 samples for Bitcoin, 1500 samples for Ripple, and 1800 samples for Digital Cash. Every collection of time series crypto-currency data used in the analysis is divided into two subsets as training and test sets. The initial 70 percent of the time series data on cryptocurrencies were used for training purposes, while the other 30 percent were used for testing. The estimate of LLE and DFA defined based on the extraction HE was used in all training and testing sub-samples to examine fractality, intrinsic chaoticity and so many other nonlinear features over all periods. A few statistical values are given in table 1 for data analysis of four cryptocurrencies datasets, namely minimum, average, mean, and standard deviation.

Table 1. Statistical results of the three datasets used during the analysis for data sampling on cryptocurrencies

Training Sets (70%)				
Datasets	Min	Average	Mean	Std. Deviation
Bit-Coin	0.09	1.5	0.6	1.33
Ripple	0.34	2.7	0.1	0.38
Digital Cash	0.29	1.4	0.7	2.3

(a) Training Datasets

Testing Sets (30%)				
Datasets	Min	Average	Mean	Std. Deviation
Bit-Coin	3.4	1.76	7.4	3.2
Ripple	2.8	0.5	3.9	8.1
Digital Cash	4.1	2.3	1.8	6.3

(b) Testing Datasets

The approximate LLE and DFA results based on the HE extracts are presented in table 2 for the training and testing of data sets of every cryptocurrency. The LLE estimates of the three different cryptocurrencies time series used in the analysis for the preparation and evaluation data sets are true and false, separately. The exchange rate survey used in the cryptocurrency logistic regression training process shows chaotic dynamics, whereas the testing process indicates consolidation with traditional convergences. Furthermore, these approximate HE results represent that three different cryptocurrencies provide long-term memory properties.

Table 2. Error criteria for hybrid configuration of three Cryptocurrencies

	Error Metrics		
Datasets	**LSTM**	**Chaotic**	**LSTM-CTS**
Bitcoin	498.1	568.3	350.7
Ripple	256.8	277.6	153
Digital Cash	110.6	178.9	249

To the researcher's knowledge, this study aims to contribute to evaluating cryptocurrency prices using deep learning, along with the technique of analysis and enhancement classifier. Compared to Lahmiri and Bekiros [28], this study shows that the Mean average results for BitCoin, Ripple, and Digital Cash were increased by 73.1 percent, 85.3 percent, and 90.4 percent, respectively, with the proposed hybrid cryptocurrency prediction models. Figure 2 shows the Error Metrics of all CryptoCurrency Model. It is important that perhaps the performance of the research methodology for crypto-currency prediction is very adequate as related to the experiments done with deep learning approaches for existing datasets.

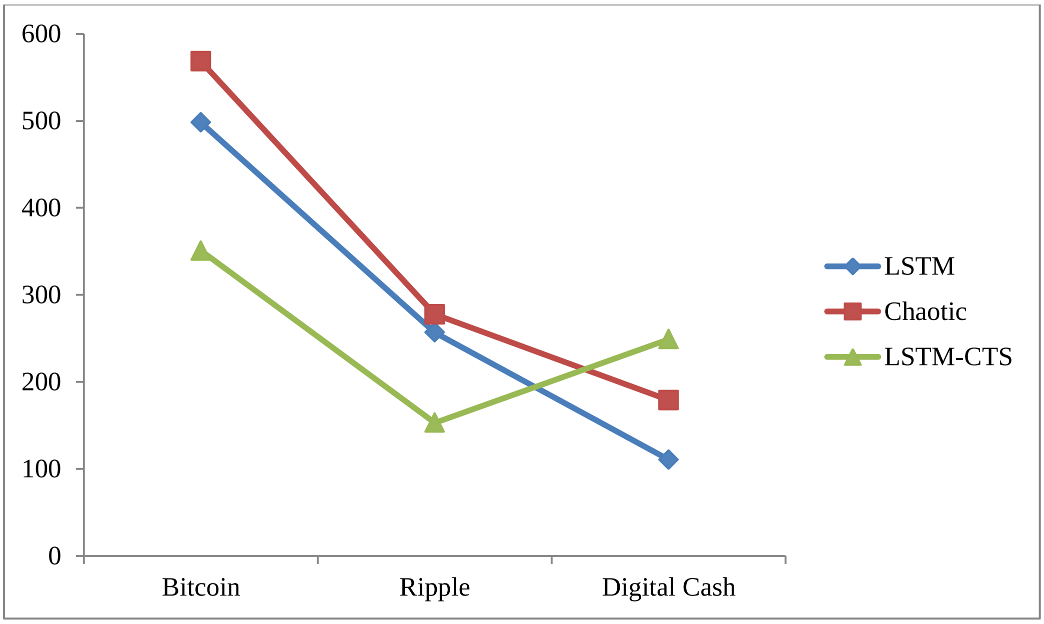

Figure 2. Error Metrics of all CryptoCurrency Model

6. CONCLUSION

It is recognized that crypto-currency prediction of excellent accuracy became quite relevant particularly after the economic crisis of the last decade. Due to non - linear structures that include intrinsic cryptocurrency fractality and chaoticity, it is considered which standard simulations are not possible to maintain extremely accurate cryptocurrencies. The hybrid methods emerge in predicting the cryptocurrency in strategies to survive with the bitcoin exchange time series' constant variance and uncertainties. In this article, researchers suggested a hybrid cryptocurrency prediction model consisting of the process of degradation, deep learning, and meta-heuristic optimization methodology for estimating high precision cryptocurrencies. This study is the only research to predict cryptocurrency values using deep learning, combined with a system of extraction and meta-heuristic optimization method. A hybrid LSTM neural network and Feature extraction removal method together with chaotic optimization algorithm were shown in the research methodology.

The proposed hybrid LSTM-Chaotic cryptocurrency prediction framework was designed by integrating the LSTM neural network system phase with the transaction date and maximizing ANN's expected performance with the Chaos-based evolutionary algorithms. In the standard evaluation stage, the proposed simulation showed only the costs of the three different greatest marketed cryptocurrencies including Bitcoin, Ripple, Digital Cash, and the proposed methodology was evaluated. The research results achieved indicate that the conceptual framework for cryptocurrency prediction is capable of capturing bitcoin exchange data set stochastic advantages. In addition, the analysis shows that the predicting implementation of the hybrid framework is stronger compared to all accurately estimated based on the sample error factors. This research is believed to contribute greatly to predicting the high-performance stability of cryptocurrencies.

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