2021 6th International Conference for Convergence in Technology (I2CT)
Pune, India. Apr 02-04, 2021

QORA-ANN: Quasi Opposition Based Rao Algorithm and Artificial Neural Network for Cryptocurrency Prediction

Ch. Sanjeev Kumar Dash
Computer Science & Engineering
Silicon Institute of Technology,
Silicon Hills, Patia,
Bhubaneswar-751024, Odisha, India
sanjeev_dash@yahoo.com

Ajit Kumar Behera
Department of MCA
Silicon Institute of Technology,
Silicon Hills, Patia,
Bhubaneswar-751024, Odisha, India
ajit_behera@hotmail.com

Sarat Chandra Nayak
Department of Computer science and Engineering,
CMR College of Engineering & Technology,
Hyderabad – 501401, India,
saratnayak234@gmail.com

Satchidananda Dehuri,
Department of Information and Communication Technology,
Fakir Mohan University,
Vyasa Vihar,
Balasore-756019, Odisha, India.
satchi.lapa@gmail.com

2021 6th International Conference for Convergence in Technology (I2CT) | 978-1-7281-8876-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/I2CT51068.2021.9417870

***Abstract*— The cryptocurrency price movement behaves randomly and fluctuates like other stock markets. Prediction of cryptocurrency is a recent area of research interest and budding fast. The underlying nonlinearities in its price series make its prediction challenging. Sophisticated methodologies for accurate prediction of cryptocurrency are highly desired. Artificial neural networks (ANNs) are good approximators, however their accuracy is greatly subjective to optimal network structure and learning method. This article designs optimal ANNs for efficient cryptocurrency prediction using quasi opposition based Rao algorithms, i.e. QORA-ANN. The model explores a set of potential ANNs in the search space and lands at an optimal network through the evolving process. Historical data from four emerging cryptocurrencies such as Bitcoin, Litecoin, Ethereum, and Ripple are used to evaluate the QORA-ANN. The prediction ability of the proposed approach is compared with few similar methods such as ANN trained with genetic algorithm, differential evolution and particle swarm optimization (i.e. ANN-GA, ANN-DE, ANN-PSO), support vector machine (SVM), and multilayer perceptron (MLP). From exhaustive simulation studies and comparative result analysis it is found that the QORA-ANN method performed better than others and hence can be suggested as an efficient tool for cryptocurrencies prediction.**

Keywords—Cryptocurrency,ANN,Rao algorithms, opposition based learning, Bitcoin, genetic algorithm.

I. INTRODUCTION

The concept of cryptocurrency is based on principle of cryptography. It is an open source and decentralized digital currency. The relevance of cryptocurrencies as an emerging market in the financial world is increasing significantly (1). Now-a-days more and more financial organizations are getting concerned about cryptocurrency trading. The trading opportunities and profitability in the cryptocurrency market are studied in (2). A survey on systems of cryptocurrency is elaborated in (3). The characteristics of this market such as high availability of market data, high volatility, smaller capitalization, and decentralized control are studied in (4). This market fluctuates like other stock markets due to inherent volatility and the confidence of investors have been reflected on it (5 – 7). The feasibility of this market in relation to other financial markets is documented in the literature (8, 9). Like other stock market, cryptocurrency market prices behave arbitrarily and coupled with high nonlinearity and dynamics. Though a few computational intelligence methods are available, sophisticated methodologies for accurate prediction of cryptocurrency are still lacking and need to be explored.

As the cryptocurrencies market prices are growing fast and behaves similarly as other stock market price movement, speculators as well as researchers are anxious about prediction of their market values. During last few years machine learning and statistical methodologies are used for prediction of Bitcoin (10 – 16).

Forecasting accuracy of a neural model is greatly subjective to the network magnitude and learning techniques. Gradient descent learning is a common method for neural network training. However, suffering from sluggish convergence rate, imprecise learning and prone to local minima are the general drawbacks of this technique. It adds computational overhead to the model (16). To eradicate this, a good number of swarm and evolutionary optimization techniques are groomed up and heavily used for ANN training. These methods are broadly classified as nature-inspired (17) and bio-inspired computing (18). So far these methods are claimed to be superior than gradient descent based methods in terms of landing at global minima with faster convergence. Mainly, their efficiency is determined by well adjusting few learning parameters and choosing optimal learning parameters for any particular problem requires numbers of trial and error methods. Improper selection of algorithm-specific parameters may land the search operation at local optima or inaccurate solutions. Quasi oppositional based Rao algorithm is recently proposed and is claimed to be simple as well as parameter free algorithm (19).

This article attempts to observe the efficacy of quasi oppositional based Rao algorithms (QORA) on searching the most favorable neural architecture, thus forming a hybrid model called ANN+QORA. The hybrid model is then used to extrapolate the historical prices of the four cryptocurrency and predict the next day price. Contrast to conventional method of segregating the dataset into two parts (i.e. training and testing), we followed a moving window method for train and test pattern generation. To assess the performance of the proposed model, five other models such as ANN+GA, ANN+DE, ANN+PSO, SVM, and MLP are developed in similar fashion. Prediction accuracies of all the methods are assessed in terms of MAPE, ARV, and computation times from four cryptocurrency datasets.

The remaining parts such as methods and materials are described in Section 2, the ANN+QORA based forecasting is described in Section 3, and simulation results are summarized in Section 4 followed by concluding remarks.

II. BACKGROUND METHODS

In this section, we discuss ANN and quasi oppositional based Rao algorithm as background methods.

A. *Artificial neural network*

ANN visualization with only one hidden layer is depicted in Figure 1. The first layer receives the inputs $x_1, x_2, ..., x_3$ and forwards to the hidden layer. The j^{th} hidden neurons calculate the product of input and associated weight adds a bias and applies an activation to compute the net output as follows.

$$a_i = \sigma(\sum_{i=1}^{n}(w_{j,i} * x_i) + b) \tag{1}$$

The output unit computes the product of weights and activations from the hidden units adds a bias and applied activation as in (2). The model estimated an output $(\hat{y})$ at the output layer. An error value is computed by comparing estimated and actual. The error function is back propagated to adjust the network parameters based on gradient descent rule.

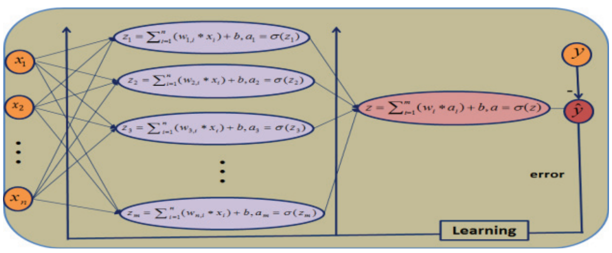

Fig. 1. ANN visualization with only one hidden layer

$$\hat{y} = \sigma(\sum_{i=1}^{m}(a_i * w_i) + b) \tag{2}$$

$$\text{error} = \text{abs}(\text{actual} - \hat{y}) \tag{3}$$

B. *Quasi oppositional based Rao algorithm*

QORA is recently proposed population based optimization algorithms. It incorporates the concept of opposition based learning in the Rao algorithms in order to diversify the search space and enhance convergence speed (19). Unlike other nature-inspired optimization techniques these are not mimicking the behavior of swarms, animals, birds, any physical or chemical phenomenon. Therefore it is claimed as metaphor-less optimization techniques by the inventor. Any algorithm specific parameters are not required by these algorithms. Only specifying the number of candidate solutions, design variables and termination criteria is sufficient to automate the search process. The techniques are simple, do not necessitate human intervention and provide effective solutions to complicated problems. The high level algorithm is presented as in Figure 2. For more details prospective authors are suggested to read the base article in (20). QORA works on identifying best and worst solution and interaction between contestants in the search space,. The lack of algorithm specific parameters eliminates any human interventions.

Let $f(w)$ is an objective function need to be optimized (i.e. the error function to be minimized here). Let the population has n number of candidate solutions each of which has m number of design variables. Each candidate solution has a fitness value (i.e. error value) and lower the error signal better is the solution. At any iteration i, let the best and worst solution of the population are $f(w)_{best}$ and $f(w)_{worst}$ respectively. The current value of a candidate solution at i^{th} iteration is updated as per the following equations.

$$W'_{j,k,i} = W_{j,k,i} + rand_{1,j,i} * (W_{j,best,i} - W_{j,worst,i}) \tag{4}$$

$$W'_{j,k,i} = W_{j,k,i} + rand_{1,j,i} * (W_{j,best,i} - W_{j,worst,i}) + rand_{2,j,i} * (|W_{j,k,i} or W_{j,l,i}| - |W_{j,l,i} or W_{j,k,i}|) \tag{5}$$

$$W'_{j,k,i} = W_{j,k,i} + rand_{1,j,i} * (W_{j,best,i} - |W_{j,worst,i}|) + rand_{2,j,i} * (|W_{j,k,i} or W_{j,l,i}| - W_{j,l,i} or W_{j,k,i}) \tag{6}$$

Where

$W_{j,k,i}$ = the value of j^{th} variable of variable of k^{th} solution $(k = 1, 2, 3, ..., n)$ at i^{th} iteration.

$W'_{j,k,i}$ = the modified value of j^{th} variable of k^{th} solution $(k = 1, 2, 3, ..., n)$ at i^{th} iteration.

$W_{j,best,i}$ = j^{th} variable value of the best solution in i^{th} iteration.

$W_{j,worst,i}$ = j^{th} variable value of the *worst* solution i^{th} iteration.

$rand_{1,j,i}$ and $rand_{2,j,i}$ are two random values in $[0,1]$.

The term "$W_{j,k,i}$ or $W_{j,l,i}$ "in Eq.5 and 6 represents the fitness comparison of k^{th} candidate solution with that of l^{th} solution which is randomly drawn from the population. An information exchange occurs based on their fitness values. This ensures the communication among the candidate solutions. To improve the rate of convergence and diversify the search process, the concept of opposition-based learning is incorporated in Rao algorithms (20). In each iteration a population opposite to the current population is generated. A quasi opposite solution $W^{q}{}_{j,k,i}$ is generated considering center of the search space (let *a*), opposite value of $W_{j,k,i}$ (let b), lower limit of j^{th} variable $(W_j{}^L)$ and upper limit of j^{th} variable (W_j^U) as:

$$W^{a}{}_{j,k,i} = rand(a,b) \tag{7}$$

$$a = \frac{w_j{}^L + W_j{}^U}{2} \tag{8}$$

$$b = W_j{}^L + W_j{}^U - W_{j,k,i} \tag{9}$$

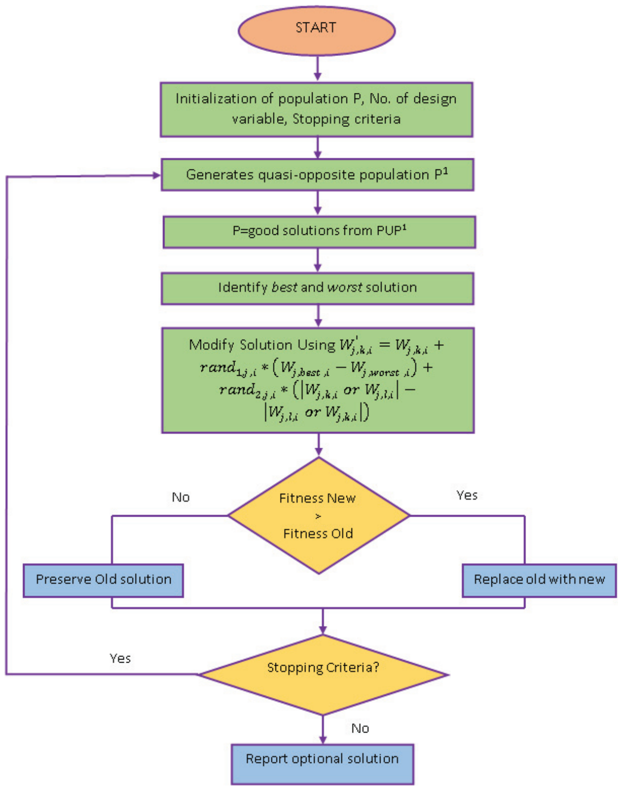

Fig. 2. Flow of QORA

C. *ANN+QORA Based Forecasting*

Here we discuss the proposed hybrid ANN+QORA method. The *(n X m X 1)* ANN shown in Figure 1 is used as the base model. The optimal number of input for the model is decided by a sliding window method. The number of input neurons (i.e., n) is equal to the window size. Since we are going to predict a single value for a given *n* inputs, the output layer size is fixed to one.

The hidden layer size is decided experimentally. For a given input vector $(x_1, x_2, \ldots, x_n)$ and corresponding target (y), an error signal is calculated at the output layer against the associated weight and bias vector $(w_{11}, w_{12}, \ldots, w_{1n}, \ldots, w_{mn})$. The objective is to find the optimal weight and bias vector with minimal error. We used QORA here to search the optimal weight and bias for the given ANN. An initial population of QORA (i.e., P_1) contains a set of potential solutions where each solution can be viewed as a set of possible weight and bias values. The quasi opposite population P_2 is generated from P1 using Eq.7. As the convergence rate of a population based optimization method depends on the quality of initial population, it is better to start the process with some more fit solution pool. The QORA considers both initial population P_1 and quasi opposite population P_2 to extract a near optimal population P. Then it apply any search operator (i.e., Eq.4, 5, or 6) to fine tune the search process. In successive iterations, the process lands at the global minima, i. e., optimal weight and bias vector of ANN. A pictorial view of ANN+QORA is depicted in Figure 3.

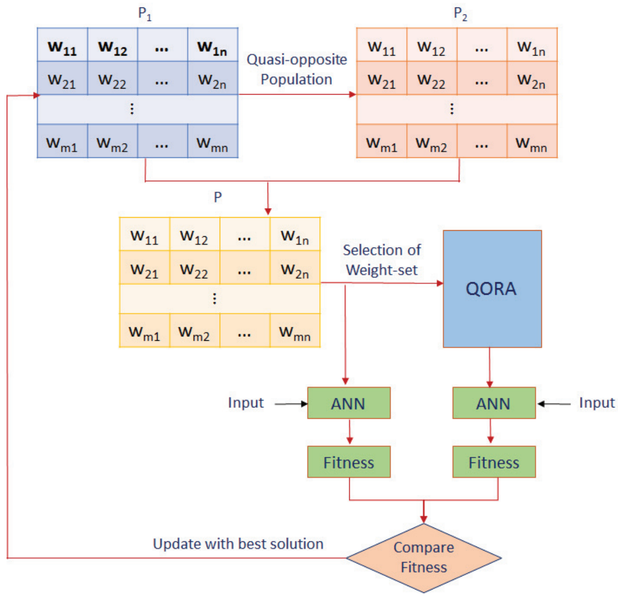

Fig. 3. QORA-ANN Training

D. *The Data*

The models are evaluated on experimenting cryptocurrencies historical closing prices collected from kaggle.com. The currencies are Bitcoin,Litecoin, Ethereum, and Ripple. A summary of statistics of the four datasets are given in Table 1. The total number of data points on the Bitcoin, Litecoin, Ethereum, and Ripple are 1760, 1760, 929, and 1662 respectively.

TABLE I. STATISTICAL SUMMARY OF BITCOIN, LITECOIN, ETHEREUM, AND RIPPLE

Statistic	***Bitcoin***	***Litecoin***	***Ethereum***	***Ripple***
Minimum	68.4300	1.1600	0.4348	0.0028
Mean	1.4857e+03	20.4966	147.7843	0.0984
Median	482.8100	3.9100	12.0200	0.0079
Variance	8.7573e+06	2.2240e+03	6.9765e+04	0.1028
Maximum	1.9497e+04	358.3400	1.3964e+03	3.3800
Std.dev.	2.9593e+03	47.1594	264.1308	0.3206
Skewness	3.5394	4.1627	2.3844	5.8039
Kurtosis	15.9671	21.5925	8.5122	42.9469
Correlation coeff.	0.00130	0.00211	-0.0052	0.0027
No. of prices	1760	1760	929	1662

E. Experimental Results and Analysis

To evaluate QORA-ANN, four cryptocurrency datasets are used separately for prediction. To access the capacity of the QORA-ANN, five other methods such as ANN-GA, ANN-DE, ANN-PSO, SVM, and MLP are developed in this study and a comparison is done. Two performance metrics such as mean absolute percentage of error (MAPE), and average relative variance (ARV) are used to measure the forecast accuracy as in (8) and (9). All the experiments are carried out in MATLAB-2015 environment, with Intel ® core TM i3 CPU, 2.27 GHz processing and 2.42 GB memory size. The mean values from fifty simulations are considered as the performance of a model. The MAPE and ARV values are summarized in Table 2. The best statistics are highlighted in bold. It may be seen that the MAPE values from the QORA+ANN are lower than others. For an instance, MAPE of QORA+ANN is 0.032275 from Bitcoin, 0.043988 from Litecoin, and 0.051363 from Ethereum. It achieved lowest MAPE as well as ARV thrice. Further, to show the goodness of the QORA-ANN the predicted prices are plotted against the actual and depicted in Figure 4 - 7 respectively. It can be seen that the proposed model predicted prices are very closer to the actual prices and following the trend accurately.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{x_i - \overline{x}_i}{x_i} \times 100\% \tag{10}$$

$$ARV = \frac{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2}{\sum_{i=1}^{N}(\hat{x}_i - \hat{x})^2} \tag{11}$$

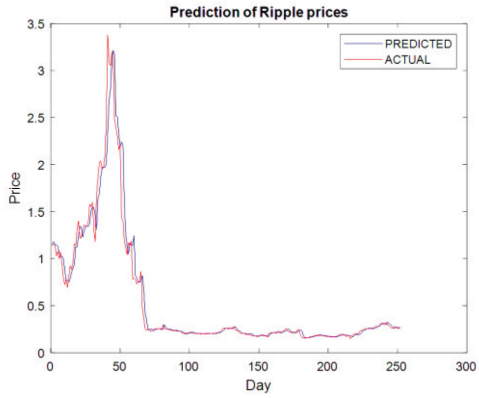

Fig. 4. Prediction of Ripple

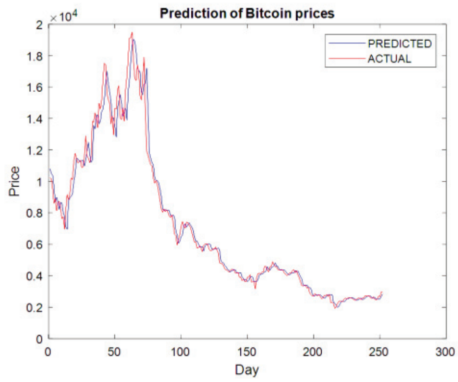

Fig. 5. Prediction of Bitcoin

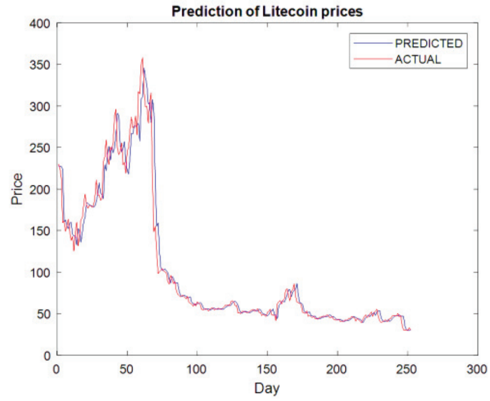

Fig. 6. Prediction of Litecoin

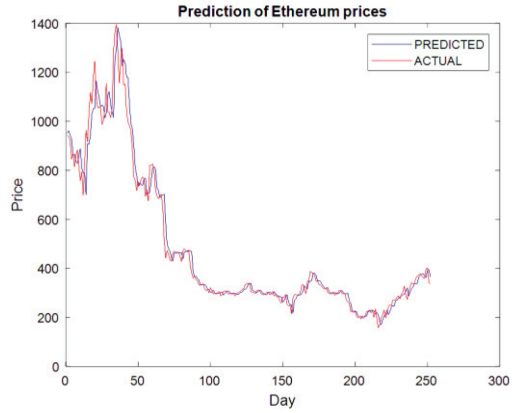

Fig. 7. Prediction of Ethereum

III. CONCLUSION

A hybrid model called ANN+QORA is proposed in this article for effective prediction of cryptocurrencies. The QORA is used to search the most feasible parameters of ANN of single hidden layer. The method explores a set of potential ANNs in the search space and lands at an optimal network through the evolving process. Historical data from four emerging cryptocurrencies such as Bitcoin, Litecoin, Ethereum, and Ripple are used to evaluate the proposed model. The faster convergence rate and parameter free characteristics of QORA helped to achieve the optimal ANN structure and better prediction accuracy of the resultant model. The outcomes from the comparative performance study suggested the superior performance of ANN+QORA based forecasting. The proposed method can be investigated in other problems of predictive analysis.

REFERENCES

[1] S. Corbet, B. Lucey, A. Urquhart, and L. Yarovaya," Cryptocurrencies as a financial asset: A systematic analysis. International Review of Financial Analysis", vol.62, pp.182-199, 2019.

[2] N. A. Kyriazis, "A survey on efficiency and profitable trading opportunities in cryptocurrency markets". Journal of Risk and Financial Management 12, 67, 2019.

[3] U. Mukhopadhyay, A. Skjellum, , O. Hambolu, J. Oakley, L. Yu, R. Brooks, "A brief survey of cryptocurrency systems", in: 2016 14th annual conference on privacy, security and trust (PST), IEEE. pp. 745–752, 2016.

[4] M. Ferreira, S. Rodrigues, C.I. Reis, M. Maximiano, "Blockchain:A Tale of Two Applications". Appl. Sci. , vol.8, pp.1506, 2018.

[5] R. Grinberg Bitcoin: "An innovative alternative digital currency". Hastings Science and Technology Law Journal. Vol-4,pp. 160–207,2011.

[6] F. Mai, et al., "How does social media impact bitcoin value? a test of the silent majority hypothesis", J. Manage. Inf. Syst. 35 (1), pp.19–52, 2018.

[7] S. Sapuric, A. Kokkinaki "Bitcoin is volatile! Isn't that right? Business Information Systems Workshops", Lecture Notes in Business Information Processing , pp. 255–265, 2014.

[8] A. Corelli, "Cryptocurrencies and Exchange Rates: A Relationship and Causality Analysis". Risks, vol. 6, pp.111, 2018.

[9] N. Trabelsi, "Are There Any Volatility Spill-Over Effects among Cryptocurrencies and Widely Traded Asset Classes?" J. Risk Financ. Manag. 11, 66, 2018.

[10] J. Chu, S. Nadarajah and S. Chan, "Statistical analysis of the exchange rate of bitcoin". PloS one, 10(7), 2015.

[11] J. A. Núñez, M. I. Contreras-Valdez, and C. A. Franco-Ruiz, "Statistical analysis of bitcoin during explosive behavior periods". PloS one, 14(3), 2019.

[12] L. Alessandretti, A. ElBahrawy, , L. M Aiello, and A. Baronchelli, "Anticipating cryptocurrency prices using machine learning". Complexity, 2018.

[13] S. McNally, J. Roche, S. Caton, "Predicting the Price of Bitcoin Using Machine Learning". In Proceedings of the 2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing(PDP), Cambridge, UK, 21–23; pp. 339–343, March 2018.

[14] M. Nakano, A. Takahashi,; S. Takahashi, "Bitcoin technical trading with artificial neural network". Phys. A Stat. Mech. Appl. Vol.510, pp.587–609, 2018.

[15] J. Rebane, I. Karlsson,; S. Denic, P. Papapetrou, "Seq2Seq RNNs and ARIMA models for Cryptocurrency Prediction: A Comparative Study". In Proceedings of the KDD Data Science in Fintech Workshop, London, UK, 20 August 2018.

[16] F. Fernández-Navarro, C. Hervás-Martínez, R. Ruiz, and J. C. Riquelme, "Evolutionary generalized radial basis function neural networks for improving prediction accuracy in gene classification using feature selection. Applied Soft Computing, 12(6), 1787-1800.

[17] X. S. Yang, "Nature-inspired optimization algorithms: challenges and open problems". Journal of Computational Science, 101104, 2020.

[18] D. Molina, J. Poyatos, J. Del Ser and S. García, A. Hussain, and F. Herrera, "Comprehensive Taxonomies of Nature-and Bio-inspired Optimization: Inspiration versus Algorithmic Behavior, Critical Analysis and Recommendations". arXiv preprint arXiv:2002.08136, 2020.

[19] R. V. Rao, and R. B. Pawar, "Quasi-oppositional-based Rao algorithms for multi-objective design optimization of selected heat sinks". Journal of Computational Design and Engineering, 2020.