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Hybrid Optimal Time Series Modeling for Cryptocurrency Price Prediction: Feature Selection, Structure and Hyperparameter Optimization

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Abstract
The prime aim of the research is to forecast the future value of Bitcoin which is commonly known as a pioneer of the Cryptocurrency market by constructing a hybrid structure over the time series. In this perspective, two separate hybrid structures were created by using Artificial Neural Network (ANN) together with Genetic Algorithm (GA) and Particle Swarm Optimization Algorithm (PSO). By using the hybrid structures created, both the network model and the hyperparameters in the network structure, together with the time intervals of the daily closing prices and how much data should be taken retrospectively, were optimized. Employing the created GA-ANN (DCP1) and PSO-ANN (DCP2) hybrid structures and the 721-day Bitcoin series, the goal of accurately predicting the values that Bitcoin will receive has been achieved. According to the comparative results obtained in line with the stated objectives and targets, it has been determined that the structure obtained with the DCP1 hybrid model has a success rate of 99% and 97.54% in training and validation, respectively. It should also, be underlined that the DCP1 model showed 47% better results than the DCP2 hybrid model. With the proposed hybrid structure, the network parameters and network model that should be used in the ANN network structure are optimized in order to obtain more efficient results in cryptocurrency price forecasting, while optimizing which input data should be used in terms of frequency and closing price to be chosen.

1. Introduction

Digital financial assets are becoming increasingly important in today's digital economy [1]. Cryptocurrencies are particularly notable for their short-term volatility and price fluctuations. Therefore, it is crucial to develop accurate and reliable forecasting approaches [2]. It is possible to express cryptocurrencies, which are one of the last rings of globalization and which have started to appear in the financial context, in the form of digitally encrypted number sequences [3]. In other words, cryptocurrencies are digital or virtual currencies that use cryptography for security. Because of this cryptography feature, a cryptocurrency is difficult to fake [4]. In addition, cryptocurrencies have the feature of being a distributed system because they are not dependent on a central authority [5]. The crypto market is becoming increasingly in demand as investors adopt it to diversify their portfolios.

The cryptocurrency market has evolved through various market cycles and bull-bear runs, public interest, technological advancements in Blockchain, speculation and adoption phases, among other natural processes. As market phases evolve, pricing factors that influenced one phase of the market no longer apply to the next phase, creating anxiety among investors looking to buy on dips or sell at a profit [6]. It is therefore difficult to predict cryptocurrency prices due to price fluctuations and instability. This gap in the field is

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filled by comparing various machine learning models to predict the market movements of Bitcoin, the most relevant cryptocurrency [6].

The terms Artificial Intelligence (AI), Machine Learning, and Deep Learning have become common and popular concepts in almost every industry [7] [8] [9]. The financial sector, as expected, is playing a leading role in integrating AI technologies into its operations. In recent years, more and more research and studies have been published on machine learning models for time series forecasting. Most of these studies point out that newer machine-learning models outperform traditional time series forecasting methods [10]. When we look at the studies on cryptocurrency price prediction in the literature: Zhou et al. [11] performed a multi-source data-driven cryptocurrency price prediction in their study. Support Vector Machines and global minimum variance models were used in the study. The findings show that the proposed model produces successful results in cryptocurrency price prediction.

Rashid and Ismail [12] used linear regression methods with the Minimum Akaike Information Criterion, quadratic trend and exponential trend for forecasting cryptocurrency prices. The study examined the trend of prices with deterministic methods by drawing graphs based on residual trend and diagnostic statistics control. The results showed that the methods used were successful in predicting cryptocurrency prices.

Mariappan et al. [13] used reinforcement learning for cryptocurrency price forecasting. Multi-Layer Perception (MLP) and The Long Short-Term Memory (LSTM) are used in the forecasting process over time series. In light of the findings, the proposed method is more successful than the comparative results with different technology strategies.

Murray et al. [14], presented an approach with Deep Learning for the prediction of cryptocurrency prices. In this study, five popular cryptocurrency prices were predicted with LSTM and successful results were obtained.

Nayak et al. [15] used Random Vector Functional Link Networks (RVFLN) for cryptocurrency price forecasting. They proposed an elitist artificial electric field algorithm (eAEFA) for RVFLN training. In the study where eAEFA + RVFLN model was proposed, ML methods such as MLP, SVM, LSTM were applied and comparative results were obtained with the proposed model. The results show that the proposed hybrid method produces more successful results than other ML methods.

Shang et al. [2] proposed a reconstructed dynamic-bound Levenberg-Marquardt neural network approach for cryptocurrency price forecasting. ML methods such as LM-Neural Networks, Artificial Neural Networks (ANN), LSTM, and CNN were also used in the study. The results show that the proposed method produces more successful results than other ML methods.

Hawi et al. [16] used three different ML methods, namely K-Nearest Neighbor, SVM, and Light Gradient Augmented Machine (LGBM), to predict cryptocurrencies. In the experimental studies conducted in two stages, successful results were obtained with KNN in the first stage and SVM in the second stage.

Ateeq et al. [17] used the LSTM model for bitcoin price prediction. In this study, minute, hourly, daily, weekly, weekly and monthly models were extracted. In the forecasting process in these different time periods, which are put forward as different models, there is no differentiation as a model other than the temporal difference. In the study where only input variables were differentiated, successful results were obtained in Bitcoin price prediction with LSTM.

Alarab and Prakoonwit [18] develop a classification model that combines long short-term memory with a GCN, called temporal-GCN, that classifies illegal transactions of elliptical data using only the characteristics of the transaction, in an active learning framework applied to a large-scale Bitcoin transaction graph dataset. As a result, it is claimed that the temporal-GCN model achieves significant success compared to previous studies with the same experimental settings on the same dataset.

Aziz et al. [19] created a model based on the Light Gradient Boosting Machine (LGBM) approach in this article in order to precisely detect fraudulent transactions. The Euclidean distance structured estimation technique is used by the modified LGBM model to optimize the Light GBM parameters. In a restricted manner, it also looks into the effectiveness of some well-known models, including ADAboost, k-Nearest Neighbors (KNN), Random Forest (RF), Multilayer Perceptron (MLP), Logistic Regression, XGBoost, and Support Vector Classification (SVC).

Li [20] focuses on utilizing CNN, LightGBM, and LSTM models to forecast the real volatility of stocks using a Kaggle data set. A thorough examination of the performance

comparison between the three models is provided by the research. Following experiments with the chosen dataset, it is discovered that LGBM performs better when it comes to short-term stock volatility predictions.

Kazeminia et al. [21] employed a novel hybrid 2D-CNNLSTM model with OPTUNA hyperparameter adjustment to forecast the closing price of Bitcoin based on historical data. In terms of R2 and MAPE, the suggested model performs better than other popular algorithms like CNN, LSTM, and GRU.

ML methods contain different hyperparameters. The differences in these hyperparameters directly affect the performance of the models used. In structures with the same hyperparameters, different input parameters produce different results. In the literature on cryptocurrency price prediction, models and studies on both feature selection and optimization of hyperparameters according to these features are very insufficient

ML methods involve different hyperparameters. Differences in these hyperparameters directly affect the performance of the models used. Different input parameters produce different results in structures with the same hyperparameters. In the literature on cryptocurrency price prediction, models and studies on both feature selection and optimization of hyperparameters according to these features are quite insufficient [22]. In the proposed study, unlike the studies in the literature, all parameters and architectural structures in the architecture targeted to be used for bitcoin price prediction are optimized with different optimization algorithms. This feature enables the model to create more complex architectures. In this context, the aim of this paper is:

- To achieve a high rate of success in bitcoin price prediction.
- To optimize both the hyperparameters and the architecture of the proposed ML method and to determine the appropriate input parameters of the structure with these optimized hyperparameters and architecture.
- To take advantage of the capabilities of both ANN and optimization algorithms.

For this purpose:

- A dataset was prepared with bitcoin price information between January 21, 2019 and January 20, 2021.
- Using the Genetic Algorithm and Particle Swarm Optimization Algorithm, 2 different hybrid models were created to optimize the input values of the model to be created, as well as to optimize all the parameters and architectural structure of the ANN structure based on time series prediction.
- The results of the experimental studies on the dataset are presented in a controversial manner.

The study's plan is outlined as follows: The next section will provide an explanation of the methods employed in the study. Subsequently, the experimental studies will be detailed, and the results will be discussed in the following section. The final section will summarize the results and delve into the discussion of future work.

2. Material Methods

In this part of the study, ANN, GA, and Particle Swarm Optimization methods, which are used for the purpose of predicting Bitcoin price movements, are mentioned in detail.

2.1. Artificial Neural Network

ANN represents a mathematical model of the events that occur in nerve cells in the brain of living things [23]. In these neural networks formed by the combination of neurons, each neuron is modeled as shown in Figure 1.

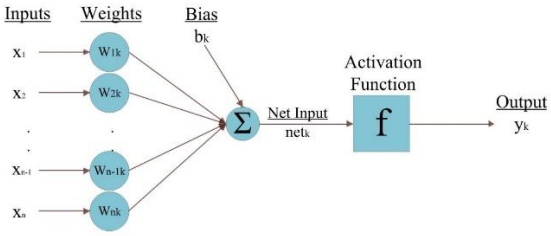


Figure 1. A single-neuron cell structure

In the single-neuron cell structure presented in Figure 1, the information that comes to the neuron as input data is multiplied by the weights and sent to the addition function. After the obtained values are combined with each other, these data collected with the bias value, which is determined by the network structure and provides the translation of the activation function used in the neuron, constitutes the net input for the neuron cell. The resulting net input value is passed through the activation function in the neuron, and the net output

value for that neuron cell is obtained from the input data.

An ANN network structure consists of many neuron cells coming together. These networks formed by neurons can be divided into different groups in terms of sequence and functioning [24]. One of the network models frequently used in the literature is feedforward and backpropagation networks [25]. A multilayer feedforward and backpropagation ANN structure is shown in Figure 2.

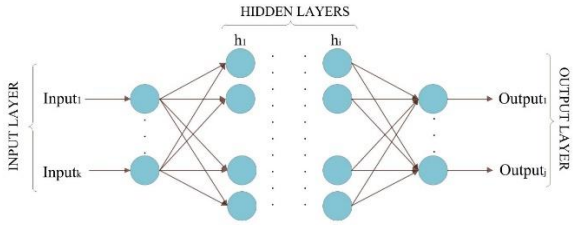


Figure 2. Structure of a simple feedforward backpropagation ANN

In Figure 2, the input information given to the network from the input layer is transmitted forward along the network by each neuron cell. ANN is capable of learning relationships by training data and predicting new data [26]. In this process, error detection is performed for each neuron cell in the last step. Weight information contained in neurons is changed during backpropagation. Hidden layer errors are determined and these errors are returned to neuron cells. Thus, the performance of the network is tried to be improved.

2.2. Genetic Algorithm

GA is an optimization method [27] that uses population-based and heuristics search to replicate the natural evolutionary process of humans. When we compare the GA with the traditional optimization algorithms, it is seen that better optimization results can usually be obtained faster [28]. The steps of GA are as follows [29]:

1. Initialize algorithms parameters.
2. s_sel selection probability, r_cross crossover rate, r_mut mutation, t_iter number of iterations, n_pop number of individuals in a population.
3. Initialize population with random values in accepted range.
4. Calculate the fitness value of individuals.
5. Selection.
6. Crossover.
7. Mutation.
8. Repeat(4.) t_iter.

The GA uses an initial population to find a quality solution within the solution space. Within the solution space formed by the values to be optimized, random solutions are first generated. These solutions form the population in the algorithm. Each solution in the population is called an individual. The algorithm applies different strategies to produce more resilient individuals from these individuals. The probability of individuals surviving to the next generation increases according to the quality of the fitness values set for the problem. Individuals are selected with different strategies according to the quality of their fitness values. Crossover and mutation processes are carried out on the selected individuals. With these processes, the individual is directed to better regions in the search space. Each individual is passed on to the next generation [30].

2.3. Particle Swarm Optimization Algorithm

PSO first emerged in a study by Reeves in 1983, using the particle system, and was introduced as an algorithm by Kennedy and Eberhart in 1995 [31]. PSO uses principles of social behavior within its population of particles [32]. The steps of the PSO are described below [31].

1. Initialize the algorithm parameters.
2. n_pop number of individuals in a population, t_iter is the number of iterations.
3. Position particles with random values within the accepted range.
4. Calculate the fitness value of the particles.
5. Determine the best position of the particles (pbest) and the best position of the population (gbest)
6. Calculate the velocity value of each particle and change their position.
7. Update particles best position (pbest) and population best position.
8. Repeat (4.) t_iter.

In PSO, the position of each particle in the population represents a solution for the problem to be optimized. Particles are in motion along the solution space based on the experience of neighboring particles. The best positions (pbest) of the particles placed in random positions in each iteration and the position (gbest) of the particle belonging to the best position in the population are

determined according to their fitness values [31]. The velocity of the particles in each iteration is calculated according to Equation 1.

$$V_{kl}(t+1)=WV_{kl}(t)+c_1 rand(1)(pbest_{kl}(t)-X_{kl}(t))+c_2 rand(1)(gbest_{kl}(t)-X_{kl}(t)) \quad (1)$$

In Equation 1, the W value represents the momentum coefficient. The value of $V_{kl}(t+1)$ represents the speed of particle k in dimension l in iteration t. The value of $pbest_{kl}(t)$ shows the best position of particle k in dimension l in iteration t. Also, the value of $X_{kl}(t)$ represents the position of particle k in dimension l in iteration t. The $gbest_{kl}(t)$ value indicates the best position in the l dimension in the t iteration. The constants c1 and c2 are the learning parameters used to find the best solution. That is, while the c1 constant provides cognitive learning, the c2 constant provides social learning skills [33]. rand(1) takes a random number between 0 and 1 [34]. The positions of the particles in each iteration are provided according to Equation 2. On the other hand, the initial velocity of each particle in the population is determined randomly.

$$X_{kl}(t+1) = X_{kl}(t) + V_{kl}(t+1) \quad (2)$$

2.4. Success Assessment Metrics

To measure the success of the models to be developed for cryptocurrency price prediction, metrics that measure the success of machine learning methods in the literature will be used [35]. These metrics are Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, R2, and the mathematical formulas of these values are shown in Equations 3-6.

$$MAE = \frac{1}{n}\sum_{i=1}^{N} |yi^r - yi^p| \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{N} (yi^r - yi^p)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N} (yi^r - yi^p)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(yi^r - yi^p)^2}{\sum_{i=1}^{N}(yi^r - yi^m)^2} \quad (6)$$

In Equation 3-6, y^r represents the predicted values of the actual values, y^p represents the predicted values and y^m represents the average of the predicted values. These evaluation metrics are used in machine learning to measure the accuracy of predicted values.

3. Models and Results

In this part of the study, hybrid structures of an ANN model that will predict cryptocurrencies (Bitcoin) over time series are created separately with GA and PSO. The number and selection of input values in ANN network structures, the hidden layer used and the number of neurons in these layers, the activation functions used in all neurons in the network and the learning function of the network directly affect the prediction success of the network [36]. It is almost impossible to select the most appropriate parameter values within certain limits with classical methods [37]. Among the networks that can be established, the parameter values that should be used to establish a network that is the most successful or close to the most successful network can only be possible with hybrid structures to be established with optimization algorithms [22].

The models created will optimize the hyperparameters and architecture within the ANN, as well as the number of inputs required for the architecture and the frequency at which data should be received retrospectively. GA and PSO were preferred in this study due to their frequent use in the literature, ease of coding, and successful results [22].

In order to create an ANN network structure with the best performance in cryptocurrency prediction and the most suitable backward input data for this network structure, a hybrid Detection Crypto Price (DCP1) model was created with GA-ANN. The flow chart of the created hybrid structure is shown in Figure 3.

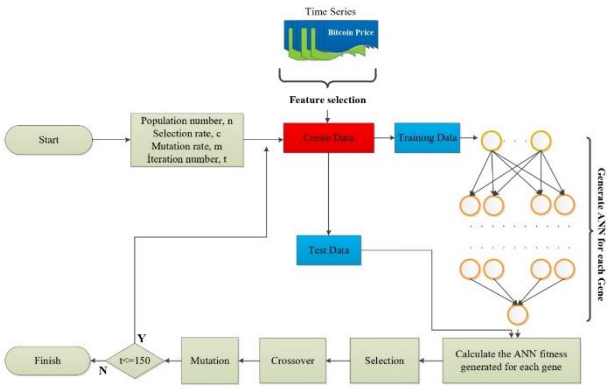


Figure 3. DCP1 hybrid model flowchart

The structure presented in Figure 3 is coded in the MATLAB programming language. The Bitcoin data that is used for training and validation data for the ANN network structure with optimum parameters to the hybrid structure are obtained from January 21, 2019 to January 20,2021 [38]. These data are shown in Figure 4.

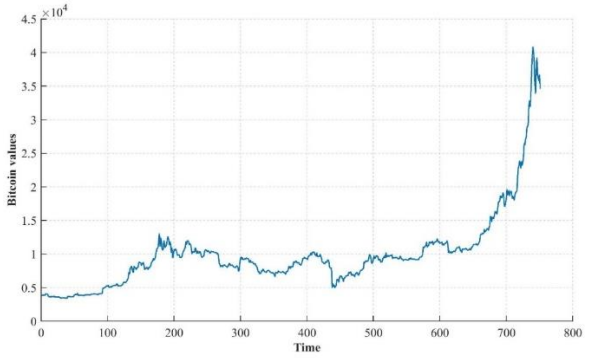


Figure 4. Bitcoin values

Figure 4 shows the graphical representation of the closing value of 756 bitcoins at the daily frequency.

In Figure 3, the initial parameters for GA were determined as shown in Table 1. Parameters presented in Table 1 were obtained as a result of experimental studies.

Table 1. DCP1 hybrid model GA parameters

Genetics Algorithm Parameters	**Values**
Population number (n)	25
Solution Space (D)	6
Selection Rate (c)	0.8
Mutation Rate (m)	0.25
Iteration Number (T)	50

Each individual in the GA will create an ANN within itself. All parameters necessary for each individual to form a network structure constitute the gene sequence. The gene sequence of each individual in the population is shown in Figure 5.

Figure 5. Gene sequencing of the DCP1 hybrid model

In the gene sequence shown in Figure 5, IN denotes the valid number of entries in the ANN to be generated for each individual. TS specifies the time series for the number of entries to be received in a given number of times. Specifies the number of hidden layers in the HLN network structure. HLNN indicates the number of neurons in each hidden layer. ActF refers to the activation function used in each neuron cell. TraF specifies the learning function of the network.

The first step of the presented DCP1 hybrid construct is to generate a random initial population. While creating the population, the parameters included in each gene (G) were determined randomly and limited to the functions presented in Equation 7 - 10.

$$G_iIN_j(x) = \begin{Bmatrix} 1, & x < 1 \\ x, & 1 \le x \le 10 \\ 10, & x > 10 \end{Bmatrix} \quad (7)$$

$$G_iTS_j(y) = \begin{Bmatrix} 1, & y < 1 \\ y, & 1 \le y \le 10 \\ 10, & y > 10 \end{Bmatrix} \quad (8)$$

$$G_iHLN_j(k) = \begin{Bmatrix} 1, & k < 1 \\ k, & 1 \le k \le 10 \\ 10, & k > 20 \end{Bmatrix} \quad (9)$$

$$G_iHLNN_j(s) = \begin{Bmatrix} 1, & s < 1 \\ s, & 1 \le s \le 10 \\ 10, & s > 20 \end{Bmatrix} \quad (10)$$

Given in Equation 7, $G_iIN_j(x)$ is the restriction function used to determine the IN value of gene i in j iteration. Given in Equation 8, $G_iTS_j(y)$ is the restriction function used to determine the TS value of gene i in j iteration . Given in Equation 9 is the $G_iHLN_j(k)$ restriction function used to determine the HLN value of gene i in j iteration . Given in Equation 10 $G_iHLNN_j(s)$, it is the limitation function used to determine the number of neurons in the hidden layers in the j iteration of the i gene. ActF value in each gene sequence is determined randomly from Equation 11 and TraF value from Equation 12.

$$ActF=\left\{\begin{matrix}\text{ttrainbfg, trainbr, traincgb,}\\ \text{traincgf, traincgp, traingd,}\\ \text{traingda, traingdm,traingdx,}\\ \text{trainoss, trainrp, trainscg,}\\ \text{trainb, trainc, trainr}\end{matrix}\right\} \quad (11)$$

$$TraF=\left\{\begin{matrix}\text{tansig, logsig, hardlim,}\\ \text{hardlims, radbas, purelin}\end{matrix}\right\} \quad (12)$$

Equations 7 to 10 are used both for population generation for GA and for mutation operations applied to genes. The next step in the created DCP1 hybrid structure is the input and output values to be created for each gene. Bitcoin in Gen In order to make an estimation of the future value , how many data will be taken before the estimation and how often these data will be taken are in the chromosomes of each gene. Within the framework of the restriction functions, since these values in each gene in the randomly determined population differ, the test and validation data for the ANN network structure created by each gene differ. At this point, input and output values are obtained for each gene according to IN and TS values.

In the population generation step, random chromosomes are generated according to the given constraint functions. Each chromosome contains a unique ANN structure and hyperparameters specific to this structure. In addition, input selection specific to the generated structure is also performed. The number of inputs and the backward time coefficient for each chromosome differ. Thanks to this feature, the model can access many regions of the multidimensional solution space.

In the next step of the proposed DCP1 hybrid construct, the quality of the fitness values of each gene will be determined. The quality of fitness values of each gene in the presented DCP1 model was determined as shown in Equation 13.

$$f(G_i)=MSE(\ ANN_i\ ) \quad (13)$$

In Equation 13, $f(G_i)$ represents the fitness value of the i gene and the $MSE(\ ANN_i\ )$ value calculated according to the test values of the ANN construct created for the ANN_i i gene. The fitness values calculated for each G will be used for the probability of survival in the next generation.

In the network structure created for each G, there are parameters that are not included in the gene and concern the training and testing stages of the network structure. These parameters were determined as shown in Table 2.

Table 2. Parameters in ANN network structure

Other parameters in ANN for each gene	Values
trainParam.epochs	500
trainParam.show	5
trainParam.goal	1e -5
trainParam.lr	0.3
trainParam.mc	0.7
trainparam.min_grad	1e -10

The next step in the DCP1 hybrid structure created is the selection process. There are different strategies in the literature as a selection operator [39]. Since it produces successful results in gene selection, the roulette wheel was chosen as the selection operator in the hybrid structure created with DCP1. In the roulette wheel method, the success of each gene in the fitness function directly affects the survival probability of that gene. The fitness value of each G is calculated as presented in Equation 13. The fitness values of all individuals in the population were cumulatively summed and placed in the roulette wheel in percentages. After this process, a random roulette value between 1-100 was generated and the individual corresponding to the generated value was selected and passed to the next generation.

The next step in the DCP1 hybrid structure created is the crossover process. The genes of the two selected parents are combined to produce new offspring in the crossover process [40]. In this context, a random point was determined on the individuals in the crossover process in DCP1, and crossover was performed over this point.

After this stage, the next step in the DCP1 hybrid structure is the mutation process. The mutation rate given in Table 1 and the restriction functions given in Equation 7 to 10 were taken into account while performing the mutation operation on the genes in the population. With the mutation process, the diversity of genes in the population increases

The generated DCP1 hybrid construct was run for 150 generations as presented in Table 1.

In order to create an ANN network structure with the best performance in estimating cryptocurrencies, a hybrid structure was created with DCP2 secondly. The flow chart of the created hybrid structure is shown in Figure 6.

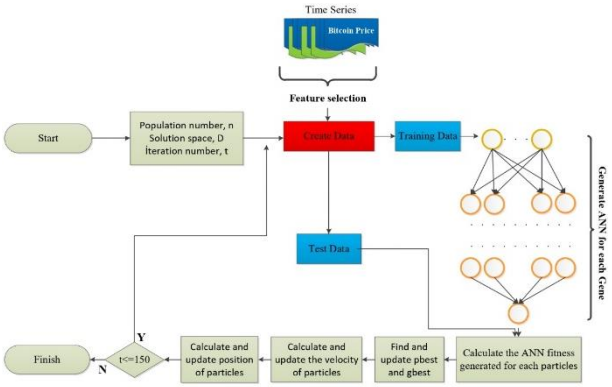


Figure 6. DCP2 hybrid model flowchart

In the flow chart of the DCP2 hybrid structure shown in Figure 6, firstly, the initial parameters for PSO were determined to be able to compare with GA, and this information is presented in Table 3.

Table 3. DCP2 hybrid model PSO parameters

PSO Algorithm parameters	Values
population number (n)	25
Solution Space (D)	6
Iteration Number (T)	50

Each particle in the PSO constitutes an ANN in itself. The network parameter values presented in Figure 5 are included in the structure of each particle.

Initially, a random initial population is created in the created DCP2 hybrid structure, and each particle is determined by the restriction functions used from Equations 7 to 10. In the following stage, pbest and gbest values were calculated in DCP2. The fitness function given in Equation 13 was used to calculate the pbest and gbest values. Since each particle in the population creates an ANN mesh structure in itself and allows a fair comparison with ANN-GA, other parameters in the ANN mesh structure were determined as presented in Table 2.

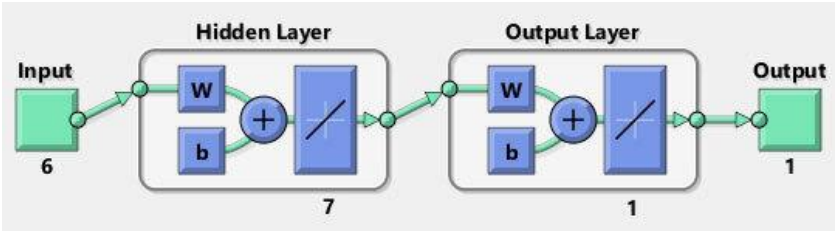
In the next step of DCP2, the velocity values of each particle and accordingly their positions were updated according to Equation 1 and Equation 2, respectively. The W value used in Equation 1 causes changes in the velocity expression. If the value of the W constant is greater than 1, the speed increases with time and the herd diverges in the algorithm. In the case of small values, the global search capability of the algorithm weakens [27]. For this reason, W value is taken as 1. The constants c1 and c2 were randomly determined to add up to about 4 [31]. Finally, the generated DCP2 hybrid construct was run for 150 generations as presented in Table 3.

The parameter values of the most successful gene and the most successful particle obtained as a result of the DCP1 and DCP2 hybrid models created by the experimental studies are shown in Table 4.

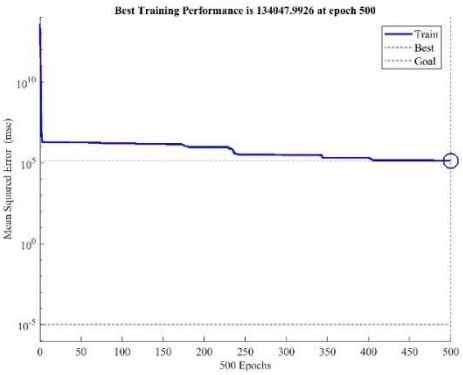
When the network structures created by the hybrid models are examined in Table 4, it has been determined that the parameter changes in the network structures differ in order to reach correct results on the same type of data. ANN network structures created by the DCP1 and DCP2 hybrid models presented in Table 4 and the performance analyzes of these network structures are presented in Figure 7.

Table 4. The most successful population members of the DCP1 and DCP2 hybrid models

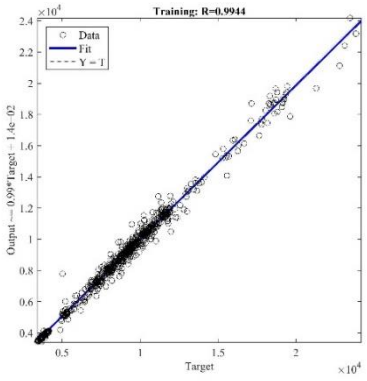
Hybrid Models	OF	TS	HLN	HLNN	ActF	TraF	MSE
HCP1	6	2	1	7	purelin _ purelin	trainoss	123.405,80
HCP2	7	4	1	5	purelin _ purelin	trainscg	135.417,05



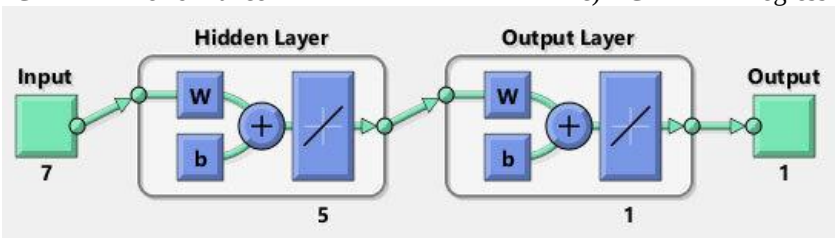
a) DCP1 ANN structures



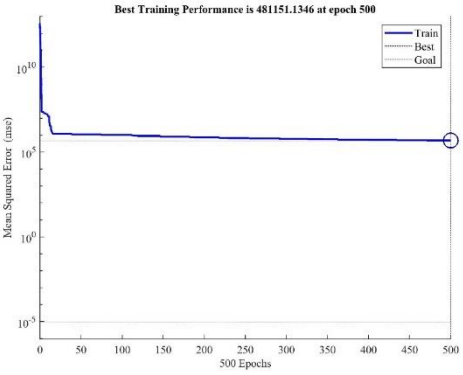
b) DCP1 ANN Performance



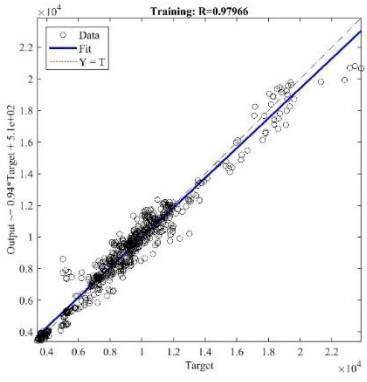
c) DCP1 ANN Regression



d) DCP2 ANN structures



e) DCP2 ANN Performance



f) DCP2 ANN Regression

Figure 7. The most successful ANN network structures and performances obtained with hybrid models

In the ANN model determined by DCP1 presented in Figure 7(a), the number of entries to be given to the network is 6 data with an interval of 2 days. In this model, 1 hidden layer is determined and the number of neurons in this hidden layer is 4. The activation functions used in this model and the learning function of the network are presented in Table 4. In the performance graph of the ANN

model determined by DCP1 presented in Figure 7(b), it is observed that the network has learned from the zeroth iteration to the 203rd iteration. In the regression graph of the ANN model determined by DCP1 presented in Figure 7(c), it is seen that the target line and the fit line overlap. In addition, the fact that the data are concentrated in this region shows that the estimation rate in the education process is high. In the ANN model determined by DCP2 presented in Figure 7(d), the number of entries to be given to the network is 7 data with an interval of 4 days. In this model, 1 hidden layer is determined and the number of neurons in this hidden layer is 5. The activation functions used in this model and the learning function of the network are presented in Table 4. In the performance graph of the ANN model determined by DCP1 presented in Figure 7(e), it is observed that the network has learned from the zeroth iteration to the 50th iteration. In the regression graph of the ANN model determined by DCP1 presented in Figure 7(f), it is seen that the target line and the fit line overlap. In addition, the fact that the data are concentrated in this region shows that the estimation rate in the education process is high.

The cryptocurrency predictions of the ANN structures created by the most successful gene of the DCP1 hybrid model and the particle belonging to the best position in the DCP2 hybrid model are shown in Figure 8.

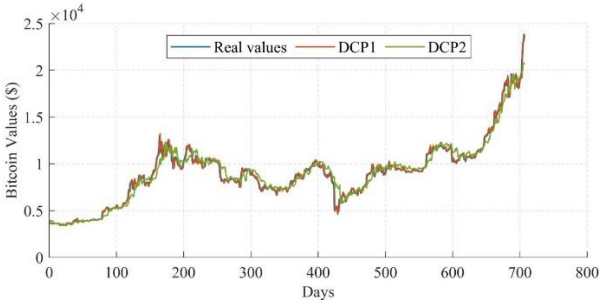


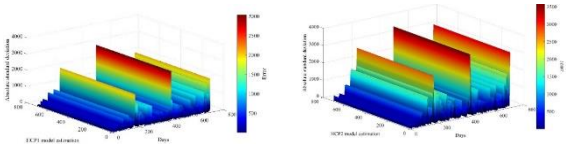
Figure 8. Bitcoin values obtained with hybrid models

Within the scope of a fair comparison, the first estimated data is ensured to be the same, considering the inputs related to the time series determined by the hybrid models. For this reason, the retrospective data used as input has been removed. Thus, the estimated data numbers were equalized and determined as 707. The performance of the models in cryptocurrency forecasting according to the prediction values presented in Figure 8 and the success evaluation metrics presented in Equations 3-6 are presented in Table 5.

Table 5. Cryptocurrency price prediction success of the models

Models	MAE	MSE	RMSE	R^2
DCP1	227,62	136.400,7	369,32	0,99
DCP2	481,33	481.105,68	693,62	0,96

The MAE, MSE, and RMSE values in Table 5, commonly employed in the literature to assess the performance of machine learning methods, are anticipated to be low, while the R^2 value is expected to approach 1. Table 5 reveals that the MAE, MSE, and RMSE values for the DCP1 model are lower than those for the DCP2 model. Furthermore, the R^2 value closely approaches 1. Considering the success of the models presented in Table 5, it is observed that the architecture of the hybrid model with GA and ANN produces more successful results than the architecture of the hybrid model with PSO and ANN. The 707-day standard deviation graph for both models is shown in Figure 9.



a) DCP1 standard deviation

b) DCP2 standard deviation

Figure 9. Standard deviation performance of the most successful ANN networks obtained with hybrid models

According to Table 5 and Figure 8, it is seen that the ANN network parameters determined with the DCP1 hybrid model produce more successful results in cryptocurrency prediction. According to Figure 9, the ANN network model created with the DCP1 model produced correct results with an average absolute error of 2.46%, while the ANN model created with the DCP2 model produced correct results with an average absolute error of 5.34%. It is noteworthy that DCP1 model produces 47.29% more successful results than DCP2 model.

4. Conclusion and Discuss

In recent years, in parallel with the development of Blockchain technology, the use of crypto assets has become increasingly widespread. Cryptocurrencies, which can be expressed as digitally encrypted sequences of numbers, are carefully followed and used by all segments of

society. As with all financial instruments or investment instruments, the sole purpose of market participants is primarily to try to predict price movements. In this context, many different technical or fundamental analysis methods have been applied. The use of artificial intelligence, which penetrates all areas of life with the developing technology, has also found its use in financial circles. Although it is claimed that it is impossible to predict price movements according to the Efficient Markets Hypothesis put forward by Fama, the existence of predictable trends or price movements is manifested in many studies as an 'anomaly'. In this perspective, there is no doubt that predicting the future positions of cryptocurrencies, as in other financial assets, is of great importance and priority. In this context, in the content of the study, it is aimed to predict the future value of Bitcoin, as the pioneer of crypto money markets, with a hybrid structure constructed over the time series. From the perspective of this purpose, two separate hybrid structures were created using ANN, GA, and PSO. With the two hybrid structures created, the time series coefficient, number of inputs and hyperparameters in the feedforward backpropagation ANN network structure to be used for prediction were optimized. The best mesh structures revealed by the proposed DCP1 and DCP2 models were arguably compared, and more successful results were obtained with the DCP1 model. In addition to revealing the optimum values of the parameters to be used in the ANN model with the hybrid models presented, the number of inputs to be used in such a problem and the time intervals that should be collected retrospectively were determined by optimization.

Ultimately, it can be claimed that the hybrid structure offered is easily usable and applicable not only for Bitcoin but also for other cryptocurrencies thanks to its flexible structure.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

References

[1] K. Meng and K. Khan, "Is cryptocurrency Efficient? A High-Frequency Asymmetric Multifractality Analysis," *Comput. Econ.*, pp. 1-22, 2023, doi: 10.1007/s10614-023-10402-6.

[2] D. Shang, Z. Yan, L. Zhang, and Z. Cui, "Digital financial asset price fluctuation forecasting in digital economy era using blockchain information: A reconstructed dynamic-bound Levenberg–Marquardt neural-network approach," *Expert Syst. Appl.*, vol. 228, 2023, doi: 10.1016/j.eswa.2023.120329.

[3] M. Campbell-Verduyn, "Bitcoin, crypto-coins, and global anti-money laundering governance," *Crime, Law Soc. Chang.*, vol. 69, pp. 283-305, 2018, doi: 10.1007/s10611-017-9756-5.

[4] J. Bhosale and S. Mavale, "Volatility of select Crypto-currencies: A comparison of Bitcoin, Ethereum and Litecoin," *Annu. Res. J. SCMS, Pune*, vol.6, no.1, pp. 132-141, 2018.

[5] U. Rahardja, I. Handayani, and A. A. Ningrum, "Pemanfaatan Sistem iMe Berbasis WordPress sebagai Official Site RCEP pada Perguruan Tinggi," *Creat. Inf. Technol. J.*, vol. 4, no. 3, pp. 207, 2018, doi: 10.24076/citec.2017v4i3.111.

[6] B. Tripathi and R. K. Sharma, "Modeling Bitcoin Prices using Signal Processing Methods, Bayesian Optimization, and Deep Neural Networks," *Comput. Econ.*, vol. 62, no. 4, pp. 1919-1945, 2023, doi: 10.1007/s10614-022-10325-8.

[7] E. Işık, N. Ademović, E. Harirchian, F. Avcil, A. Büyüksaraç, M. Hadzima-Nyarko, … and B. Antep, "Determination of Natural Fundamental Period of Minarets by Using Artificial Neural Network and Assess the Impact of Different Materials on Their Seismic Vulnerability," *Appl. Sci.*, vol. 13, no. 2, pp. 809, 2023, doi: 10.3390/app13020809.

[8] I. Ayus, N. Natarajan, and D. Gupta, "Prediction of Water Level Using Machine Learning and Deep Learning Techniques," *Iran. J. Sci. Technol. - Trans. Civ. Eng.*, vol. 47, no. 4, pp. 2437–2447, 2023, doi: 10.1007/s40996-023-01053-6.

[9] J. V. Tembhurne, N. Hebbar, H. Y. Patil, and T. Diwan, "Skin cancer detection using ensemble of machine learning and deep learning techniques," *Multimed. Tools Appl.*, vol. 82, no. 18, pp. 27501-27524, 2023, doi: 10.1007/s11042-023-14697-3.

[10] S. Goutte, H. V. Le, F. Liu, and H. J. von Mettenheim, "Deep learning and technical analysis in

cryptocurrency market," *Financ. Res. Lett.*, vol. 54, pp. 103809, 2023, doi: 10.1016/j.frl.2023.103809.
[11] Z. Zhou, Z. Song, H. Xiao, and T. Ren, "Multi-source data driven cryptocurrency price movement prediction and portfolio optimization," *Expert Syst. Appl.*, vol. 219, pp. 119600, 2023, doi: 10.1016/j.eswa.2023.119600.
[12] N. A. Rashid and M. T. Ismail, "Modelling and Forecasting the Trend in Cryptocurrency Prices," *J. Inf. Commun. Technol.*, vol. 22, no. 3, pp. 449–501, 2023, doi: 10.32890/jict2023.22.3.6.
[13] L. T. Mariappan, J. A. Pandian, V. D. Kumar, O. Geman, I. Chiuchisan, and C. Năstase, "A Forecasting Approach to Cryptocurrency Price Index Using Reinforcement Learning," *Appl. Sci.*, vol. 13, no.4, pp.2692, 2023, doi: 10.3390/app13042692.
[14] K. Murray, A. Rossi, D. Carraro, and A. Visentin, "On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles," *Forecasting*, vol. 5, no. 1, pp. 196–209, 2023, doi: 10.3390/forecast5010010.
[15] S. C. Nayak, S. Das, S. Dehuri, and S. B. Cho, "An Elitist Artificial Electric Field Algorithm Based Random Vector Functional Link Network for Cryptocurrency Prices Forecasting" *IEEE Access*, 2023, doi: 10.1109/ACCESS.2023.3283571.
[16] L. Al Hawi, S. Sharqawi, Q. A. Al-Haija, and A. Qusef, "Empirical Evaluation of Machine Learning Performance in Forecasting Cryptocurrencies," *J. Adv. Inf. Technol.*, vol. 14, no. 4, pp. 639–647, 2023, doi: 10.12720/jait.14.4.639-647.
[17] K. Ateeq, A. A. Al Zarooni, A. Rehman, and M. A. Khan, "A Mechanism for Bitcoin Price Forecasting using Deep Learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 8, 2023, doi: 10.14569/IJACSA.2023.0140849.
[18] I. Alarab and S. Prakoonwit, "Graph-Based LSTM for Anti-money Laundering: Experimenting Temporal Graph Convolutional Network with Bitcoin Data," *Neural Process. Lett.*, vol. 55, no. 1, pp. 689-707, 2023, doi: 10.1007/s11063-022-10904-8.
[19] R. M. Aziz, M. F. Baluch, S. Patel, and P. Kumar, "A Machine Learning Based Approach to Detect the Ethereum Fraud Transactions with Limited Attributes," *Karbala Int. J. Mod. Sci.*, vol. 8, no. 2, pp. 139-151, 2022, doi: 10.33640/2405-609X.3229.
[20] J. Li, "The comparison of lstm, lgbm, and cnn in stock volatility prediction," *In: 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022)*, pp. 905–909 2022. Atlantis Press. doi: 10.2991/aebmr.k.220307.147.
[21] S. Kazeminia, H. Sajedi, and M. Arjmand, "Real-time bitcoin price prediction using hybrid 2d-cnn lstm model," *In: 2023 9th International Conference on Web Research (ICWR)*, pp. 173–178, 2023. IEEE. doi: 10.1109/ICWR57742.2023.10139275.
[22] M. A. Bülbül and C. Öztürk, "Optimization, Modeling and Implementation of Plant Water Consumption Control Using Genetic Algorithm and Artificial Neural Network in a Hybrid Structure," *Arab. J. Sci. Eng.*, vol. 47, no. 2, pp. 2329-2343, 2022, doi: 10.1007/s13369-021-06168-4.
[23] P. Matić, O. Bego, and M. Maleš, "Complex Hydrological System Inflow Prediction using Artificial Neural Network," *Teh. Vjesn.*, vol. 29, no. 1, pp. 172-177, 2022, doi: 10.17559/TV-20200721133924.
[24] D. Nahavandi, R. Alizadehsani, A. Khosravi, and U. R. Acharya, "Application of artificial intelligence in wearable devices: Opportunities and challenges," *Computer Methods and Programs in Biomedicine*. vol. 213, pp. 106541, 2022. doi: 10.1016/j.cmpb.2021.106541.
[25] S. S. Ul Hasan, A. Ghani, I. U. Din, A. Almogren, and A. Altameem, "IoT devices authentication using artificial neural network," *Comput. Mater. Contin.*, vol. 70, pp. 3701-3716, 2022, doi: 10.32604/cmc.2022.020624.
[26] D. P. Soman, P. Kalaichelvi, and T. K. Radhakrishnan, "Density modelling and apparent molar volume of ionic liquid 1-butyl-3-methylimidazolium bromide in water," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 44, no. 3, pp. 1–14, 2022, doi: 10.1007/s40430-021-03248-2.
[27] M. A. Bülbül, "Optimization of artificial neural network structure and hyperparameters in hybrid model by genetic algorithm: iOS–android application for breast cancer diagnosis/prediction," *J. Supercomput.*, vol. 80, no. 4, pp. 4533-4553, 2023, doi: 10.1007/s11227-023-05635-z.
[28] B. Sun and Y. Zhou, "Bayesian network structure learning with improved genetic algorithm," *Int. J. Intell. Syst.*, vol. 37, no. 9, pp. 6023-6047, 2022, doi: 10.1002/int.22833.
[29] A. Taha and O. Barukab, "Android Malware Classification Using Optimized Ensemble Learning Based on Genetic Algorithms," *Sustain.*, vol. 14, no. 21, pp. 14406, 2022, doi: 10.3390/su142114406.

[30] X. Liu, D. Jiang, B. Tao, G. Jiang, Y. Sun, J. Kong, X. Tong, G. Zhao and B. Chen, "Genetic Algorithm-Based Trajectory Optimization for Digital Twin Robots," *Front. Bioeng. Biotechnol.*, vol. 9, pp. 7937822, 022, doi: 10.3389/fbioe.2021.793782.

[31] M. A. Bülbül, C. Öztürk, and M. F. Işık, "Optimization of Climatic Conditions Affecting Determination of the Amount of Water Needed by Plants in Relation to Their Life Cycle with Particle Swarm Optimization, and Determining the Optimum Irrigation Schedule," *Comput. J.*, vol. 65, no. 10, pp. 2654-2663, 2022, doi: 10.1093/comjnl/bxab097.

[32] R. P. de Gusmão and F. de A. T. de Carvalho, "Clustering of multi-view relational data based on particle swarm optimization," *Expert Syst. Appl.*, vol. 123, pp. 34-53, 2019, doi: 10.1016/j.eswa.2018.12.053.

[33] S. Papadakis and M. Markaki, "An in depth economic restructuring framework by using particle swarm optimization," *J. Clean. Prod.*, vol. 215, pp. 329–342, 2019, doi: 10.1016/j.jclepro.2019.01.041.

[34] J. Zhu, J. Liu, Y. Chen, X. Xue, and S. Sun, "Binary Restructuring Particle Swarm Optimization and Its Application," *Biomimetics*, vol. 8, no. 2, pp. 266, 2023, doi: 10.3390/biomimetics8020266.

[35] S. Xu , X. Yang, S. Zhang, X. Zheng, F. Zheng, Y. Liu, H. Zhang, Q. Ye and L. Li, "Machine learning models for orthokeratology lens fitting and axial length prediction," *Ophthalmic Physiol. Opt.*, vol. 43, no. 6, pp. 1462-1468, 2023, doi: 10.1111/opo.13212.

[36] M. A. Bülbül, E. Harirchian, M. F. Işık, S. E. Aghakouchaki Hosseini, and E. Işık, "A Hybrid ANN-GA Model for an Automated Rapid Vulnerability Assessment of Existing RC Buildings," *Appl. Sci.*, vol. 12, no. 10, 2022, doi: 10.3390/app12105138.

[37] M. F. Işık, F. Avcil, E. Harirchian, M. A. Bülbül, M. Hadzima-Nyarko, E. Işık, R. İzol and D. Radu, "A Hybrid Artificial Neural Network—Particle Swarm Optimization Algorithm Model for the Determination of Target Displacements in Mid-Rise Regular Reinforced-Concrete Buildings," *Sustainability*, vol. 15, no. 12, pp. 9715, 2023, doi: 10.3390/su15129715.

[38] coinmarketcap.com: Bitcoin price today. https://coinmarketcap.com/currencies/ bitcoin/historical-data/. [Date of access: September 2022]

[39] N. M. Razali, J. Geraghty, "Genetic algorithm performance with different selection strategies in solving tsp," *In: Proceedings of the World Congress on Engineering*, vol. 2, pp. 1–6, 2011. International Association of Engineers Hong Kong, China.

[40] I. Jannoud, Y. Jaradat, M. Z. Masoud, A. Manasrah, and M. Alia, "The role of genetic algorithm selection operators in extending wsn stability period: A comparative study," *Electron.*, vol. 11, no. 1, pp.28, 2022, doi: 10.3390/electronics11010028.