Engineering Science and Technology, an International Journal 60 (2024) 101897

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

Full Length Article

Objective-based survival individual enhancement in the chimp optimization algorithm for the profit prediction using financial accounting information system

Guomeng Zhao [a], Diego Martín [b], Mohammad Khishe [c,d,e,*], Leren Qian [f], Pradeep Jangir [g,h,i,j,k]

[a] *Henan Polytechnic Institute, Nanyang, Henan Province, China*
[b] *Department of Computer Science, Escuela de Ingeniería Informática de Segovia, Universidad de Valladolid, Segovia 40005, Spain*
[c] *Innovation Center for Artificial Intelligence Applications, Yuan Ze University, Taiwan*
[d] *Applied Science Research Center, Applied Science Private University, Amman 11937, Jordan*
[e] *Department of Electrical Engineering, Imam Khomeini Naval Science University of Nowshahr, Nowshahr, Iran*
[f] *School of Computing and Augmented Intelligence, Arizona State University, Tempe 85281, AZ, USA*
[g] *Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai 602 105, India*
[h] *University Centre for Research and Development, Chandigarh University, 3. Adjunct Department of CSE, Gharuan, Mohali 140413, India*
[i] *Department of CSE, Graphic Era Deemed To Be University, Dehradun, 248002, Uttarakhand, India*
[j] *Department of CSE, Graphic Era Hill University, Dehradun, 248002, India*
[k] *Jadara University Research Center, Jadara University, Irbid, Jordan*

A R T I C L E I N F O

Keywords:
Optimization
Profit prediction
Financial accounting
Deep learning

A B S T R A C T

This paper develops an innovative Objective-based Survival Individual Enhancement approach for the Chimp Optimization Algorithm (OSIE-CHOA) designed to enhance financial accounting profit prediction using information systems. The OSIE-CHOA focuses on improving the search process by simultaneously elevating the fitness of under-performing individuals within a population and strengthening the diversity among the top-performing ones. Within the OSIE-CHOA, we identify the four most promising chimps during each iteration. Subsequently, half of the highest-performing chimps are selected for elimination and repositioning around these fortunate individuals, with an equal probability assigned to each chimp. According to the experimental findings, it is clearly seen that OSIE-CHOA considerably enhances prediction accuracy, allowing a decrease in the root mean square error (RMSE) by 15% and the mean absolute error (MAE) by 18% compared to the traditional CHOA. Moreover, OSIE-CHOA shows a convergence rate that is 20% higher, which makes it a good and efficient tool for financial analysts who require accurate and reliable profit forecasting. By facilitating the optimization of profit prediction models, OSIE-CHOA leads to the improvement of decision-making within the context of financial accounting information systems.

1. Introduction

In the past few years, there has been a shift toward technology that can forecast profit with high accuracy. Profit forecasts provide firms and investors with valuable information [1]. Such information includes market conditions, feedback on a company's performance, and critical investment decisions [2]. However, in today's challenging environment, accurately forecasting future profits is a daunting task due to the availability of numerous data points, which are often high-dimensional, non-linear, and complex. This is a common feature of financial accounting systems. Often, dealing with such futuristic data presents a challenge for linear statistical forecasts or rules-based systems, as they frequently fail to accurately forecast profit [3].

The majority of profit prediction models, such as autoregressive integrated moving averages (ARIMA) and profit prediction models, are linear models that frequently rely on historical data and typically require linear approximations [4–6]. Unfortunately, these models overlook the complexity and the intricate dynamics that come with financial datasets [7]. Due to their ability to learn and identify complex non-linear relationships without imposing data constraints, machine

* Corresponding author.
E-mail addresses: diego.martin.andres@uva.es (D. Martín), m_khishe@alumni.iust.ac.ir (M. Khishe), lqian15@asu.edu (L. Qian), sbp_140310707009@gtu.edu.in (P. Jangir).

https://doi.org/10.1016/j.jestch.2024.101897
Received 27 July 2024; Received in revised form 4 November 2024; Accepted 7 November 2024
Available online 12 November 2024

learning has become increasingly common with techniques such as deep learning [8–10]. However, models like DNNs continue to pose challenges due to factors such as resource intensiveness, overfitting, and the need for extensive labeled training data, which often renders them unreliable in profit forecasting scenarios [11].

Recently, finance-specific areas have utilized nature-inspired algorithms like the genetic algorithm, particle swarm optimization, and grey wolf optimizer. Based on biology, these algorithms efficiently search and optimize large, enormous solution sets [12–15]. However, these algorithms also exhibit certain limitations, including early convergence and a deficiency in diversity maintenance mechanisms, which become particularly apparent when dealing with high-dimensional financial datasets [16,17]. This early convergence limits the prediction ability of the models by preventing most solutions from being an absolute optimal solution.

This research aims to address this issue by introducing a new optimization strategy known as objective-based survival individual enhancement, which enhances algorithms for financial accounting information system-based profit prediction or a combination of both. The chimp optimization algorithm [18], one of the novel optimization techniques based on chimpanzee social life, serves as the foundation for the OSIE-CHOA. This algorithm addresses optimization problems [19]. The OSIE enhances CHOA by incorporating an objective-based subordinate survival strategy, which helps reduce early convergence and enhances underperforming strategies.

The OSIE-CHOA framework has something new to offer in dealing with two fundamental issues of optimization: the search for better and more fitting solutions and diversity in the solution set. By strategically moving and improving at the objective level, OSIE-CHOA reduces the likelihood of settling on a local optimal too early, thereby improving prediction precision and convergence of time series in profit margin forecasting.

1.1. Motivations

Complex Financial Landscape: Due to the ever-changing and intricate nature of financial markets, novel approaches like OSIE-CHOA are required to deliver trustworthy profit prediction tools and methods.

Data Abundance: Financial accounting systems have a plethora of data, which has both advantages and disadvantages. The enormous data reservoirs strongly incentivize developing methods that can effectively extract insightful information [20].

Decision-Making Impact: Inaccurate profit predictions may significantly impact a company's or investor's financial decisions. The objective is to provide stakeholders with more dependable forecasting resources [21].

Nature-inspired Algorithms: Nature-inspired algorithms, such as the CHOA, are being explored in financial accounting for profit prediction because of their ability to solve complicated problems in various fields [22,23].

Objective-Based Survival Enhancement: OSIE-CHOA was developed and investigated because improving individuals within a population while diversifying the top-performing entities presents an enticing promise for improving predictive models.

2. Primary contributions

OSIE-CHOA Framework: Using financial accounting information systems, this article presents the OSIE-CHOA framework, a novel way to enhance profit forecast. The CHOA and objective-based survival methods are integrated within the framework to improve prediction abilities.

Maximizing Efficiency: Showing how OSIE-CHOA significantly improved efficiency by optimizing profit prediction models, resulting in more trustworthy predictions.

Decision-Making Empowerment: The present study showcases the notable enhancements in performance resulting from implementing OSIE-CHOA in deep neural networks (DNN) to optimize profit prediction models. These improvements have yielded more precise and dependable forecasts.

The following is the paper's structure: Section 2 represent the most related works. Concepts like "CHOA" and "DNN" are defined in Section 3. Dataset preparation, OSIE-CHOA development, and DNN training using OSIE-CHOA are all part of the suggested technique, which is presented in Section 4. Section 5 details the experiments and Section 6 discusses the findings. The research is concluded, and further research directions are proposed in section 7.

3. Related works

The domain of profit prediction in financial markets has experienced significant progress due to deep learning and optimization methodologies [24,25].

Each of these approaches has been thoroughly discussed in a number of research articles, and each has its own set of advantages and disadvantages [3]. To select the best approach for a specific financial forecasting project, it is essential to understand the benefits and drawbacks of different approaches [26].

The capacity of deep learning to successfully capture complex relationships in financial time series data has garnered much attention [27]. The effectiveness of deep neural networks (DNNs) in achieving high levels of prediction accuracy in financial time series analysis is demonstrated in the studies [28,29]. Even with a small amount of data, the overfitting problem remains, and DNN's processing requirements might be substantial.

Additionally, researchers have used recurrent neural networks (RNNs) [30] and convolutional neural networks (CNNs) [31] to successfully capture temporal relationships in financial data and spatial relationships in DNNs, respectively. One use of CNNs for pattern recognition in space is shown in the publication [32]. However, RNNs are primarily highlighted in the research [30] when it comes to modeling sequential financial data. However, getting RNNs and other deep networks to converge during training could be tricky, and the fine-tuning of hyperparameters is needed [33]. To strengthen prediction skills, hybrid models combine traditional statistical models with deep learning techniques, as discussed in [34]. The numerous features of hybrid models make them difficult to apply and interpret despite the fact that they show improved performance [35].

Evolutionary techniques, such as genetic algorithms and particle swarm optimization [36], have been included in financial prediction endeavors. The paper [37] highlights the significance of feature selection in enhancing the interpretability of models and mitigating overfitting. Nevertheless, it is worth noting that these approaches may not possess the same level of efficacy in capturing intricate non-linear interactions compared to deep learning methodologies.

A fascinating and potentially fruitful area to explore is the merging of deep learning with optimization techniques. The research study [38] examines the strengths and weaknesses of several evolutionary algorithms, with a particular emphasis on deep learning methods. With a broad range of applications and an exploration of possible synergistic effects, the research article named [39] provides a thorough review of the employment of evolutionary algorithms in deep learning.

In conclusion, the existing body of literature presents a diverse range of methodologies employed for profit prediction, each with distinct advantages and disadvantages. The selection of an appropriate method should be influenced by factors such as the accessibility of data, the processing capacity at hand, and the particular objectives of the financial forecasting endeavor. Given the dynamic nature of financial forecasting, a thorough understanding of these approaches is crucial for navigating the complex landscape of the field.

4. Related terminology

This section presents the relevant concepts, including CHOA and DNN.

4.1. Chimp optimization algorithm

The CHOA is a nature-inspired optimization algorithm that draws inspiration from chimpanzees' social behavior and problem-solving abilities. CHOA is part of the family of population-based optimization algorithms and is used to find optimal solutions to various optimization problems. The mathematical model for CHOA's hunting can be represented by Eqs. (1) to (4) [40]:

$$q_{chimp}^{t+1} = q_{\text{prey}}^{t} - \boldsymbol{\kappa}\cdot\left|\boldsymbol{J}\cdot q_{\text{prey}}^{t} - \zeta\cdot q_{chimp}^{t}\right| \tag{1}$$

$$\boldsymbol{J} = 2\cdot(\boldsymbol{r}_2) \tag{2}$$

$$\boldsymbol{\kappa} = (2\cdot\boldsymbol{r}_1\cdot\boldsymbol{\beta}) - \boldsymbol{\beta} \tag{3}$$

$$\zeta = \text{chaos value} \tag{4}$$

In this context, the coefficient denoted as $\boldsymbol{\beta}$ follows a non-linear drop from 2.5 to 0. The variable t represents the iteration numbers, q_{prey} represents the current optimal solution, and q_{chimp} represents the position of the chimp. The variables $\mathbf{r_1}$ and $\mathbf{r_2}$ are variables whose values can take on any value between zero and one. The chaotic map vectors are also meant by $\boldsymbol{\zeta}$.

The best chimpanzee is to utilize prey to replicate chimpanzee behavior, considering the lack of knowledge regarding the position of the first prey. Four of the top chimps thus far will be stored by CHOA, after which other individuals will be forced to move concerning the best chimps' location as determined by Eqs. (5) and (6) [40].

$$q^{t+1} = \frac{1}{4}\times(q_1 + q_2 + q_3 + q_4) \tag{5}$$

where

$$\begin{aligned} q_1 &= q_A - \boldsymbol{a}_1\cdot|\boldsymbol{c}_1 q_A - \boldsymbol{m}_1 q| \\ q_2 &= q_B - \boldsymbol{a}_2\cdot|\boldsymbol{c}_2 q_B - \boldsymbol{m}_2 q| \\ q_3 &= q_C - \boldsymbol{a}_3\cdot|\boldsymbol{c}_3 q_C - \boldsymbol{m}_3 q| \\ q_4 &= q_D - \boldsymbol{a}_4\cdot|\boldsymbol{c}_4 q_D - \boldsymbol{m}_4 q| \end{aligned} \tag{6}$$

Moreover, it can be observed that the presence of chaotic values in CHOA (depicted in Fig. 1 and Eq. (7)) closely resembles the patterns of social motivating activity.

$$q^{t+1} = \begin{cases} \text{Eq. (5)} \; \eta_m < 0.5 \\ \zeta\eta_m \geqslant 0.5 \end{cases} \tag{7}$$

where η_m represents a randomly generated number within the interval (0,1]. This oversimplified perspective on learning may result in premature convergence behavior. The subsequent section will propose an OSIE technique to rectify these shortcomings. The same method can be applied to a search area with D dimensions, wherein chimpanzees will transfer in hyperbolic geometry (or hyperspheres), surrounding the best possible position as far as discovered.

4.2. Deep neural network

Dominant Neural Networks (DNNs) are ANNs that have multiple hidden layers in input and output layers. It is possible for DNNs, like shallow ANNs, to show complex non-linear interactions [41]. The primary job of ANN is to gather inputs, analyze them by more complex calculations, and provide outputs that can deal with practical problems, including prediction.

5. Proposed methodology

The section provides an overview of the dataset, processing approaches, and the proposed methodology, OSIE-CHOA. Profit forecasting utilizing a DNN-based financial accounting information system is the current focus. In order to train the network, we will use the OSIE-CHOA framework.

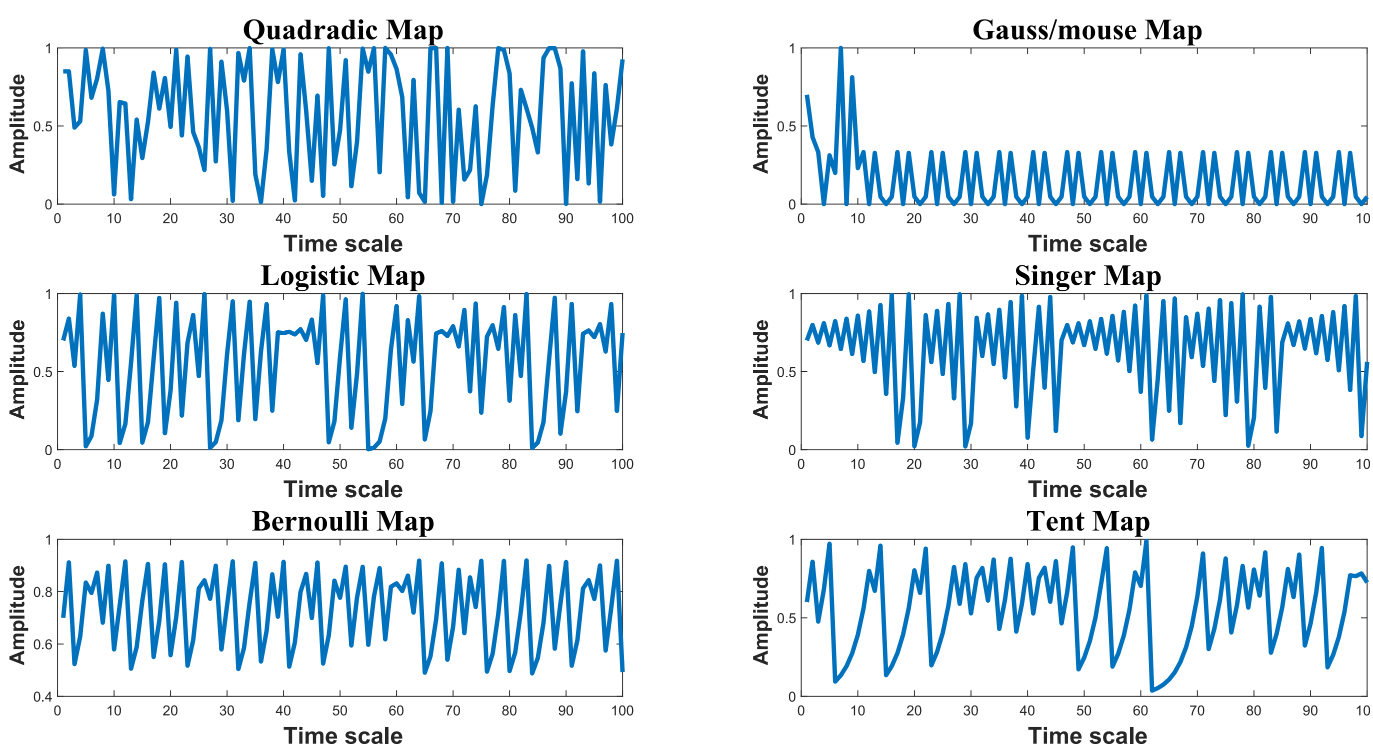

Fig. 1. The utilized chaotic maps.

5.1. Dataset

It is possible to generate a sufficient dataset for profit prediction using the same dataset that was used to forecast the stock, which can be obtained from Kaggle. From January 4, 2005, to May 11, 2022, is the time frame that is encompassed. Daily data is readily accessible, containing several parameters, such as the price-to-earnings ratio and fundamental indicators like market capitalization. Gathering detailed information and statistics regarding the tradable stocks listed on the stock exchanges of Shenzhen and the stock exchanges of Shanghai is essential. This data collection process should be conducted over time, encompassing 4714 stocks.

5.1.1. Preprocessing

Lastly, each new datum was assigned a binary value of 0 or 1 depending on the profits witnessed the following year. We generated sixteen datasets in all. After the preparation phase was completed, sixteen further datasets were developed. There are 2,350 businesses, and each one has 15 unique characteristics.

5.1.2. Novel profit forecasting dataset

A set of fifteen distinct characteristics was drawn from sixteen separate datasets and applied to 37,600 samples. Table 1 shows the selected properties with their associated labels. For further insight into the database, see Fig. 2 for the correlation matrix showing the interrelationships of the various variables. Generalized variables are shown in Fig. 3 using violin plots.

5.2. Objective-based survival individual enthusiastic for CHOA (OSIE-CHOA)

The OSIE-CHOA algorithm's strategy to enhance the improvement and refinement of solutions in the search process involves implementing adjustments to the locations of various groups of the population of chimps. When solving a given problem, in each iteration, the algorithm applies various equations to identify, evaluate, and rearranging the best-fitted, the most enthusiast, and the worst-fitted solutions.

Top-performing chimps (best-fitted solutions)

In this context, individual fitness or the objective value for each chimp q^j_{chimp} is evaluated concerning a single objective defined in Eq. (8):

$$f(q^j_{chimp}) \tag{8}$$

where q^j_{chimp} is the position of the j-th chimp and f (.) denotes the objective function. After measuring the fitness of each chimp, the population is ordered in ascending order of progress towards the objective function, selecting the first half as ***best-fitted solutions***.

Four chimps with an enthusiasm index E_i higher than the rest have been selected to be enthusiastic chimpanzees out of the best-fitted solutions obtained amongst the rest. The computation of the enthusiasm index E_i for each best-fitted solution is as follows:

$$E_i = \sum_{j=1}^{N/2} \left| f(q^i_{chimp}) - f(q^j_{chimp}) \right| \tag{9}$$

where N denotes the total number of individuals in the population, i indexes the chimp in consideration, j indexes the other top-performing chimps, any one of the four chimpanzees with the highest E_i values are labeled as enthusiastic chimps who assist in exploration by seeking out ***worst-fitted solutions***.

Underperforming chimps (Worst-Fitted Solutions)

The worst 50 % of the chimps, or the least-fitted solutions, will be taken for a rework to increase their fitness. For every worst-fitted chimp q chimp, the new position q new is computed to locate it next to a few enthusiastic chimps. This type of displacement around the enthusiastic chimps aids in the exploration aspect during the search and is formulated in Eq. (10).

$$q^{worst}_{new} = q^k_{enth} + r \cdot (q^k_{enth} - q^{worst}_{chimp}) \tag{10}$$

where q^k_{enth} denotes the position of the k-th randomly chosen enthusiastic chimp, and r is a random scaling factor that lies within 0 and 1. This type of movement allows the worst-fitted chimps to wander around the enthusiastic chimps.

Enthusiastic chimps Repositioning

In order to prevent enthusiastic chimpanzees from converging on the solution too early, their locations are also adjusted within each iteration. The new value of q^{enth}_{new} assigned to an enthusiastic chimp is obtained by adding a random difference for larger searching, as shown in Eq. (11).

$$q^{enth}_{new} = q_{enth} + \alpha \cdot rand(-1, 1) \tag{11}$$

Global best solution updating

In every iteration, the algorithm improves the global best solution q global_best, which is the position of the chimp who has the least objective value:

$$q_{global\_best} = \underset{j}{\mathrm{argmin}} f(q^j_{chimp}) \tag{12}$$

This process of updating is repeated as many times as needed till the algorithm has been run for the maximum number of times, which is represented by T or any other stopping condition is met.

The algorithmic representation of the OSIE-CHOA algorithm can be found in Algorithm 1, while a visual depiction of its functioning is presented in Fig. 4.

Table 1
Features and corresponding labels.

Number	ID	Features
1	F_1	Cash flow to debt ratio
2	F_2	margin ratio
3	F_3	margin of free cash flow
4	F_4	return on equity
5	F_5	cash ratio
6	F_6	gross margin ratio
7	F_7	debt to equity ratio
8	F_8	debt ratio
9	F_9	current ratio
10	F_{10}	quick ratio
11	F_{11}	return on assets
12	F_{12}	SGA to revenue
13	F_{13}	operating cash flow sales ratio
14	F_{14}	R&D to revenue
15	F_{15}	CAPEX to revenue

Algorithm 1 Pseudo-code of the OSIE-CHOA

Initialize OSIE-CHOA parameters,
  population size (N),
  maximum number of iterations (T)
  Set iteration counter t = 1
    While t < T **do**
    For j = 1: N **do**
      Initialize random positions for the jth solution
      Calculate the objective value.
      Sort the objective value in ascending.
      Identify the first 50 % solutions to be repositioned.
      Identify the four best-fitted solutions.
      Save them in the algorithm's memory.
      Save the best-fitted solution found so far.
      Calculate the enthusiastic index (E_i).
      Identify four solution positions with the highest E_i values.
      Reposition the 50 % of the best-fitted solutions around these diversified
  solutions randomly.
      Adopt the repositioned solution as their new position.
      Increment t by 1.
      Return attacker as the final result.

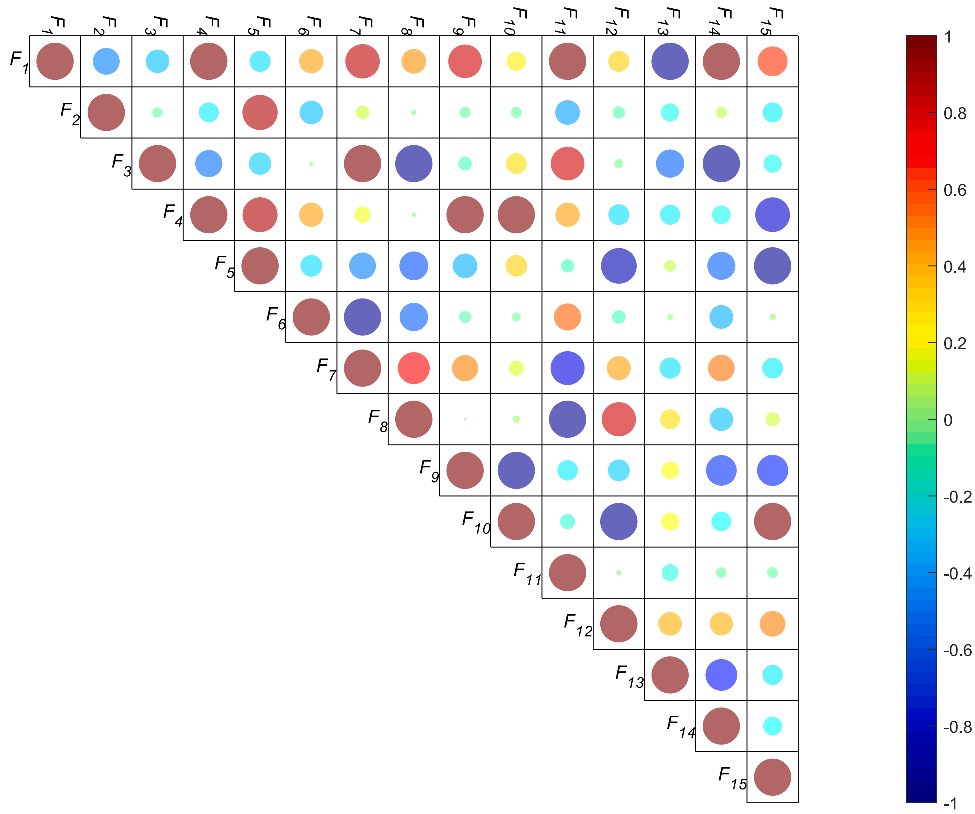
Fig. 2. Correlation matrix of features that were chosen.

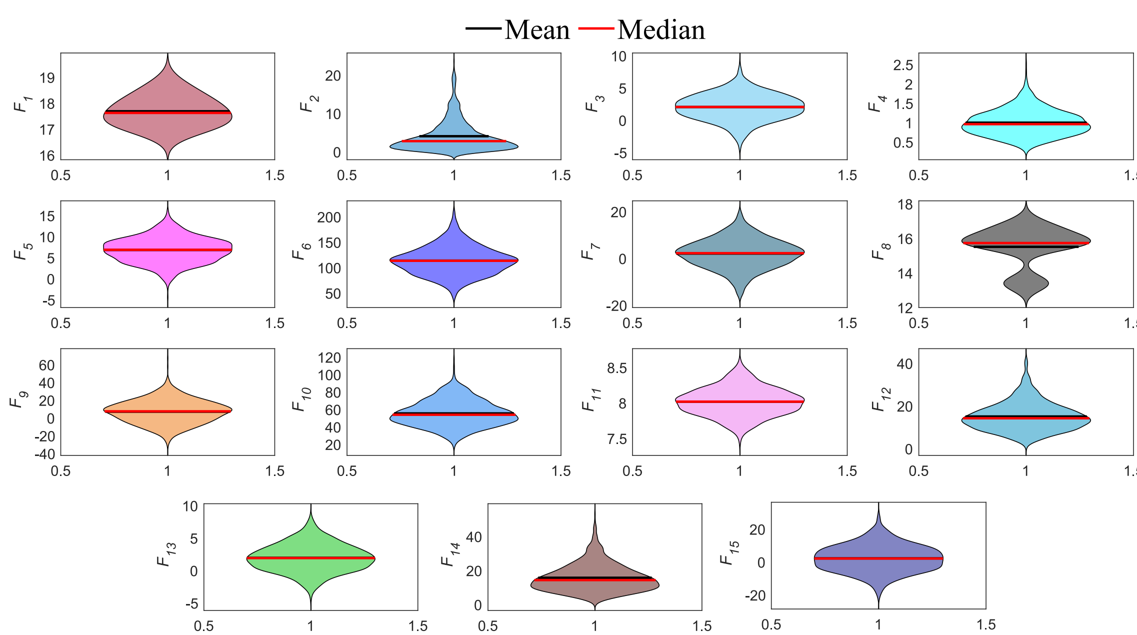

Fig. 3. Showing the distribution of selected features by Violin plots,

5.3. Problem definition

When optimizing a deep network, there are typically two primary concerns to resolve. The Chimps should first precisely explain the structure's specifications. The next step is to find the objective function by applying the analysis to the challenge. Presenting the network variables is one stage in adjusting a DNN using CHOA. As a result, crucial DNN parameters, such as the biases and weights, must be set appropriately to obtain the best prediction accuracy. For the purpose of determining the objective function, OISE-CHOA optimizes the biases and weights. In the CHOA, chimpanzees stand in for weights and biases.

Binary representations, matrices, and vectors are specific expressions of optimization approaches that are often used to describe the biases and weights of a DNN. The person is represented in this study by Eq. (18) since the OISE-CHOA requires parameters that are vector-based:

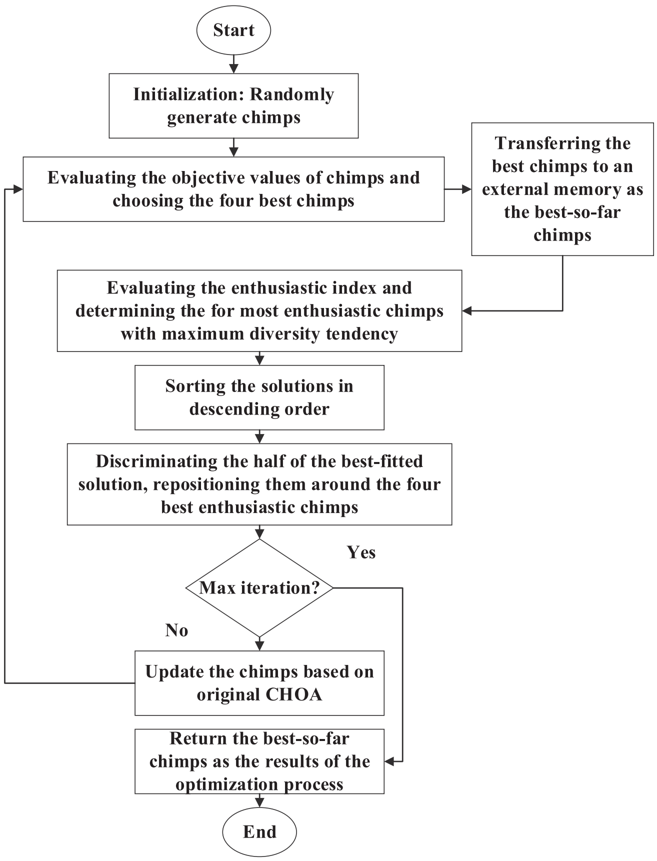

Fig. 4. Flowchart of OSIE-CHOA.

$$\textbf{\textit{Chimps}} = [W_{11}, W_{12}, ..., W_{nh}, b_1, ..., b_h, M_{11}, ..., M_{hm}] \tag{13}$$

The number of input neurons is denoted by n in this setting. The W_{ij}, Mjo, and b_j symbols represent the input weights, output weights, and biases, respectively. In Fig. 5, we can observe the DNN-OSIE-CHOA block design.

6. Experimentation

The framework above will be put to the test in a subsequent experiment. The DNN's input layer, which had fifteen nodes, was its fundamental structural component. There are four hidden layers in the neural network design, with three thousand, one thousand, one thousand, and fifty nodes each. The output layer, the fourth layer, is made up of two nodes. Sensitivity analysis is used to generate the values indicated above. All of the hidden layers used the Rectified Linear Unit activation function, while the output layer made use of the SoftMax activation function). By splitting the dataset in half, the framework is prepared to apply the hold-out strategy during training. Training data made up 70 % of the dataset, while test data made up the other 30 %. Overfitting occurred when the model was being trained. A normalization approach called L_1 is thus employed for the hidden layer. After the first three hidden layers, 10 % dropout regularization was also included.

In order to maintain an unbiased comparison of the algorithms, the iteration count and population size were set as constant for each algorithm. This configuration allows all algorithms to undergo the same number of fitness evaluations and hence provides an impartial ground for assessing their performance. With respect to the iteration count as well as the size of the population, a uniform amount of processing is done in all these algorithms so that the comparison may be drawn in terms of the convergence rate, accuracy, and efficiency.

Multiple regularization strategies were used in order to counterbalance overfitting. Dropout regularization was implemented for the hidden layers to reduce the chances of becoming too dependent on specific neurons. To prevent the model from overfitting to the noise in the data, early stopping was also utilized based on the validation loss metrics to indicate when further training provided no benefit. Cross-validation tested the model's reliability with different splits in the data, while L1 and L2 weight regularization kept the model less complex if necessary. All these methods reduced overfitting while improving the generalization of the model.

Various developed models, such as DNN-SSA [42], DNN-CBBO [43], DNN-DA [44], DNN-IWT [45], DNN-SCA [46], and DNN-OSIE-CHOA,

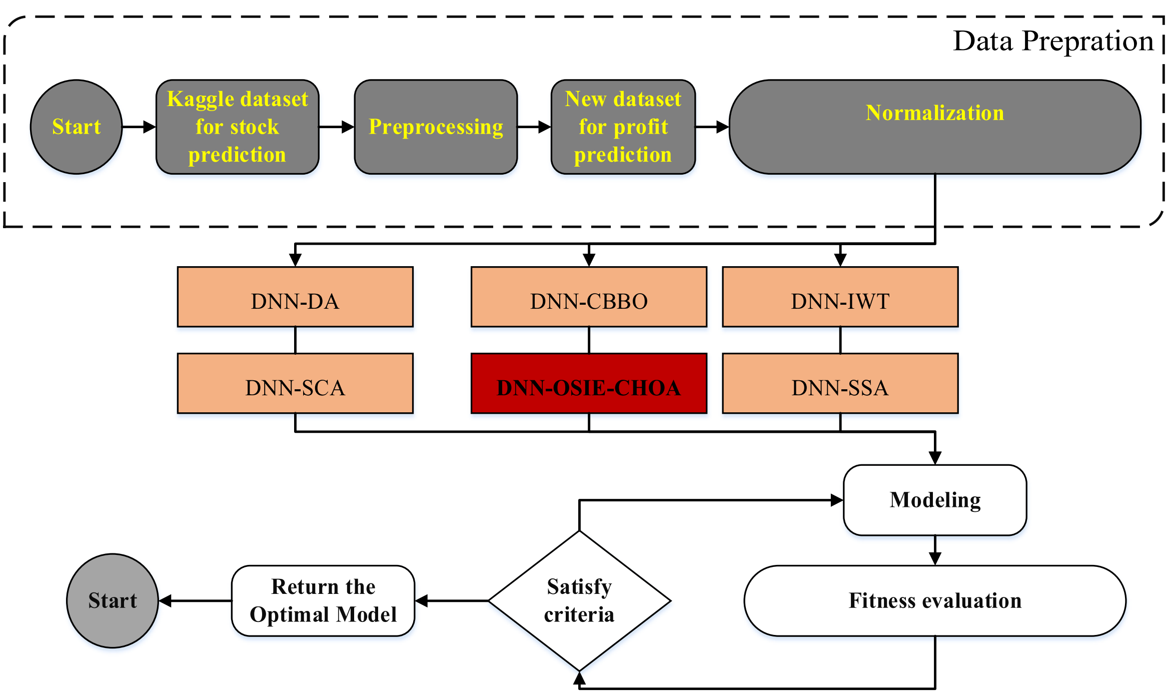

Fig. 5. The block diagram of DNN-OSIE-CHOA.

have been utilized to optimize the profit prediction model. All of the predictors' default values and configurable parameters mentioned above are shown in Table 2.

6.1. Statistical metrics

The evaluation of the efficacy of predictive methods involves the consideration of many statistical criteria, such as the coefficient of determination (R^2) [47], mean absolute percentage error (MAPE) [48], root mean square error (RMSE) [49], mean absolute percentage error (MAPE), relative root mean square error (RRMSE), mean relative error (MRE), and mean absolute error (MAE) [50]:

$$MAE = \left(\frac{1}{m}\right)\sum_{i=1}^{m}\left|Av_i - Pv_i'\right| \tag{14}$$

$$R^2 = 1 - \frac{SSR}{SST} \tag{15}$$

$$RMSE = \sqrt{\left(\frac{1}{m}\right)\sum_{i=1}^{m}\left(Av_i - Pv_i'\right)^2} \tag{16}$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Av_i - Pv_i'}{Av_i}\right| \times 100\% \tag{17}$$

$$RRMSE = \sqrt{\left(\frac{1}{m}\right)\sum_{i=1}^{m}\left(\frac{Av_i - Pv_i'}{Av_i}\right)^2} \tag{18}$$

$$MRE = \left(\frac{1}{m}\right)\sum_{i=1}^{m}\frac{\left|Av_i - Pv_i'\right|}{\left|Av_i\right|} \tag{19}$$

The terms Av_i and Pv_i' indicate the actual and predicted values of the output, respectively, while "m" indicates the entire number of observations. SSR and SST stand for the sum of square regression and total, respectively [51].

6.2. Profit prediction model using DNN-OSIE-CHOA

The DNN structure was not initially executed using optimization approaches [52]. The statistical measures employed for evaluating the predictive performance of DNN are presented in Table 3. The findings of this study indicate that the performance of the DNN's forecasts does not fall below the expected standard. However, more accurate predictions are needed to firmly endorse it as a dependable estimator for financial profit estimates. Hence, the application of nature-inspired optimization approaches is crucial in the development of a reliable DNN framework.

The subsequent experiment uses CBBO, SSA, SCA, DA, and IWT in addition to CHOA. The statistical findings for the DNN-OSIE-CHOA and other composite predictors for training datasets are presented in Table 3. The paper presents six DNN-based algorithms that demonstrate notable training efficiency. This improvement is evident from the R^2 values of six models, which surpass 0.81 by a considerable margin.

Table 2
The configuration settings for the comparison predictors.

Algorithm	Parameter	Value
CHOA	Number of chimps	20
	Max (iterations)	500
	Maximum (I)	2
CBBO	Maximum (E)	2
	Mutation	0.003
SSA	$\vec{vc}$	(0,1]
SCA	r_1	(0,1]
	r_2	(0,2]
	r_3	(0,1]
IWT	a	[2,0)
DA	Initial velocity	3 m/s
	Wing area	10^{-4} m^2

Table 3
The measurement metrics used for DNN's evaluation.

MAE	RRMSE	RMSE	MAPE	R^2	MRE
3.09E-02	0.037954	0.05451	1.278	0.5879	0.0231

Validation and assessment of the proposed predictors employing the testing sets follow the learning phase—the test sets' statistical outcomes are presented in Table 4. According to the results, although six utilized forecasters may surpass the average DNN when it comes to predicting financial success, the DNN-OSIE-CHOA stands out as the most promising.

The ranking methodology is subsequently employed to evaluate the differences between the prediction results of the proposed predictors, as depicted in Table 4. The utilization of stacked bars in Fig. 6 serves the purpose of visually representing the final order of position. Fig. 7 illustrates six statistical indicators for the DNN and the proposed predictors. The study's findings demonstrate that the DNN-OSIE-CHOA predictor exhibits higher levels of trustworthiness and accuracy in both the training and testing phases compared to the other predictors that were put forth. The application of the OSIE-CHOA in optimizing DNNs offers several advantages, such as rapid convergence and reduced error rates. The convergence curves of proposed predictors are contrasted in Fig. 8. Fig. 9 displays a Taylor diagram that bases its comparison on the coefficient of correlation and standard deviation. Notably, the DNN-OSIE-CHOA seems to have a favorable effect compared to other proposed predictors.

Fig. 8 shows results from 30 separate runs of each of the algorithms, depicting average convergence curves. Since each run is started with random initial conditions, the starting points of the curves may be expected to be slightly different from each other, raising the starting values of the curves. 'Average best so far' on the y-axis denotes the average of best fitness values retrieved in each iteration during 30 runs. Such a method enables an overall perspective of convergence of each algorithm as various discrepancies from each run are averaged out.

As shown in Fig. 9, it is clear that all of the proposed predictors employed in this paper outperform the formal DNN in prediction performance. The DNN-OSIE-CHOA, however, surpasses all other proposed predictors in terms of accuracy. As a result, this paper suggests utilizing the hybrid DNN-OSIE-CHOA model to forecast profit.

6.3. The comparative analysis of formal algorithms

In order to conduct a thorough assessment, the efficacy of formal predictors such as support vector regression (SVR) [53], autoregressive integrated moving average (ARIMA) [4], random forest (RF) [54], and multilayer perceptron (MLP) [55] were examined in comparison to DNN-OSIE-CHOA.

Similar statistics and examination methodologies were employed for all predictors in order to ensure a comprehensive and unbiased evaluation. Additionally, we examined the algorithms' capability to predict their findings to unforeseen datasets. The comparative models' detail sets are shown in Table 5. The results of the comparison between the conventional models and DNN-OSIE-CHOA are graphically shown in Table 6.

The findings derived from the comparative analysis demonstrate that the DNN-OSIE-CHOA exhibited superior accuracy and predictive capabilities in comparison to the conventional predictors. When compared to the usual predictors, the results showed improved accuracy, lower MSE, and lower RMSE.

7. Discussion

It appears that the DNN framework's predictive skills are improved

Table 4
Results for the DNN and other predictors.

	Method	RMSE	R^2	RRMSE	MAPE	MAE	MRE	Rank
Training	DNN	0.075	0.61	0.087	2.601	0.049	0.023	6
	DNN-OSIE-CHOA	0.017	0.98	0.010	0.641	0.013	0.010	48
	DNN-CHOA	0.032	0.94	0.019	1.170	0.021	0.011	36
	DNN-IWT	0.031	0.95	0.019	1.169	0.020	0.011	42
	DNN-SSA	0.039	0.92	0.029	1.252	0.024	0.012	30
	DNN-SCA	0.049	0.90	0.048	1.649	0.029	0.016	24
	DNN-CBBO	0.060	0.79	0.060	1.841	0.034	0.020	18
	DNN-DA	0.063	0.79	0.063	2.110	0.049	0.022	12
Testing	DNN	0.062	0.60	0.042	2.401	0.044	0.019	6
	DNN-OSIE-CHOA	0.012	0.97	0.009	0.568	0.010	0.005	48
	DNN-CHOA	0.020	0.92	0.014	0.980	0.014	0.009	36
	DNN-IWT	0.019	0.93	0.014	0.979	0.014	0.009	42
	DNN-SSA	0.032	0.90	0.017	1.169	0.020	0.012	30
	DNN-SCA	0.036	0.87	0.021	1.460	0.023	0.014	24
	DNN-CBBO	0.039	0.79	0.026	1.671	0.026	0.017	18
	DNN-DA	0.046	0.77	0.029	1.863	0.029	0.018	12

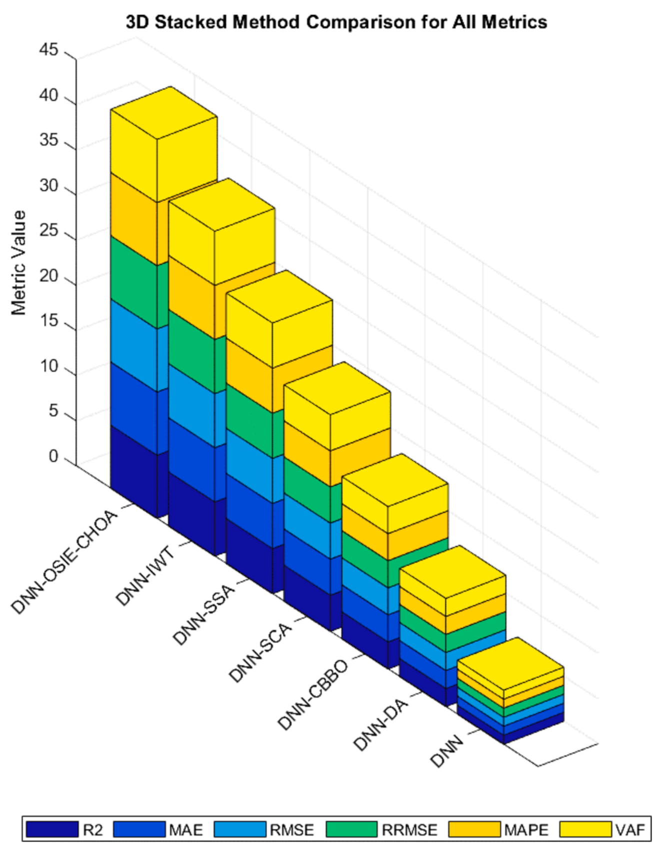

Fig. 6. Overall stacked ranking results.

when the OSIE-CHOA is used.

The study's findings can be enumerated as follows:

- The DNN model, albeit showing promising results, required improved prediction accuracy in order to be considered a reliable financial profit estimator.
- The DNN-OSIE-CHOA model demonstrated enhanced predicting abilities in comparison to the other predictors that were proposed, hence surpassing their level of accuracy.
- The hybrid model, which integrates a DNN with the optimal subset input elimination and choice of hyperparameters algorithm (OSIE-CHOA), showed effective convergence and decreased error rates. Consequently, this particular model demonstrates its reliability as a viable choice for predicting profitability.
- The comparative analysis of different benchmark optimization algorithms revealed that DNN-OSIE-CHOA displayed the most rapid convergence rate, hence offering more substantiation of its efficacy.
- All of the predictors that were proposed, including DNN-OSIE-CHOA, exhibited improved performance when compared to the typical DNN model. This comparison highlights the advantages of integrating deep neural networks with optimization methods that draw inspiration from natural processes.
- The statistical criteria, such as RMSE, R^2, RRMSE, MAPE, MAE, and MRE, consistently demonstrated the improved performance of the DNN-OSIE-CHOA model.
- The findings underscore the capacity of combining deep learning techniques with metaheuristic optimization algorithms in order to predict profits utilizing financial accounting information systems.

The findings mentioned above make a significant contribution to the understanding and advancement of profit prediction techniques in the field of financial accounting. Furthermore, these findings provide significant contributions to scholars and professionals in the field.

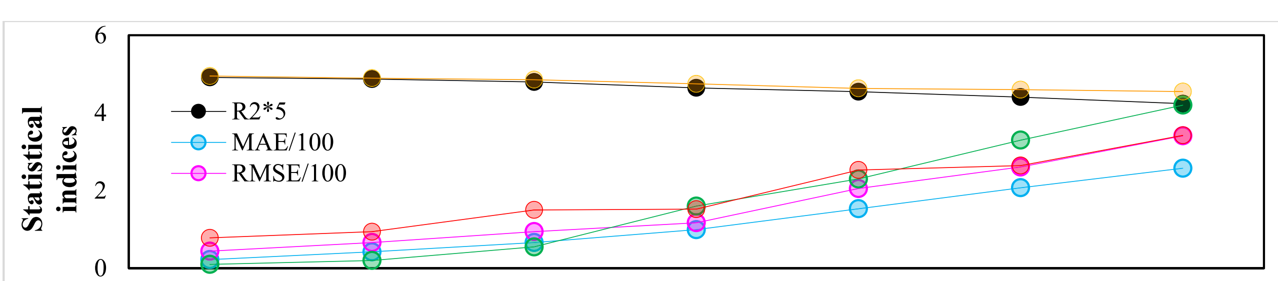

Fig. 7. The statistical indices of the proposed predictors.

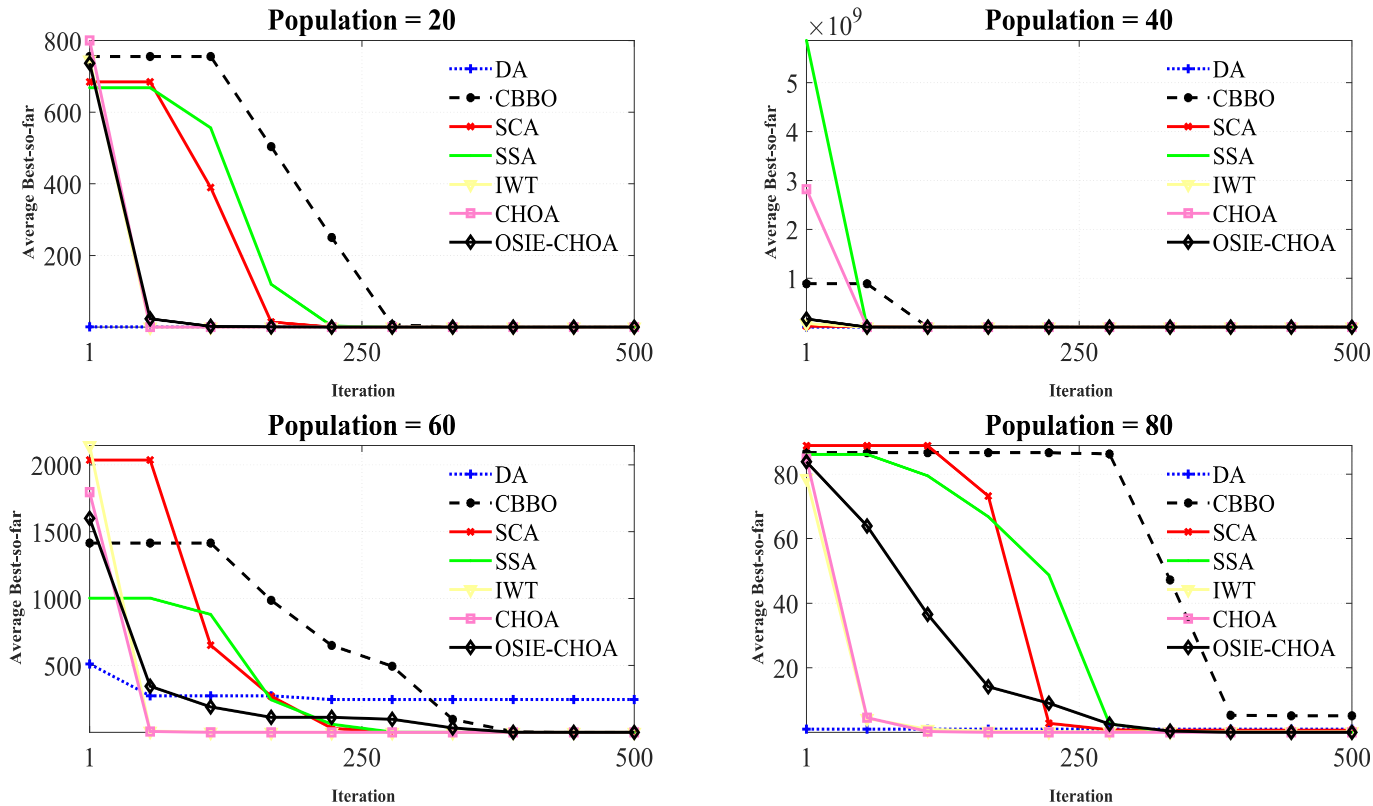

Fig. 8. Proposed predictors' convergence curves.

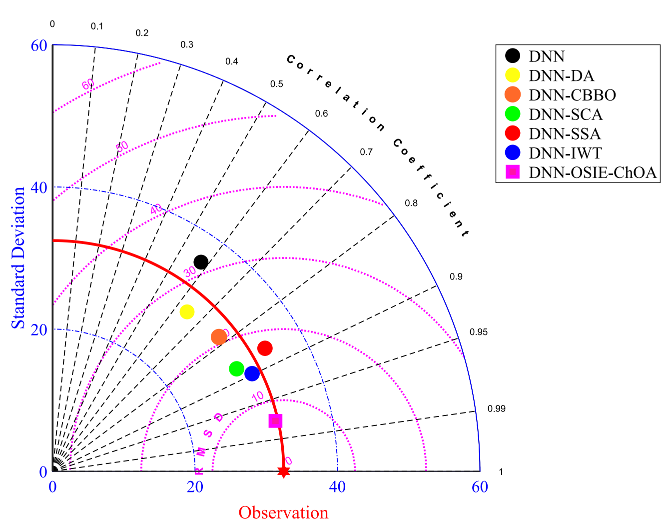

Fig. 9. Taylor diagram for the proposed predictors.

Table 5
Setup parameters for the formal algorithms.

Model	Parameters	Values
SVR	C	1.0
	ε	0.1
ARIMA	p, d, q	1, 0, 1
MLP	Number of hidden layer neurons	50
	Learning rate	0.001
RF	Number of trees	100
	Samples split	2
	Samples leaf	1

Table 6
The comparative outcomes were obtained from the formal models and DNN-OSIE-CHOA.

Model	Accuracy	RMSE	RRMSE
SVR	0.699	0.037	0.180
ARIMA	0.660	0.038	0.196
MLP	0.721	0.027	0.144
RF	0.720	0.028	0.146
DNN-OSIE-CHOA	0.925	0.009	0.096

8. Conclusion

This research introduced a hybrid DNN network and OSIE-CHOA technique (DNN-OSIE-CHOA) system to enhance the prediction of financial accounting profit. The system consisted of a DNN predictor that accounted for the novel OSIE-CHOA-based learning technique as a learning algorithm. A complete dataset of 15 features was generated to provide a precise comparative analysis. Consequently, the DNN-based model employed in these studies had six layers. This study involved the development of five deep predictors to forecast financial accounting profit alongside the inclusion of OSIE-CHOA. The IWT, SCA, CBBO, DA, and SSA were these predictors. The study revealed that the DNN-OSIE-CHOA, DNN-IWT, DNN-SSA, DNN-SCA, DNN-CBBO, DNN-DA, and classic DNN models achieved rank grades of 48, 42, 36, 30, 24, 18, 12, and 6, respectively. Listed in order of decreasing value, the DL-based systems outperformed their peers when it came to predicting the worth of financial accounting profits. The DNN-OSIE-CHOA model was found to be the most precise predictor for financial accounting profit.

The model might be improved by adding and modifying features or by using Principal Component Analysis (PCA) to reduce the bias of the generated dataset. Additionally, lowering the bias would improve the model's performance. Researchers may utilize various improved variants of CHOA, like weighted CHOA, IP-based CHOA, and variable levy flight CHOA, to explore potential avenues for future research.

CRediT authorship contribution statement

Guomeng Zhao: Writing – original draft, Visualization, Validation, Software. **Diego Martín:** Software, Validation, Writing – review & editing. **Mohammad Khishe:** Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Leren Qian:** Investigation, Formal analysis, Data curation. **Pradeep Jangir:** Formal analysis, Software, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Not applicable.

References

[1] F. Ning, Y. Shi, X. Tong, M. Cai, W. Xu, Manufacturing cost estimation based on similarity, Int. J. Comput. Integr. Manuf. 36 (8) (2023) 1238–1253.
[2] X. Zhang, Y. Li, Z. Xiong, Y. Liu, S. Wang, D. Hou, A resource-based dynamic pricing and forced forwarding incentive algorithm in socially aware networking, Electronics 13 (15) (2024) 3044.
[3] R.G. Schroeder, M.W. Clark, J.M. Cathey, Financial Accounting Theory and Analysis: Text And Cases, John Wiley & Sons, 2022.
[4] G.E.P. Box, D.A. Pierce, Distribution of residual autocorrelations in autoregressive-integrated moving average time series models, J. Am. Stat. Assoc. 65 (332) (1970) 1509–1526.
[5] I.M.R. Najjar, A.M. Sadoun, A. Ibrahim, H. Ahmadian, A. Fathy, A modified artificial neural network to predict the tribological properties of Al-SiC nanocomposites fabricated by accumulative roll bonding process, J. Compos. Mater. 57 (21) (2023) 3433–3445.
[6] H. Ahmadian, A.M. Sadoun, A. Fathy, T. Zhou, Utilizing a unified conceptual dynamic model for prediction of particle size of duel-matrix nanocomposites during mechanical alloying, Powder Technol. 418 (2023) 118291.
[7] I.M.R. Najjar, A.M. Sadoun, M. Abd Elaziz, H. Ahmadian, A. Fathy, A.M. Kabeel, Prediction of the tensile properties of ultrafine grained Al–SiC nanocomposites using machine learning, J. Mater. Res. Technol. 24 (2023) 7666–7682.
[8] M.I. Elamy, M. Abd Elaziz, M.A. Al-Betar, A. Fathy, M. Elmahdy, Enhanced random vector functional link based on artificial protozoa optimizer to predict wear characteristics of Cu-ZrO2 nanocomposites, Results Eng. 24 (2024) 103007.
[9] S. Ali, A.M. Sadoun, A. Fathy, A.W. Abdallah, Numerical modeling of magnetohydrodynamic buoyancy-driven convection for enhanced energy applications, Case Stud. Therm. Eng. 52 (2023) 103823.
[10] G.S. Alsoruji, A.M. Sadoun, M. Abd Elaziz, M.A. Al-Betar, A.W. Abdallah, A. Fathy, On the prediction of the mechanical properties of ultrafine grain Al-TiO2 nanocomposites using a modified long-short term memory model with beluga whale optimizer, J. Mater. Res. Technol. 23 (2023) 4075–4088.
[11] S. Garcia-Mendez, F. de Arriba-Perez, A. Barros-Vila, F.J. Gonzalez-Castano, Detection of temporality at discourse level on financial news by combining Natural Language Processing and Machine Learning, Expert Syst. Appl. 197 (2022) 116648.
[12] E. Çelik, A powerful variant of symbiotic organisms search algorithm for global optimization, Eng. Appl. Artif. Intell. 87 (2020) 103294.
[13] E. Çelik, IEGQO-AOA: information-exchanged gaussian arithmetic optimization algorithm with quasi-opposition learning, Knowledge-Based Syst. 260 (2023) 110169.
[14] E. Çelik, Exponential PID controller for effective load frequency regulation of electric power systems, ISA Trans. 153 (2024) 364–383.
[15] E. Çelik, N. Öztürk, Y. Arya, Advancement of the search process of salp swarm algorithm for global optimization problems, Expert Syst. Appl. 182 (2021) 115292.
[16] M.-J. Seow, L. Qian, Knowledge augmented intelligence using large language models for advanced data analytics. SPE Eastern Regional Meeting, SPE, 2024. D021S001R003.
[17] L. Chang, M. Li, L. Qian, G.G. de Oliveira, Developed multi-objective honey badger optimizer: Application to optimize proton exchange membrane fuel cells-based combined cooling, heating, and power system, Int. J. Hydrogen Energy 50 (2024) 592–605.
[18] M. Yu, M. Khishe, L. Qian, D. Martín, L. Abualigah, T.M. Ghazal, Quantum chimp optimization algorithm: a novel integration of quantum mechanics into the chimp optimization framework for enhanced performance, J. Artif. Intell. Soft Comput. Res. 14 (4) (2024) 321–359.
[19] Z. Zhang, M. Khishe, L. Qian, D. Martín, L. Abualigah, T.M. Ghazal, Evolving chimp optimization algorithm using quantum mechanism for engineering applications: a case study on fire detection, J. Comput. Des. Eng. 11 (5) (2024) 143–163.
[20] Z. Wang, K. Li, S.Q. Xia, H. Liu, Economic recession prediction using deep neural network, J. Financ. Data Sci. 4 (3) (2022) 108–127.
[21] M.A. Haider, M.A. Khan, S. Saddique, S.H. Hashmi, The impact of stock market performance on foreign portfolio investment in China, Int. J. Econ. Financ. Issues 7 (2) (2017) 460–468.
[22] W. Febrianti, K.A. Sidarto, N. Sumarti, Solving constrained mean-variance portfolio optimization problems using spiral optimization algorithm, Int. J. Financ. Stud. 11 (1) (2022) 1.
[23] W. Shen, X. Guo, C. Wu, D. Wu, Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm, Knowledge-Based Syst. (2011), https://doi.org/10.1016/j.knosys.2010.11.001.
[24] M. Heidary, S. Ziari, A. Shayan Nia, A. Rashidi Kemijan, Financial Bankruptcy prediction using artificial neural network and firefly algorithms in companies listed in Tehran Stock Exchange, Financ. Eng. Portf. Manag. 12 (46) (2021) 691–716.
[25] F. Soleymani, E. Paquet, Financial portfolio optimization with online deep reinforcement learning and restricted stacked autoencoder—DeepBreath, Expert Syst. Appl. 156 (2020) 113456.
[26] S. Makridakis, N. Bakas, Forecasting and uncertainty: A survey, Risk Decis. Anal. 6 (1) (2016) 37–64.
[27] O.B. Sezer, M.U. Gudelek, A.M. Ozbayoglu, Financial time series forecasting with deep learning: A systematic literature review: 2005–2019, Appl. Soft Comput. 90 (2020) 106181.
[28] H. Yan, H. Ouyang, Financial time series prediction based on deep learning, Wirel. Pers. Commun. 102 (2018) 683–700.
[29] A. Dingli, K.S. Fournier, Financial time series forecasting-a deep learning approach, Int. J. Mach. Learn. Comput. 7 (5) (2017) 118–122.
[30] G. Tsang, J. Deng, X. Xie, Recurrent neural networks for financial time-series modelling, in: 2018 24th International Conference on Pattern Recognition (ICPR), 2018, pp. 892–897.
[31] D.M. Durairaj, B.H.K. Mohan, A convolutional neural network based approach to financial time series prediction, Neural Comput. Appl. 34 (16) (2022) 13319–13337.
[32] H. Chung, K. Shin, Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction, Neural Comput. Appl. 32 (2020) 7897–7914.
[33] T. Wilberforce, A. Alaswad, A. Garcia-Perez, Y. Xu, X. Ma, C. Panchev, Remaining useful life prediction for proton exchange membrane fuel cells using combined convolutional neural network and recurrent neural network, Int. J. Hydrogen Energy 48 (1) (2023) 291–303.
[34] S.R. Polamuri, K. Srinivas, A.K. Mohan, Multi model-based hybrid prediction algorithm (MM-HPA) for stock market prices prediction framework (SMPPF), Arab. J. Sci. Eng. 45 (2020) 10493–10509.
[35] G. Li, A. Zhang, Q. Zhang, D. Wu, C. Zhan, "Pearson correlation coefficient-based performance enhancement of broad learning system for stock price prediction, IEEE Trans Circuits Syst. II Express Briefs 69 (5) (2022) 2413–2417.
[36] Y. Guo, J. Guo, B. Sun, J. Bai, Y. Chen, A new decomposition ensemble model for stock price forecasting based on system clustering and particle swarm optimization, Appl. Soft Comput. 130 (2022) 109726.
[37] S. Jiang, K.-S. Chin, L. Wang, G. Qu, K.L. Tsui, Modified genetic algorithm-based feature selection combined with pre-trained deep neural network for demand forecasting in outpatient department, Expert Syst. Appl. 82 (2017) 216–230.
[38] Y. Hu, K. Liu, X. Zhang, L. Su, E.W.T. Ngai, M. Liu, Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review, Appl. Soft Comput. 36 (2015) 534–551.
[39] R. Rotrattanadumrong, Y. Yokobayashi, Experimental exploration of a ribozyme neutral network using evolutionary algorithm and deep learning, Nat. Commun. 13 (1) (2022) 4847.
[40] M. Khishe, M.R. Mosavi, Chimp optimization algorithm, Expert Syst. Appl. (2020), https://doi.org/10.1016/j.eswa.2020.113338.
[41] Y. LeCun, "LeNet-5, convolutional neural networks," *URL http//yann. lecun. com/exdb/lenet*, vol. 20, no. 5, p. 14, 2015.
[42] S. Mirjalili, A.H. Gandomi, S.Z. Mirjalili, S. Saremi, H. Faris, S.M. Mirjalili, Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems, Adv. Eng. Softw. (2017), https://doi.org/10.1016/j.advengsoft.2017.07.002.
[43] S. Saremi, S. Mirjalili, A. Lewis, Biogeography-based optimisation with chaos, Neural Comput. Appl. (2014), https://doi.org/10.1007/s00521-014-1597-x.
[44] Ç.I. Aci, H. Gülcan, A modified dragonfly optimization algorithm for single- and multiobjective problems using brownian motion, Comput. Intell. Neurosci. (2019), https://doi.org/10.1155/2019/6871298.
[45] M. Li, X. Yu, B. Fu, X. Wang, A modified whale optimization algorithm with multi-strategy mechanism for global optimization problems, Neural Comput. Appl. (2023) 1–14.
[46] R. Akay, M.Y. Yildirim, Multi-strategy and self-adaptive differential sine-cosine algorithm for multi-robot path planning, Expert Syst. Appl. (2023) 120849.
[47] A. Mohammadzadeh, H. Taghavifar, Y. Zhang, W. Zhang, A fast nonsingleton type-3 fuzzy predictive controller for nonholonomic robots under sensor and actuator faults and measurement errors, IEEE Trans. Syst. Man. Cybern. Syst. (2024).
[48] A. Mohammadzadeh, C. Zhang, K.A. Alattas, F.F.M. El-Sousy, M.T. Vu, Fourier-based type-2 fuzzy neural network: Simple and effective for high dimensional problems, Neurocomputing 547 (2023) 126316.
[49] A. Mohammadzadeh, H. Taghavifar, C. Zhang, K.A. Alattas, J. Liu, M.T. Vu, A non-linear fractional-order type-3 fuzzy control for enhanced path-tracking performance of autonomous cars, IET Control Theory Appl. 18 (1) (2024) 40–54.
[50] X. Chang, H. Gao, W. Li, Discontinuous distribution of test statistics around significance thresholds in empirical accounting studies, J. Account. Res. (2023).

[51] J. Luo, et al., Role of perceived ease of use, usefulness, and financial strength on the adoption of health information systems: the moderating role of hospital size, Humanit. Soc. Sci. Commun. 11 (1) (2024) 1–12.
[52] S.-R. Yan, W. Guo, A. Mohammadzadeh, S. Rathinasamy, Optimal deep learning control for modernized microgrids, Appl. Intell. 53 (12) (2023) 15638–15655.
[53] P.S. Yu, S.T. Chen, I.F. Chang, Support vector regression for real-time flood stage forecasting, J. Hydrol. (2006), https://doi.org/10.1016/j.jhydrol.2006.01.021.
[54] S.J. Rigatti, Random forest, J. Insur. Med. 47 (1) (2017) 31–39.
[55] H. Bourlard, Y. Kamp, Auto-association by multilayer perceptrons and singular value decomposition, Biol. Cybern. 59 (4–5) (1988) 291–294, https://doi.org/10.1007/BF00332918.