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Profit prediction optimization using financial accounting information system by optimized DLSTM

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A R T I C L E I N F O

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A B S T R A C T

Financial accounting information systems (FAISs) are one of the scientific fields where deep learning (DL) and swarm-based algorithms have recently seen increased use. Nevertheless, the application of these hybrid networks has become more challenging as a result of the heightened complexity imposed by extensive datasets. In order to tackle this issue, we present a new methodology that integrates the twin adjustable reinforced chimp optimization algorithm (TAR-CHOA) with deep long short-term memory (DLSTM) to forecast profits using FAISs. The main contribution of this research is the development of the TAR-CHOA algorithm, which improves the efficacy of profit prediction models. Moreover, due to the unavailability of an appropriate dataset for this particular problem, a newly formed dataset has been constructed by employing fifteen inputs based on the prior Chinese stock market Kaggle dataset. In this study, we have designed and assessed five DLSTM-based optimization algorithms, for forecasting financial accounting profit. The performance of various models has been evaluated and ranked for financial accounting profit prediction. According to our research, the best-performing DL-based model is DLSTM-TAR-CHOA. One constraint of our methodology is its dependence on historical financial accounting data, operating under the assumption that past patterns and relationships will persist in the future. Furthermore, it is important to note that the efficacy of our models may differ based on the distinct attributes and fluctuations observed in various financial markets. These identified limitations present potential avenues for future research to investigate alternative methodologies and broaden the extent of our findings.

1. Introduction

The FAIS is an accounting concept used to maintain current organizations' financial data [1]. Any activity that decreases or increases the account balance is included in financial data [2,3]. The FAIS must be established before using a billing and customer relationship management solution [4]. The FAIS procedure aims to impart knowledge of account management [5]. Accounting is a technique used to produce financial data outlining a company's earnings, liabilities, and organizational performance [6]. To sum up, the system that keeps track of these financial details is known as FAIS [7].

The difference between a company's total income and direct costs is known as its accounting profit, often referred to as accounting

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or financial profit [8]. Accounting profit is a measure used to assess a company's profitability and compare its financial status to that of competitors [9].

FAISs contain automated financial advice or investment management models. These models forecast financial system conditions and offer recommendations for actions based on these presumptions. Therefore, incorrect projections may lead to undue risk and financial losses. The core problem is that previous data is often a poor predictor of future occurrences, and the complex adaptive aspects of FAISs make it challenging to include past knowledge about the target distributions, as mentioned in a conventional financial statement that "historical outcomes are not a guarantee of the future returns [10]." FAIS experts are often limited to using frameworks trained on historical data and have few options for improving their predictive models. Furthermore, these "back-testing" models do not account for the impact of financing costs and FAIS, which could be of equivalent size to the expected gains [11].

In recent years, the application of deep neural networks (DNN) and artificial neural networks (ANN) [12,13] in predictive modeling has garnered significant attention across various fields [14,15]. These models have demonstrated exceptional performance in various domains, including finance, economics, and business. ANN and DNN models can capture nonlinear relationships [16], complex patterns [17], and high-dimensional data representations [18], making them well-suited for predictive tasks [19–21].

In the realm of financial accounting, the use of ANN and DNN models for profit prediction has emerged as a promising research area. Several studies have explored the effectiveness of these models in forecasting financial outcomes, providing valuable insights for decision-making processes [22].

To enhance the performance of ANN and DNN models, the selection of an appropriate optimization algorithm is crucial [23]. In this study, we have chosen to utilize the CHOA for optimizing the performance of the DLSTM-based profit prediction model [24]. CHOA is a swarm intelligence optimization algorithm inspired by the behaviors and social structures of chimpanzees. It offers several advantages that make it suitable for our research purposes.

One advantage of CHOA is its ability to efficiently explore complex search spaces, enabling the identification of optimal or near-optimal solutions. The algorithm incorporates various mechanisms such as random exploration, local exploitation, and adaptive learning to strike a balance between exploration and exploitation [25]. This capability enhances the model's ability to find robust and accurate solutions for profit prediction.

Another advantage of CHOA is its adaptability to different problem domains and datasets. It can handle both continuous and discrete variables, making it versatile for various optimization tasks [26]. Additionally, CHOA has shown robust performance in addressing optimization problems with noise and uncertainties, which are common challenges in financial accounting data analysis.

The selection of CHOA over other swarm intelligence optimization methods is based on its specific advantages for our profit prediction task. While there are other well-established swarm intelligence algorithms [27,28], CHOA offers unique features that align with the complexities and characteristics of financial accounting data [29].

By leveraging the strengths of CHOA and combining them with DLSTM, we aim to develop a hybrid model that enhances the performance of profit prediction in FAIS. This combination capitalizes on the efficiency and adaptability of CHOA and the DL capabilities of DLSTM, providing a powerful framework for accurate and robust profit forecasting.

2. Contribution

- We present TAR-CHOA to improve the conventional technique's adaptation and the rate of convergence.
- TASR-CHOA incorporates two innovative approaches. One is a probabilistic alternative technique to increase the convergence rate and the other is a dual adaptive weighting strategy to improve the initial tendency of exploration search and the subsequent development tendency.
- The design and validation of a DL framework for teaching effective trading strategies using the TAR-CHOA.
- Evolving a conventional DLSTM to address the two primary shortcomings of gradient descent-based algorithms by using the TAR-CHOA method and five baseline optimization algorithms.

The remaining sections of the paper are organized as follows: The second section contains the most relevant works. Section 3 presents the pertinent concepts, including the DLSTM framework and the CHOA mathematics. Section 4 describes the suggested approach. Section 5 then describes the setup of the experiment, data set, and results. Section 6 provides a summary and conclusion of the findings.

3. Related works

The advent of the digital transformation revolution has significantly influenced accounting information systems, particularly within the Chinese context [30]. The introduction of advanced technologies, including neural machines [31], multi-modal fusion [32], natural experiments [33], and corporate innovation [34], has resulted in substantial transformations in accounting practices and systems. The advent of these technological advancements has resulted in enhanced efficiency, precision, and availability in the processing, analysis, and reporting of financial data.

Within the Chinese context, the advent of the digital transformation revolution has precipitated the automation of accounting processes, resulting in a reduction of manual errors and the optimization of financial operations. Cloud-based accounting systems have become increasingly popular because they offer businesses the ability to store and retrieve financial data remotely while maintaining a high level of data security. Furthermore, the incorporation of artificial intelligence and DL methodologies has enabled enhanced data analysis and predictive capabilities [35], empowering organizations to make more knowledgeable financial decisions.

In addition, the arrival of digital changes played a key role in enabling the timely distribution of financial information and increasing the transparency and accountability of accounting. The Chinese accounting ecosystem has experienced improved data integrity and immutability as a result of the adoption of blockchain technology [36]. The aforementioned advancements have not only fostered enhanced trust among various parties involved but have also played a significant role in the advancement of emerging concepts such as smart contracts and decentralized finance.

In conclusion, the advent of the digital transformation revolution has significantly Impacted accounting information systems within the Chinese context, facilitating the automation of processes, utilization of advanced analytics, and improvement of transparency. The aforementioned advancements have significantly contributed to the enhancement of financial operations and decision-making processes within Chinese businesses.

The limitations of traditional statistical methods in the field of financial forecasting have been the subject of extensive scholarly research. According to research, the capacity of linear regression models to effectively capture non-linear interactions for forecasting stock prices is constrained [37]. Additionally, standard autoregressive integrated moving average (ARIMA) models are ineffective at forecasting market patterns [38]. Simple moving averages have come under fire for their alleged insufficient capacity to adapt to complex data patterns [39].

In the field of ANNs, researchers have tried to overcome the challenges of overfitting, a phenomenon that can lead to models with poor generalization ability. Previous studies have looked into a variety of methods for reducing overfitting in neural network models [40]. Additionally, researchers studying the consequences of increased network complexity, such as the addition of hidden layers and parameters, have given important insights into the limitations of models with fewer parameters and shallower architectures [41]. In order to increase the effectiveness of neural networks in forecasting financial time series, academics have also focused on the identification of appropriate network designs [42].

DL models have gained popularity, which has generated a lot of attention [43], but their restricted interpretability poses major challenges in the context of financial applications. In the context of financial forecasting initiatives, efforts have been made to improve the understandability of DL models [44]. Additionally, academic research into methods for easing the limitations imposed by little data in the context of DL for financial forecasting has been stimulated by the recognition of the dependence on large volumes of training data [45]. Additionally, other studies have looked at the potential challenges that could come up while working with noisy or unstructured data in the context of DL applications [46].

Hybrid systems consisting of different technologies and models are gaining attention as a potential solution to overcome the limitations associated with a single approach [47,48]. A hybrid method integrating neural networks and genetic algorithms has been proposed to improve financial forecasting [49]. Nevertheless, the potential increase in the integration process and computational complexity of these hybrid models has been recognized as a challenge, as reviewed in Ref. [50].

An invaluable tool in the field of financial forecasting, sentiment analysis has some distinct limitations. Several studies have shown varying accuracy of sentiment classification in predicting stock market movements [51]. As pointed out in previous studies [52–54], the performance impact of sentiment analysis can be influenced by our reliance on the accessibility and quality of news sources. Moreover, the challenge of extracting significant sentiment from financial market text data has stimulated research into innovative methods aimed at improving the accuracy of sentiment analysis [55].

In sum, academic research to date has highlighted the limitations associated with traditional statistical methods and explored

Table 1
The brief review of recent research studies and the shortcomings.

No	Core Concept	Related Works	Shortcomings
1	**Conventional statistical approaches**	Linear regression [37]	Inability to capture non-linear relationships
		ARIMA models [38]	Limited effectiveness in financial prediction
		Moving averages [39]	Insufficient flexibility for complex data patterns
2	**Machine learning**	Neural networks [40]	Overfitting issues
		Analyzes the impact of structure depth on neural network efficiency [41]	Limited complexity with fewer parameters and hidden layers
		The impact of different structures for neural networks in financial time series prediction [42]	Challenges in selecting optimal network architecture
3	**Deep learning**	Investigation of the performance of DL models in financial applications [44]	Lack of interpretability in DL models
		Data limitations in DL for financial prediction [45]	Dependency on large quantities of training data
		The noise challenge in DL for financial time series data [46]	Challenges in handling unstructured noisy or data
4	**Hybrid systems**	Hybrid neural networks and optimization algorithms for financial forecasting [48,49]	The complex integration of various algorithms and models
		Computational challenges of hybrid models in financial prediction [50]	computational complexity issue
5	**Sentiment analysis**	Analyzes the limitations of sentiment analysis in predicting stock market movements [51]	Degrees of accuracy in sentiment classification.
		Effect of news source on sentiment analysis performance [52]	Reliance on the quality and availability of news sources
		Challenges in sentiment analysis for financial markets and proposes novel techniques [55]	Difficulty in extracting meaningful sentiments from texts.

alternative strategies to improve financial forecasting. As summarized in Table 1, progress in this area has been made possible by efforts aimed at overcoming limitations associated with artificial neural networks, DL models, hybrid systems, and sentiment analysis. Using insights gained from these related studies, our goal is to develop new methodologies that consider the limitations and improve the accuracy of profit forecasting using FAIS.

4. Related terminology

This section presents associated terminologies, which include CHOA and DLSTM.

4.1. Chimp optimization algorithm

Pushing, chasing, blocking, and assaulting are the four distinct phases of hunting in CHOA. Chimpanzees are initially produced at random to start the CHOA. The chimpanzees are then randomly divided into the four abovementioned categories, with a mathematical model for each grouping. It was proposed that Eqs. (1)–(4) represent the CHOA's hunting mathematical model [24]:

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

$$\boldsymbol{\kappa} = 2 \cdot \boldsymbol{\beta} \cdot \mathbf{r}_1 - \boldsymbol{\beta} \tag{2}$$

$$\mathbf{J} = 2 \cdot (\mathbf{r}_2) \tag{3}$$

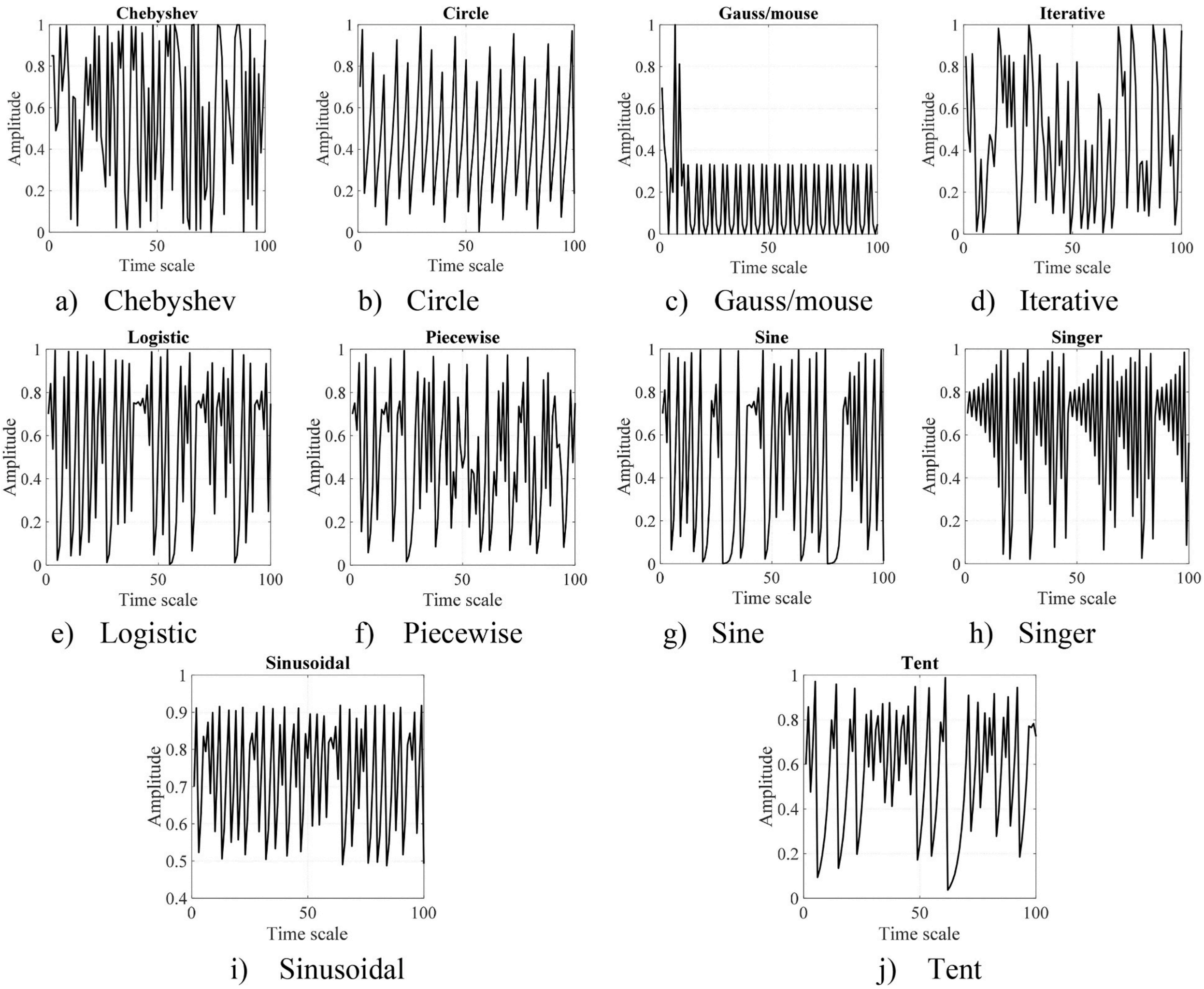


Fig. 1. The utilized chaotic map: a) Chebyshev, b) Circle, c) Gauss/mouse, d) Iterative, e) Logistic f) Piecewise, g) Sine, h) Singer, i) Sinusoidal, j) Tent.

$$\boldsymbol{\zeta} = \text{according to chaotic maps} \tag{4}$$

where t denotes the iteration numbers, $\boldsymbol{\kappa}$, $\mathbf{J}$, and $\boldsymbol{\zeta}$ signify the coefficient vectors, $\mathbf{p_{prey}}$ is the optimal solution obtained so far, and $\mathbf{p_{chimp}}$ is the optimal position of the chimp. Also, $\boldsymbol{\beta}$ is a non-linearly decreased coefficient ranging from 2.5 to 0, $\mathbf{r_1}$ and $\mathbf{r_2}$ are random values in the range (0,1], and $\boldsymbol{\zeta}$ denotes the chaotic mapping vectors. It should be mentioned that reference [24] provides a thorough description of these coefficients and mappings.

The primary and most effective approach to duplicate chimpanzee behavior statistically is by using prey, given the limited understanding of the initial prey's location. The CHOA will be responsible for housing four of the most highly-ranked chimpanzees. Subsequently, additional individuals will be compelled to relocate based on the chosen location of these superior chimpanzees, as indicated by Eqs. (5) and (6) [24].

$$\mathbf{p}^{t+1} = \frac{1}{4} \times (\mathbf{p}_1 + \mathbf{p}_2 + \mathbf{p}_3 + \mathbf{p}_4) \tag{5}$$

where

$$\begin{aligned} \mathbf{p}_1 &= \mathbf{p}_A - \mathbf{a}_1 \cdot |\mathbf{c}_1 \mathbf{p}_A - \mathbf{m}_1 \mathbf{x}| \\ \mathbf{p}_2 &= \mathbf{p}_B - \mathbf{a}_2 \cdot |\mathbf{c}_2 \mathbf{p}_B - \mathbf{m}_2 \mathbf{x}| \\ \mathbf{p}_3 &= \mathbf{p}_C - \mathbf{a}_3 \cdot |\mathbf{c}_3 \mathbf{p}_C - \mathbf{m}_3 \mathbf{p}| \\ \mathbf{p}_4 &= \mathbf{p}_D - \mathbf{a}_4 \cdot |\mathbf{c}_4 \mathbf{p}_D - \mathbf{m}_4 \mathbf{p}| \end{aligned} \tag{6}$$

Furthermore, chaotic values mimic social motivation activity in conventional CHOA, as shown by Eq. (7) and Fig. 1:

$$\mathbf{p}^{t+1} = \begin{cases} \boldsymbol{\zeta} & \eta_m \geq \frac{1}{2} \\ \text{Eq. (5)} & \eta_m < \frac{1}{2} \end{cases} \tag{7}$$

where η_m stands for stochastic values in the range of (0,1]; This simplified view of learning could lead to a premature or moderate convergence behavior, however. The following section will suggest a quantum mechanism to address these flaws.

4.2. Deep long short-term memory

To understand and predict sequences, several researchers have turned to the RNN structure known as deep LSTM. In contrast to conventional RNNs, which can experience the issue of vanishing gradients while training on lengthy sequences, LSTMs are optimized to identify long-term dependencies [5].

LSTMs are built with memory cells that are capable of retaining data for very long periods, allowing the network to retain and utilize important information from earlier time steps. LSTMs also have gates that control the flow of information, including the forget gate, input gate, and output gate. The aforementioned gates are responsible for the regulation of incoming and outgoing information within the memory cells, enabling the LSTM to selectively retain or discard information based on its relevance. A typical representation of LSTM is shown in Fig. 2.

Deep LSTM networks pertain to the employment of several LSTM layers that are arranged hierarchically. Each layer of the neural network is capable of capturing varying levels of abstraction, enabling it to learn intricate patterns within the input sequences. The subsequent layer in the LSTM architecture receives the output from the preceding layer, enabling the neural network to acquire hierarchical visualizations of the input information [29]. Fig. 3 illustrates a standard depiction of a deep LSTM.

To initiate the LSTM network process, the first step involves the utilization of the forget gate, denoted $fg(t)$, which plays a crucial role in deciding which information from the previous state should be discarded by the memory cell unit. The forget gate, $fg(t)$, is represented by Eq. (8) [56]:

$$fg(t) = \sigma\left(\alpha_{fg} x(t) + \beta_{fg} h(t-1) + \delta_{fg}\right) \tag{8}$$

In the equation, $fg(t)$ denotes the forget gate, which assumes values between 0 and 1. The logistic sigmoid function, σ, is applied. The configurable weight matrices and the bias vector can be referred to as α_{fg}, β_{fg}, and δ_{fg}.

Subsequently, the next step focuses on determining the information that needs to be incorporated into the memory cell unit for updating purposes. The input gate, denoted as $i(t)$, is determined by the sigmoid function and is responsible for identifying the values that need to be updated. In addition, a hyperbolic tangent (*tanh*) layer is employed to generate a possible update vector, denoted as $C(t)$. Eqs. (9) and (10) provide a detailed explanation of the computation for $i(t)$ and $C(t)$ [56]:

$$i(t) = \sigma(\beta_i h(t-1) + \alpha_i x(t) + \delta_i) \tag{9}$$

$$c(t) = \tanh(\beta_c h(t-1) + \alpha_c x(t) + \delta_c) \tag{10}$$

In the equations, it is a vector that assumes values between 0 and 1. The symbols α_i, β_i, and δ_i denote a set of trainable parameters linked to the input gate, whereas α_c, β_c, and δ_c pertain to a set of trainable parameters.

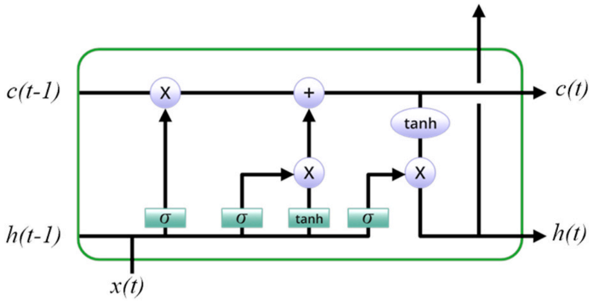


Fig. 2. A typical representation of LSTM.

After the determination is made concerning the data that is eliminated and preserved, the cell state, denoted as $C(t)$, which is subjected to an update process, can be calculated using Eq. (11) [56]:

$$c(t) = i(t) \circ c(t) + fg(t) \circ c(t-1) \tag{11}$$

The symbol $\circ$ used here denotes element-wise multiplicity. The term " $g(t) \circ c(t-1)$" is used to indicate the data that is accumulated $c(t-1)$ and can eventually be missed, whereas the term " $\circ c(t)$" is used to represent new data that will be integrated into the cell state.

Ultimately, the final step entails the computation of the output gate, playing a crucial role in determining the state that is hidden, $h(t)$. The computation of the output, denoted as $o(t)$, is achieved through the utilization of the sigmoid function. On the other hand, the output is achieved by performing a multiplication operation between $o(t)$ and the hyperbolic tangent output. The procedure is exemplified by Eqs. (12) and (13) [56]:

$$o(t) = \sigma(\alpha_o x(t) + \beta_o h(t-1) + \delta_o) \tag{12}$$

$$h(t) = o(t) \circ \tanh(c(t)) \tag{13}$$

In this equation, $o(t)$ denotes a vector [0,1], while α_o, β_o, and δ_o represent trainable parameters associated with the input gate.

5. Proposed methodology

This section provides an overview of the preprocessing techniques, the dataset used, and the suggested approach for predicting the profitability of FAIS using DLSTM. Specifically, it focuses on establishing the issue statement and outlining how CHOA would be utilized for training purposes.

5.1. Dataset

A suitable dataset for predicting profits can be created by using a dataset used to make the stock prediction. Kaggle has the dataset available.[1] In addition to OHLC prices and volume data, this dataset for the Chinese stock market also includes various financial statistics at a daily frequency, including the PB, PS, PE ratio, profitability, and others. All data is available daily, including financial ratios, such as the PE ratio, and some fundamentals, such as market capitalization.

5.1.1. Preprocessing

The last step involves giving each new formed dataset a binary value of zero or one, according to the revenue seen in the subsequent year. Due to the limited availability of future profit values beyond 2021, 16 datasets were produced. There are 16 new datasets after the preprocessing phase is finished. There are each 2350 companies, each with 15 attributes.

5.1.2. Developing a new dataset

Just one file containing 37,600 instances drawn from sixteen different datasets and fifteen different features. Table 2 presents the chosen characteristics together with their corresponding labels. Fig. 4 presents the correlation matrix depicting the relationships among the different variables, hence providing additional elucidation of the data set. Violin plots in Fig. 5 illustrate the representation of distributed information.

5.2. Twin adjustable reinforced chimp optimization algorithm

In nature-inspired algorithms, weight is an important parameter. To enhance the algorithm's performance, numerous studies have

[1] https://www.kaggle.com/datasets/franciscofeng/augmented-china-stock-data-with-fundamentals.

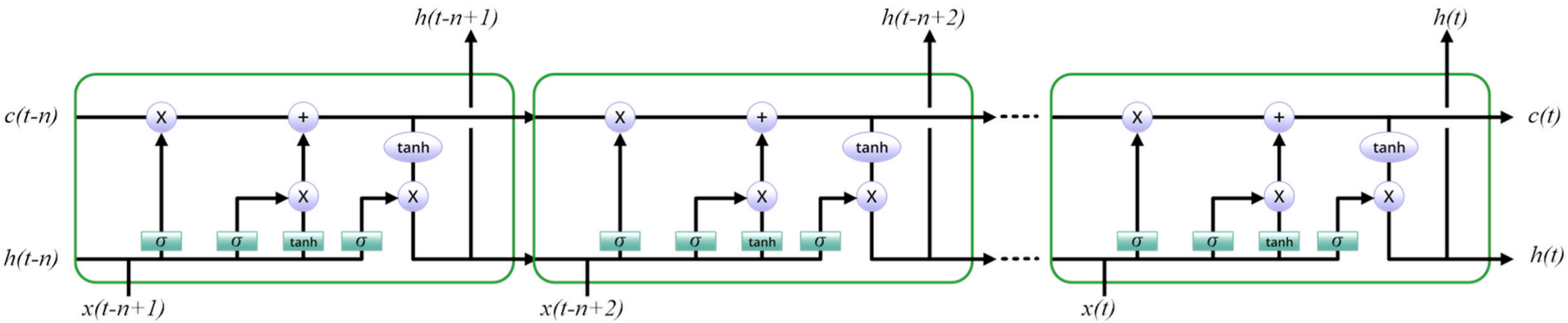


Fig. 3. A typical representation of deep LSTM.

Table 2
The chosen attributes and their corresponding labels.

No.	F_1	F_2	F_3	F_4
Feature	gross margin ratio	profit margin ratio	free cash flow margin	return on assets
No.	F_5	F_6	F_7	F_8
Feature	quick ratio	return on equity	ratio of cash	ratio of current
No.	F_9	F_{10}	F_{11}	F_{12}
Feature	flow of cash	ratio of debt	debt to equity ratio	sales ratio
No.	F_{13}	F_{14}	F_{15}	
Feature	SGA to revenue	R&D to revenue	CAPEX to revenue	

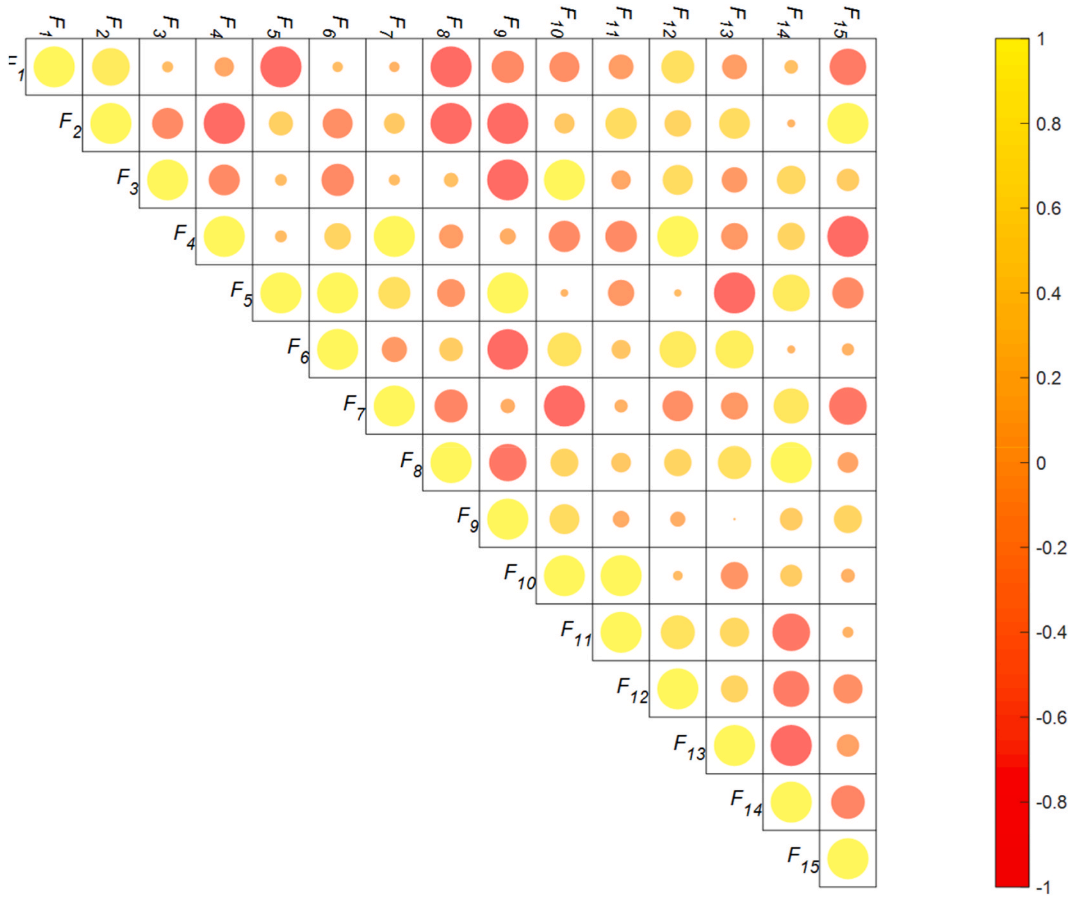


Fig. 4. Features' correlation matrix.

altered adaptive weighting. By including twofold adjustable weightings, TAR-CHOA also attempts to alter the algorithm's ability to do local and global searches. The conventional CHOA will quickly enter the local optimum when coping with multi-peak systems. Weight λ1 was introduced to enhance the capability of global search, and weight λ2 was afterward added to enhance the capability of local search. λ1 and λ2 can be modeled as shown in Eq. (14) and Eq. (15).

$$\lambda_1 = \left(1 - \frac{\varphi}{\max(\varphi)}\right)^{1-\tan\left(\left(r-\frac{1}{2}\right)\times\pi\times\frac{\theta}{\max(\varphi)}\right)} \tag{14}$$

$$\lambda_2 = \left(2 - \frac{2\varphi}{\max(\varphi)}\right)^{1-\tan\left(\left(r-\frac{1}{2}\right)\times\pi\times\frac{\theta}{\max(\varphi)}\right)} \tag{15}$$

where the algorithm's local optimum degree changes the value of θ. It should be noted that θ is added automatically while the chimps' position is not updated, whereas θ is split by two when it is updated to manage its size. The Cauchy Stochastic numbers and the addition

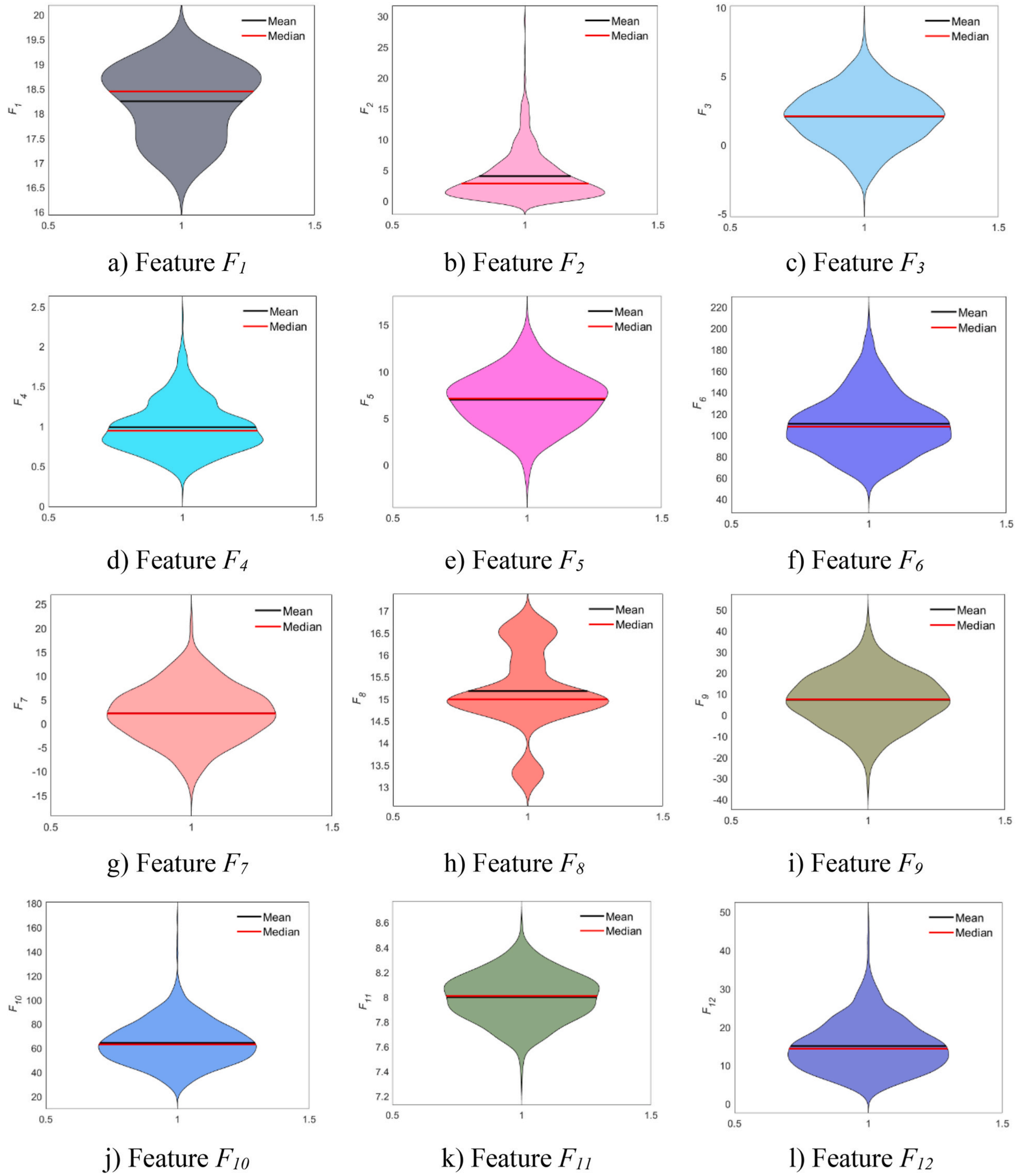
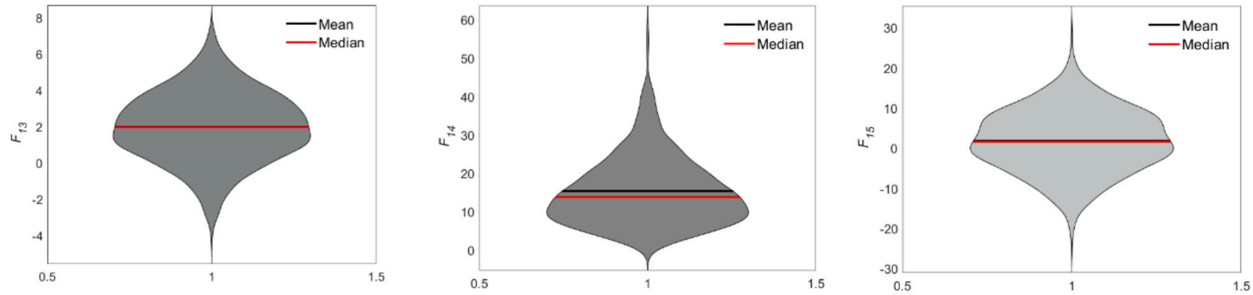


Fig. 5. Violin plots that effectively illustrate the distributions of the attributes: a) Feature F_1, b) Feature F_2, c) Feature F_3, d) Feature F_4, e) Feature F_5, f) Feature F_6, g), Feature F_7, h) Feature F_8, i) Feature F_9, j) Feature F_{10}, k) Feature F_{11}, l) Feature F_{12}, m) Feature F_{13}, n) Feature F_{14}, o) Feature F_{15}.

of s cause λ1 and λ2 to vary rather than decline linearly as the algorithm approaches the local optimum. The current number of evaluations is shown by φ. For each evaluation, the value φ is automatically incremented by one. max(φ) is the number of evaluations that can be performed, where Its value in the test is 300000. The ranges of λ1 and λ2 are [0,1] and [0.5,1], respectively. Finally, Eq. (6) is changed into Eq. (16) as followed by the addition of λ_1 in the algorithm's first half:



m) Feature F_{13} n) Feature F_{14} o) Feature F_{15}

Fig. 5. (*continued*).

$$\begin{aligned}
\mathbf{p}_1 &= \lambda_1 \mathbf{p}_A - \mathbf{a}_1 \cdot |\mathbf{c}_1 \mathbf{p}_A - \mathbf{m}_1 \mathbf{x}| \\
\mathbf{p}_2 &= \lambda_1 \mathbf{p}_B - \mathbf{a}_2 \cdot |\mathbf{c}_2 \mathbf{p}_B - \mathbf{m}_2 \mathbf{x}| \\
\mathbf{p}_3 &= \lambda_1 \mathbf{p}_C - \mathbf{a}_3 \cdot |\mathbf{c}_3 \mathbf{p}_C - \mathbf{m}_3 \mathbf{p}| \\
\mathbf{p}_4 &= \lambda_1 \mathbf{p}_D - \mathbf{a}_4 \cdot |\mathbf{c}_4 \mathbf{p}_D - \mathbf{m}_4 \mathbf{p}|
\end{aligned} \tag{16}$$

where Eq. (6) is converted to Eq. (17) by adding λ2 in the second period of the technique, as follows:

$$\begin{aligned}
\mathbf{p}_1 &= \lambda_2 \mathbf{p}_A - \mathbf{a}_1 \cdot |\mathbf{c}_1 \mathbf{p}_A - \mathbf{m}_1 \mathbf{x}| \\
\mathbf{p}_2 &= \lambda_2 \mathbf{p}_B - \mathbf{a}_2 \cdot |\mathbf{c}_2 \mathbf{p}_B - \mathbf{m}_2 \mathbf{x}| \\
\mathbf{p}_3 &= \lambda_2 \mathbf{p}_C - \mathbf{a}_3 \cdot |\mathbf{c}_3 \mathbf{p}_C - \mathbf{m}_3 \mathbf{p}| \\
\mathbf{p}_4 &= \lambda_2 \mathbf{p}_D - \mathbf{a}_4 \cdot |\mathbf{c}_4 \mathbf{p}_D - \mathbf{m}_4 \mathbf{p}|
\end{aligned} \tag{17}$$

Fig. 6 displays the proposed method's flowchart.

5.3. Problem definition

When employing optimization methods to fine-tune a deep network, often two primary concerns must be taken into consideration. It is imperative for the researchers to provide a detailed and accurate description of the structure's specs. The problem being analyzed should thereafter be utilized for the determination of the fitness function. The presentation of network variables constitutes a crucial step in the process of updating a DLSTM model utilizing the Temporal Attention Regularization with the TAR-CHOA technique. In order to achieve optimal prediction accuracy, it is imperative to appropriately configure essential parameters of DLSTM, including biases and weights. In order to establish the fitness function for the loss function, TAR-CHOA undertakes the optimization of weights and biases. The TAR-CHOA utilizes chimpanzees as symbolic representations of biases and weights.

The biases and weights of a Deep Long Short-Term Memory (DLSTM) model are commonly represented in matrix, vector, and digital forms, which are specific manifestations of optimization techniques. The person is represented by Eq. (18) in this study, as the TAR-CHOA requires vector-based parameters.

$$\mathbf{Chimps} = [W_{11}, W_{12}, \ldots, W_{nh}, b_1, \ldots, b_h, M_{11}, \ldots, M_{hm}] \tag{18}$$

where n is the inputs' number, M_{jo} is the weighted connection between the jth hidden nodes and the oth output nodes, and W_{ij} is the weighted connection between the ith input and the jth hidden node, b_j is the bias of the jth hidden neurons.

Where n denotes the number of input neurons, W_{ij} stands for the connection weights among the i_{th} input and the j_{th} hidden nodes, b_j denotes the j_{th} hidden neurons' bias, and Mjo is the connection weight between the j_{th} hidden node and the o_{th} output nodes.

In this context, the symbol "n" represents the quantity of input neurons. The notation " W_{ij}" refers to the connection weights between the ith input neuron and the jth hidden neuron. The symbol " b_j " represents the bias of the jth hidden neuron. Lastly, " Mjo" defines the connection weight among the jth hidden neuron and the oth output neuron.

5.4. Loss function

The DLSTM model is trained using the TAR-CHOA methodology to optimize precision and limit the occurrence of evaluated prediction errors (i.e., DLSTM-TAR-CHOA). Eq. (19) is the loss function used in DLSTM-TAR-CHOA:

$$y = \frac{1}{2}\sqrt{\frac{\sum_{i=0}^{N} (\mathrm{o} - d)^2}{N}} \tag{19}$$

In the given context, the symbols "d" and "o" are used to indicate the intended and actual results, respectively. The variable "N" represents the number of training samples. The two termination criteria for TAR-CHOA are a predetermined loss function and the

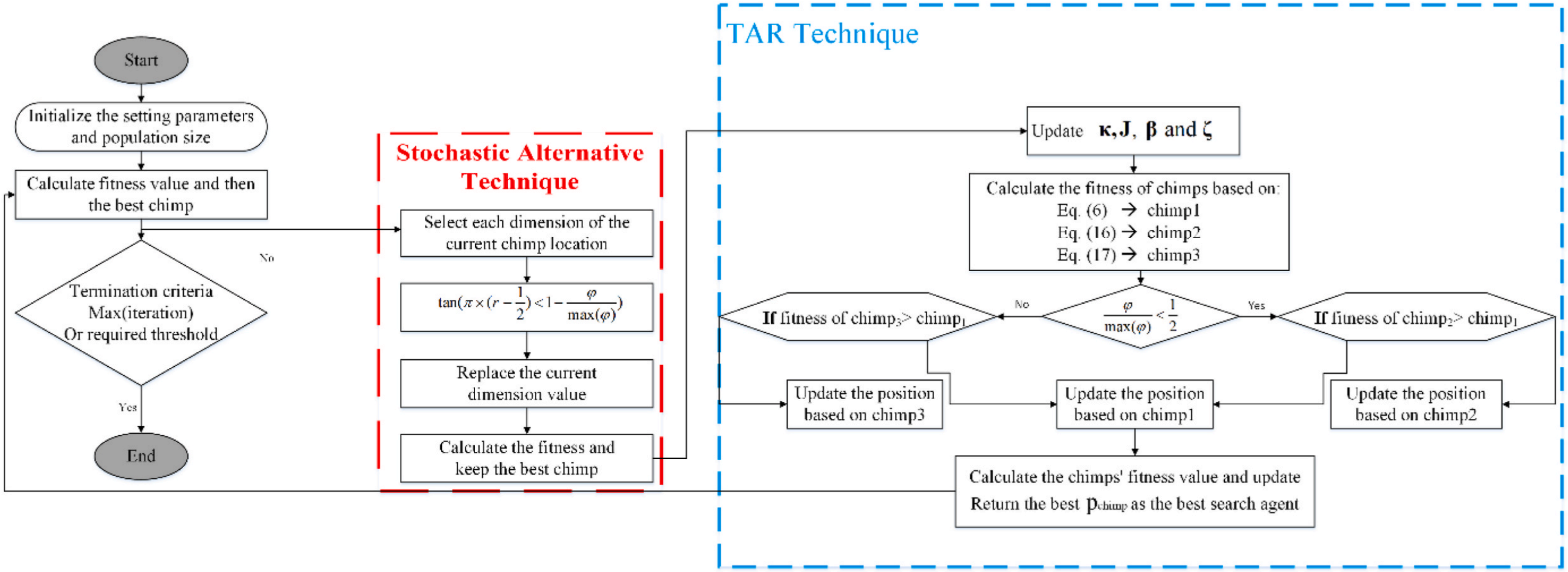


Fig. 6. Block diagram of the proposed methodology.

completion of the highest possible number of iterations. Fig. 7 illustrates the block diagram of the DLSTM-TAR-CHOA.

6. Experimental results and discussion

Python programming language and relevant libraries for data processing and deep learning were used to implement the models, and all the implementation codes were developed using PyTorch. The hardware utilized during the research was the Tesla T4 GPU unit, accessed through the free platform offered by Google called "Google Colaboratory." Additionally, Google Drive is used for storing models and data. The number of epochs is 30. The primary structural component of the DLSTM was its input layer, which consisted of 15 nodes. The neural network architecture consists of four concealed levels with node quantities of 4000, 2000, 2000, and 30, respectively. The fourth layer, known as the output layer, comprises two nodes. The aforementioned values are derived through the utilization of sensitivity analysis. The Rectified Linear Unit (ReLU) activation function was employed for all the hidden layers, whereas the SoftMax activation function was utilized for the output layer. The model was developed using the hold-out method, where the dataset was divided into separate sets for training and testing. The dataset consisted of 70% training data and 30% test data. During the training process, the occurrence of overfitting was observed. Consequently, a regularization technique known as L_1 regularization was implemented on the initial hidden layer. Additionally, a dropout regularization of 10% was incorporated after each of the first three hidden layers.

The developed models, including DLSTM-ARWOA, DLSTM-WCHOA, DLSTM-CHOA, DLSTM-GOCHOA, DLSTM-ARGA, and DLSTM-TAR-CHOA are employed to optimize the model of profit predictions. Table 3 displays the setup values for the utilized optimizers.

6.1. Statistical metrics

The effectiveness of the forecasting modeling techniques is evaluated by taking into account some statistical metrics, such as the coefficient of determination (R^2) (Eq. (20)), root mean square error (RMSE) (Eq. (21)), and mean absolute percentage error (MAPE) (Eq. (22)) [57]:

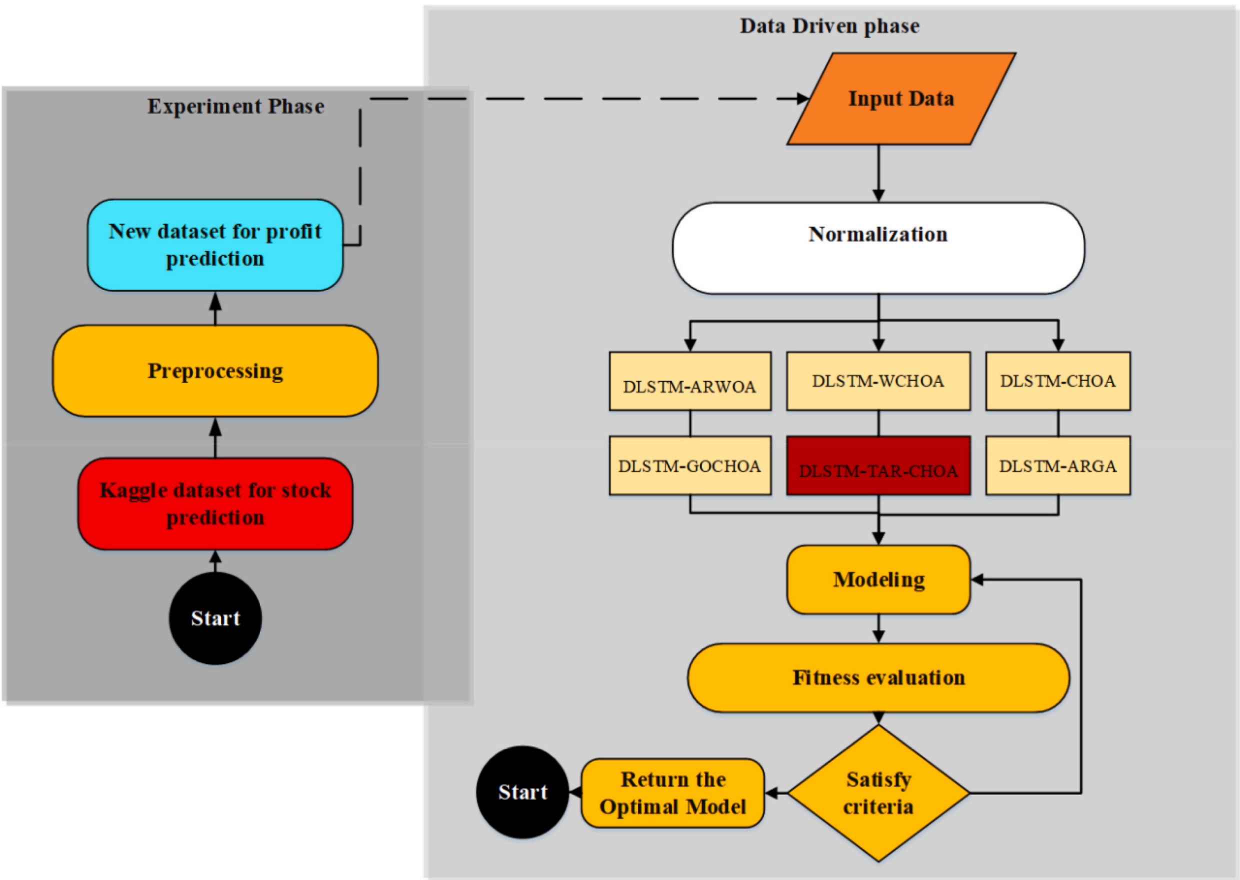


Fig. 7. The flowchart for the DLSTM-TAR-CHOA.

Table 3
Setup values for the utilized optimizers.

Techniques	Parameter	Value
CHOA	Chimps	200
	Maximum (iterations)	250
ARGA	r_1	(0,1]
	a	[1.5 to 0)
ARWOA	a	[2,0)

$$R^2 = 1 - \frac{SSR}{SST} \tag{20}$$

$$\text{RMSE} = \sqrt{\left(\frac{1}{m}\right)\sum_{i=1}^{m}\left(Av_i - Pv_i^{'}\right)^2} \tag{21}$$

$$\text{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Av_i - Pv_i^{'}}{Av_i}\right| \times 100\% \tag{22}$$

In this context, SSR refers to the sum of squared regression, SST represents the sum of squares total, Av_i symbolizes the actual value of the output, $Pv_i^{'}$ represents the value that was expected, and m signifies the total number of samples.

Where SST is the sum of squares total, SSR is the sum squared regression, and Av_i denotes the actual value outputs *and* $Pv_i^{'}$ stands for the predicted value, and m is the instance number.

6.2. DLSTM-CHOA for profit prediction

The DLSTM model was not initially run using optimization techniques. The statistical metrics used to assess the prediction capability of DLSTM are displayed in Table 4. These results suggest that the DLSTM's forecasts are not subpar, but we require more precise forecasts before we can confidently recommend it as a reliable financial profit forecast estimator. Therefore, to create a reliable DLSTM model, nature-inspired optimization techniques should be applied.

The subsequent experiment uses TAR-CHOA, ARWOA, ARGA, WCHOA, GOCHOA, and standard CHOA. Table 5 tabulates the statistical findings pertaining to the DLSTM-CHOA and alternative hybrid models in relation to the training datasets. The six DLSTM-based approaches proposed in this study have significant training efficiencies, as indicated by the fact that the R^2 for the six models is substantially over 0.81.

After completing the training stage, the suggested predictors were evaluated and validated using test sets. The findings of this study suggest that while all six predictors under consideration have the potential to anticipate the financial profit dataset more accurately than the normal DLSTM model, the DLSTM-TAR-CHOA predictor demonstrates the most notable prediction capability.

The ranking methodology is thereafter employed for each metric listed in Table 5 in order to evaluate and differentiate the prediction outcomes of the suggested predictors. In Fig. 8, stacked bars are employed, which are used to indicate the final ranking position. In Fig. 9, six statistical metrics are depicted for the DLSTM and proposed predictors. Results indicate that DLSTM-TAR-CHOA is more trustworthy and accurate during training and testing than the other proposed predictors. The intelligent optimization of the DLSTM based on the TAR-CHOA learning algorithm has many benefits, including quick convergence and lower error rates.

The rate at which metaheuristic methods converge is a significant parameter for comparative analysis. In order to enable comparisons, the convergence curves of comparative methodologies are presented in Fig. 10, alongside the preceding metrics and figures. These convergence curves are provided under the specific parameters of 10 (Figs. 10a), 20 (Fig. 10b), 30 (Figs. 10c), and 40 (Fig. 10d) individuals.

The convergence graph depicted in Fig. 10 provides evidence that DLSTM-TAR-CHOA exhibits the most favorable convergence rate among the benchmarks under consideration. Following DLSTM-TAR-CHOA, DLSTM-GOCHOA has a relatively strong convergence rate. Conversely, conventional DLSTM exhibits the least favorable convergence rate when contrasted with the other approaches.

6.3. Conventional methods' comparison

In order to facilitate a thorough comparison, the performance of traditional models such as ARIMA [58], random forest (RF) [59], support vector regression (SVR) [48], and MLP [60] were assessed in conjunction with the suggested model, DLSTM-TAR-CHOA. This

Table 4
The DLSTM's metrics.

RMSE	MAPE %	R^2
0.05451	1.278	0.5879

Table 5
Statistical metrics for comparison models.

	Method	MAPE	R^2	RMSE	Rank
Training	DLSTM	2.601	0.61	0.075	3
	DLSTM-TAR-CHOA	0.641	0.98	0.017	21
	DLSTM-GOCHOA	1.169	0.95	0.031	18
	DLSTM-ARWOA	1.252	0.92	0.039	15
	DLSTM-ARGA	1.649	0.90	0.049	12
	DLSTM-WCHOA	1.841	0.79	0.060	9
	DLSTM-CHOA	2.110	0.79	0.063	6
Testing	DLSTM	2.401	0.60	0.062	3
	DLSTM-TAR-CHOA	0.568	0.97	0.012	21
	DLSTM-GOCHOA	0.979	0.93	0.019	18
	DLSTM-ARWOA	1.169	0.90	0.032	15
	DLSTM-ARGA	1.460	0.87	0.036	12
	DLSTM-WCHOA	1.671	0.79	0.039	9
	DLSTM-CHOA	1.863	0.77	0.046	6

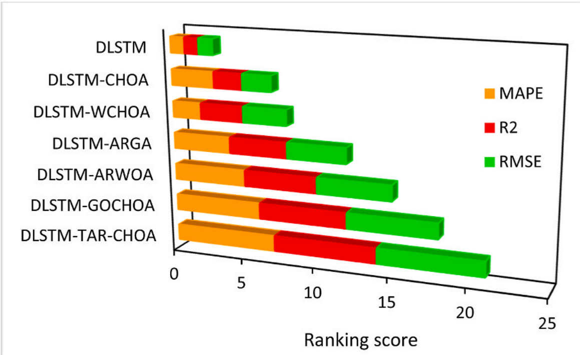


Fig. 8. Overall stacked ranking results.

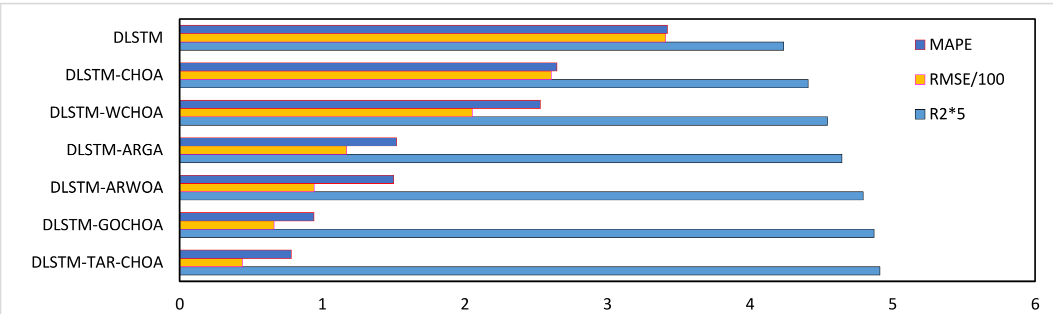


Fig. 9. The comparison of statistical indices.

facilitated a more thorough evaluation of several models.

In order to ensure an equitable contrast, we employed identical datasets and assessed metrics across all models. Additionally, we took into account the models' capacity to extrapolate their performance to novel datasets. Table 6 displays the setup values for the aforementioned models. Table 7 presents a visual representation of the comparative outcomes of the conventional profit prediction methods and DLSTM-TAR-CHOA.

6.4. Computation complexity

As previously said, achieving a balance between precision and complexity is essential. In this paragraph, an evaluation was conducted to determine the time complexities of the suggested approach concerning several benchmarks. In order to obtain significant insights, we conducted a comparative analysis of the floating point operations per second (FLOPS), parameter count, and training duration of our created approach in relation to other existing models. The studies were carried out using a computer that was fitted

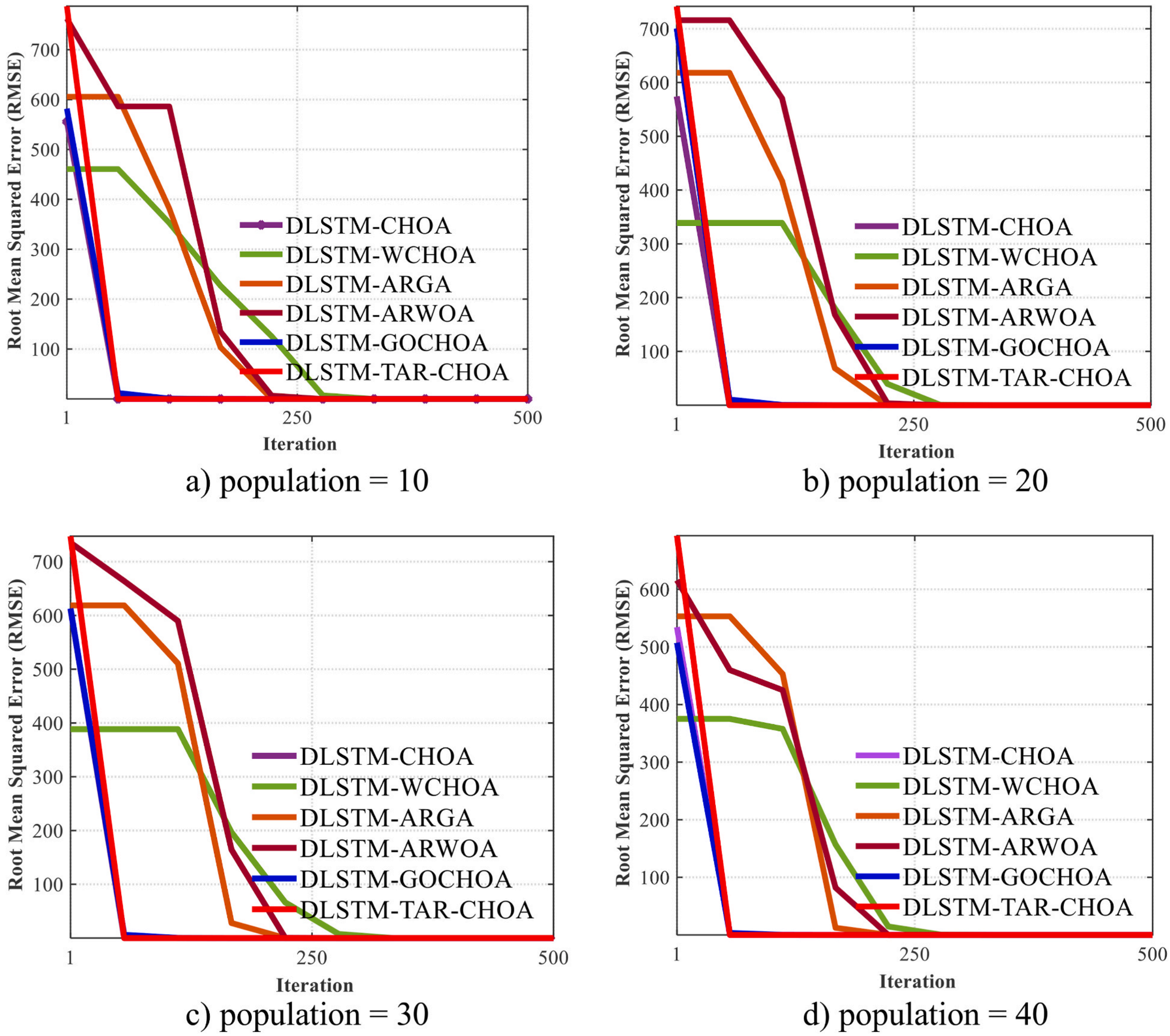


Fig. 10. The convergence curves of TAR-CHOA and other comparison algorithms: a) population = 10, b) population = 20, c) population = 30, d) population = 40.

Table 6
The values of setting parameters.

Model	Initial Parameters	Value
RF	Trees number	100
	Minimum split	2
	Minimum leaf	1
MLP	Number of hidden layers	30
	Learning rate	0.002
ARIMA	p = q	1
	d	0
SVR	Kernel	RBF
	C	1
	€	0.2

with an NVidia Tesla K20 Graphics Processing Unit (GPU). Table 8 presents the temporal data, wherein the most favorable outcomes are emphasized in bold to facilitate ease of reference.

Additionally, the results of DLSTM-TAR-CHOA were compared with other benchmarks in Table 8 using Wilcoxon's rank-sum test

Table 7
The results of conventional benchmarks and DLSTM-TAR-CHOA.

Model	Accuracy	RMSE	RRMSE
MLP [60]	0.763	0.027	0.169
RF [59]	0.745	0.028	0.168
SVR [48]	0.722	0.032	0.165
ARIMA [58]	0.633	0.039	0.188
Proposed Model (DLSTM-TAR-CHOA)	0.924	0.011	0.116

The values of the startup and settingsThe findings of the comparison analysis demonstrated that our suggested hybrid model, DLSTM-TAR-CHOA, had superior performance in accuracy and prediction capabilities compared to the conventional models. The results exhibited superior accuracy, reduced mean squared error (MSE), and decreased root mean squared error (RMSE) in comparison to the conventional models. The utilization of the TAR-CHOA for optimizing parameters in the DLSTM model appears to boost its predictive powers in comparison to the conventional models.

[61], a widely used non-parametric technique for assessing statistical significance. In this particular instance, the significance threshold was established at a value of 5%. The presence of "N/A″ in the data indicates that the approach in question cannot be subjected to comparison with itself.

Based on the findings of our study, it can be observed that the DLSTM-TAR-CHOA model exhibits a marginal increase in training duration in contrast with the conventional DLSTM model. Conversely, the p-value indicates that there is no statistically significant difference in training time between the two techniques. Additionally, it is worth noting that DLSTM-TAR-CHOA exhibits a reduced training time in comparison to alternative models that rely on optimization methods, hence underscoring its enhanced efficiency. The combination of TAR-CHOA and DLSTM demonstrates a favorable influence on the duration of the training, presenting possible benefits in comparison to the original DLSTM model and alternative variations utilizing optimization methods. This implies that DLSTM-TAR-CHOA achieves a harmonious equilibrium by simultaneously enhancing training efficiency and prediction accuracy. The reduced duration of training observed in DLSTM-TAR-CHOA can be attributed to the efficacy of TAR-CHOA in improving hyperparameters within DLSTM models. By capitalizing on the advantages offered by the TAR-CHOA algorithm, the training procedure can be enhanced in terms of efficiency, while yet maintaining the predictive capabilities of the model. Based on the statistical analysis conducted, it can be concluded that there is no statistically significant distinction in the amount of training time between DLSTM-TAR-CHOA and the preliminary DLSTM model. This suggests that the computational complexity added by TAR-CHOA is either negligible or within an acceptable range. In general, the findings indicate that DLSTM-TAR-CHOA presents a viable option for profit prediction. This is attributed to its similar training duration compared to the original DLSTM model, along with the potential enhancement in forecasting precision resulting from the incorporation of the TAR-CHOA methodology. The findings of this study underscore the potential advantages of integrating optimization techniques and GRU models to enhance the efficiency and precision of profit forecasting.

7. Conclusion

This study presents the introduction of the combination of DLSTM and TAR-CHOA approach (DLSTM-TAR-CHOA) system as a means to improve the process of design and profit prediction of FAIS. The objective of our study was to enhance the precision of profit prediction by employing the DLSTM model in conjunction with the TAR-CHOA. A complete dataset was generated, comprising 15 input parameters, derived from the Chinese stock market Kaggle dataset, in order to facilitate precise comparisons.

Our evaluation of various DL-based models revealed that the DLSTM-TAR-CHOA model, along with DLSTM-GOCHOA, DLSTM-ARWOA, DLSTM-ARGA, DLSTM-WCHOA, DLSTM-CHOA, and conventional DLSTM models, ranked highest to lowest in terms of their performance scores (42, 36, 30, 24, 18, 12, and 6 respectively). These DL-based models demonstrated promising results in financial accounting profit prediction.

However, it is important to acknowledge the limitations of the presented technique. Firstly, our approach relies on historical financial accounting data and assumes that past patterns and relationships will continue to hold in the future. This assumption may not always be accurate, as financial markets are subject to various external factors and uncertainties. Secondly, the performance of our models may vary depending on the specific characteristics and dynamics of different financial markets. It is essential to consider the uniqueness of each market and adapt the models accordingly.

Furthermore, while the DLSTM-TAR-CHOA model showed accuracy in profit prediction, there is still a need to address potential biases in the generated dataset. Future improvements could involve incorporating additional features or leveraging dimensionality reduction techniques such as Principal Component Analysis (PCA) to reduce bias and enhance the model's performance.

In conclusion, the DLSTM-TAR-CHOA model, along with other DL-based models examined in this study, holds promise for financial accounting profit prediction. Nevertheless, it is crucial to exercise caution regarding the constraints and difficulties linked to the aforementioned methodology. Future research should focus on refining the model's performance, addressing biases, and considering market-specific dynamics to further enhance the predictive capabilities of financial accounting information systems.

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Table 8
Computational complexity.

Method	Training time	Number of parameters	FLOPS	p-value
DLSTM	**7 m 29 s**	**9.6K**	**6.2 M**	**0.41**
DLSTM-CHOA	8 m 44 s	11.9 k	6.99 M	0.021
DLSTM-GOCHOA	11 m 33s	12.9 M	7.33 M	0.014
DLSTM-ARWOA	8 m 33 s	11.9 k	6.98 M	0.015
DLSTM-ARGA	9 m 84 s	12.8 k	7.14 M	0.018
DLSTM-WCHOA	8 m 33 s	11.5k	6.82 M	0.013
DLSTM-TAR-CHOA	7 m 82 s	10.0k	6.54 M	**N/A**

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Data availability statement

The datasets presented in this article are not publicly available by the following link:
https://www.kaggle.com/datasets/franciscofeng/augmented-china-stock-data-with-fundamentals.

Code availability

The source code of the models can be available by request.

Additional information

No additional information is available for this paper.

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.

References

[1] H. Yi, X. Meng, Y. Linghu, Z. Zhang, Can financial capability improve entrepreneurial performance? Evidence from rural China, Economic research-Ekonomska istraživanja 36 (1) (2023) 1631–1650.
[2] M. Al-Okaily, Does AIS Usage Matter in SMEs Performance? an Empirical Investigation under Digital Transformation Revolution, Information Discovery and Delivery, 2023.
[3] M. Al-Okaily, M. Al-Kofahi, F.S. Shiyyab, A. Al-Okaily, Determinants of user satisfaction with financial information systems in the digital transformation era: insights from emerging markets, in: Global Knowledge, Memory and Communication, 2023.
[4] S. Li, Z. Liu, Scheduling uniform machines with restricted assignment, Math. Biosci. Eng. 19 (2022) 9697–9708.
[5] M. Al-Okaily, Toward an integrated model for the antecedents and consequences of AIS usage at the organizational level, EuroMed J. Bus. (2022) ahead-of-print.
[6] M. Al-Okaily, A. Al-Okaily, An empirical assessment of enterprise information systems success in a developing country: the Jordanian experience, The TQM Journal 34 (6) (2022) 1958–1975.
[7] R.G. Schroeder, M.W. Clark, J.M. Cathey, Financial Accounting Theory and Analysis: Text and Cases, John Wiley & Sons, 2022.
[8] X. Li, M. Khishe, L. Qian, Evolving deep gated recurrent unit using improved marine predator algorithm for profit prediction based on financial accounting information system, Complex & Intelligent Systems (2023) 1–17.
[9] S.K. Asnawi, T. Wiranata, C. Samsuki, S. Julanda, The evaluation of firm performance among eva and accounting profit: harmony? Journal of Management and Leadership 5 (2) (2022) 14–27.
[10] M.E. Barth, K. Li, C. McClure, Evolution in Value Relevance of Accounting Information, 2022.
[11] O.S. Pereira, Algorithmic Trading Strategies: Automating and Back-Testing the Perfect Order Strategy, 2022.
[12] H. Wang, Z. Cui, R. Liu, L. Fang, Y. Sha, A multi-type transferable method for missing link prediction in heterogeneous social networks, IEEE Trans. Knowl. Data Eng. (2023).
[13] X. Li, Y. Sun, Application of RBF neural network optimal segmentation algorithm in credit rating, Neural Comput. Appl. 33 (2021) 8227–8235.
[14] Y. Liu, K. Wang, L. Liu, H. Lan, L. Lin, Tcgl: temporal contrastive graph for self-supervised video representation learning, IEEE Trans. Image Process. 31 (2022) 1978–1993.

[15] Z. Lu, R. Cheng, Y. Jin, K.C. Tan, K. Deb, Neural Architecture Search as Multiobjective Optimization Benchmarks: Problem Formulation and Performance Assessment, IEEE transactions on evolutionary computation, 2023.
[16] H. Zhu, M. Xue, Y. Wang, G. Yuan, X. Li, Fast visual tracking with siamese oriented region proposal network, IEEE Signal Process. Lett. 29 (2022) 1437–1441.
[17] B. Wu, Q. Gu, Z. Liu, J. Liu, Clustered institutional investors, shared ESG preferences and low-carbon innovation in family firm, Technol. Forecast. Soc. Change 194 (2023), 122676.
[18] J. Zhang, X. Li, B. Wu, L. Zhou, X. Chen, Order matters: effect of use versus outreach order disclosure on persuasiveness of sponsored posts, J. Res. Indian Med. (2023).
[19] X. Xie, X. Jin, G. Wei, C.-T. Chang, Monitoring and early warning of SMEs' shutdown risk under the impact of global pandemic shock, Systems 11 (5) (2023) 260.
[20] Y. Ren, H. Jiang, N. Ji, H. Yu, TBSM: a traffic burst-sensitive model for short-term prediction under special events, Knowl. Base Syst. 240 (2022), 108120.
[21] M. Li, M. Yang, Y. Yu, W.-J. Lee, A wind speed correction method based on modified hidden Markov model for enhancing wind power forecast, IEEE Trans. Ind. Appl. 58 (1) (2021) 656–666.
[22] Y. Tang, et al., A survey on machine learning models for financial time series forecasting, Neurocomputing 512 (2022) 363–380.
[23] Y. Mao, Y. Zhu, Z. Tang, Z. Chen, A novel airspace planning algorithm for cooperative target localization, Electronics 11 (18) (2022) 2950.
[24] M. Khishe, M.R. Mosavi, Chimp optimization algorithm, Expert Syst. Appl. 149 (2020), 113338.
[25] M. Khishe, M. Nezhadshahbodaghi, M.R. Mosavi, D. Martín, A weighted chimp optimization algorithm, IEEE Access 9 (2021) 158508–158539.
[26] Q. Bo, W. Cheng, M. Khishe, Evolving chimp optimization algorithm by weighted opposition-based technique and greedy search for multimodal engineering problems, Appl. Soft Comput. 132 (2023), 109869.
[27] S. Li, Efficient algorithms for scheduling equal-length jobs with processing set restrictions on uniform parallel batch machines, Math. Biosci. Eng. 19 (2022) 10731–10740.
[28] A. Chakraborty, A.K. Kar, Swarm intelligence: a review of algorithms, in: Nature-inspired Computing and Optimization: Theory and Applications, 2017, pp. 475–494.
[29] W. Kaidi, M. Khishe, M. Mohammadi, Dynamic levy flight chimp optimization, Knowl. Base Syst. 235 (2022), 107625.
[30] W. Chen, W. Cai, Y. Hu, Y. Zhang, Q. Yu, Gimmick or revolution: can corporate digital transformation improve accounting information quality? Int. J. Emerg. Mark. (2022).
[31] X. Liu, J. He, M. Liu, Z. Yin, L. Yin, W. Zheng, A scenario-generic neural machine translation data augmentation method, Electronics 12 (10) (2023) 2320.
[32] S. Lu, M. Liu, L. Yin, Z. Yin, X. Liu, W. Zheng, The multi-modal fusion in visual question answering: a review of attention mechanisms, PeerJ Computer Science 9 (2023) e1400.
[33] H. Gao, D. Shi, B. Zhao, Does good luck make people overconfident? Evidence from a natural experiment in the stock market, J. Corp. Finance 68 (2021), 101933.
[34] H. Gao, P.-H. Hsu, K. Li, J. Zhang, The real effect of smoking bans: evidence from corporate innovation, J. Financ. Quant. Anal. 55 (2) (2020) 387–427.
[35] H. Jiang, M. Wang, P. Zhao, Z. Xiao, S. Dustdar, A utility-aware general framework with quantifiable privacy preservation for destination prediction in LBSs, IEEE/ACM Trans. Netw. 29 (5) (2021) 2228–2241.
[36] M. Palmié, J. Wincent, V. Parida, U. Caglar, The evolution of the financial technology ecosystem: an introduction and agenda for future research on disruptive innovations in ecosystems, Technol. Forecast. Soc. Change 151 (2020), 119779.
[37] F.S. Gharehchopogh, T.H. Bonab, S.R. Khaze, A linear regression approach to prediction of stock market trading volume: a case study, International Journal of Managing Value and Supply Chains 4 (3) (2013) 25.
[38] S. Stevenson, A comparison of the forecasting ability of ARIMA models, J. Property Invest. Finance 25 (3) (2007) 223–240.
[39] P.R. Winters, Forecasting sales by exponentially weighted moving averages, Manag. Sci. 6 (3) (1960) 324–342.
[40] X. Xu, Y. Zhang, Residential housing price index forecasting via neural networks, Neural Comput. Appl. 34 (17) (2022) 14763–14776.
[41] L. Lin, et al., Understanding the impact on convolutional neural networks with different model scales in AIoT domain, J. Parallel Distr. Comput. 170 (2022) 1–12.
[42] M. Qi, G.P. Zhang, An investigation of model selection criteria for neural network time series forecasting, Eur. J. Oper. Res. 132 (3) (2001) 666–680.
[43] X. Liu, et al., Emotion classification for short texts: an improved multi-label method, Humanities and Social Sciences Communications 10 (1) (2023) 1–9.
[44] A.M. Ozbayoglu, M.U. Gudelek, O.B. Sezer, Deep learning for financial applications: a survey, Appl. Soft Comput. 93 (2020), 106384.
[45] W. Wang, W. Li, N. Zhang, K. Liu, Portfolio formation with preselection using deep learning from long-term financial data, Expert Syst. Appl. 143 (2020), 113042.
[46] N. Passalis, M. Kirtas, G. Mourgias-Alexandris, G. Dabos, N. Pleros, A. Tefas, Training noise-resilient recurrent photonic networks for financial time series analysis, in: 2020 28th European Signal Processing Conference (EUSIPCO), IEEE, 2021, pp. 1556–1560.
[47] Y. Zheng, X. Lv, L. Qian, X. Liu, An optimal bp neural network track prediction method based on a ga–aco hybrid algorithm, J. Mar. Sci. Eng. 10 (10) (2022) 1399.
[48] X. Li, Y. Sun, Stock intelligent investment strategy based on support vector machine parameter optimization algorithm, Neural Comput. Appl. 32 (2020) 1765–1775.
[49] D.K. Sharma, H. Hota, K. Brown, R. Handa, Integration of genetic algorithm with artificial neural network for stock market forecasting, International Journal of System Assurance Engineering and Management 13 (Suppl 2) (2022) 828–841.
[50] S. Bhanja, A. Das, A Black Swan event-based hybrid model for Indian stock markets' trends prediction, in: Innovations in Systems and Software Engineering, 2022, pp. 1–15.
[51] P. Rajendiran, P. Priyadarsini, Survival study on stock market prediction techniques using sentimental analysis, Mater. Today: Proc. 80 (2023) 3229–3234.
[52] X. Li, H. Xie, L. Chen, J. Wang, X. Deng, News impact on stock price return via sentiment analysis, Knowl. Base Syst. 69 (2014) 14–23.
[53] L. Li, X. Wu, M. Kong, J. Liu, J. Zhang, Quantitatively interpreting residents happiness prediction by considering factor–factor interactions, IEEE Transactions on Computational Social Systems (2023).
[54] Q. Guo, J. Zhong, The effect of urban innovation performance of smart city construction policies: evaluate by using a multiple period difference-in-differences model, Technol. Forecast. Soc. Change 184 (2022), 122003.
[55] I. Almalis, E. Kouloumpris, I. Vlahavas, Sector-level sentiment analysis with deep learning, Knowl. Base Syst. 258 (2022), 109954.
[56] A. Graves, A. Graves, Long short-term memory, in: Supervised Sequence Labelling with Recurrent Neural Networks, 2012, pp. 37–45.
[57] Y. Zhang, Z. Shao, J. Zhang, B. Wu, L. Zhou, The effect of image enhancement on influencer's product recommendation effectiveness: the roles of perceived influencer authenticity and post type, J. Res. Indian Med. (2023).
[58] G.E. 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.
[59] S.J. Rigatti, Random forest, J. Insur. Med. 47 (1) (2017) 31–39.
[60] M.W. Gardner, S. Dorling, Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences, Atmos. Environ. 32 (14–15) (1998) 2627–2636.
[61] J. Cuzick, A Wilcoxon-type test for trend, Stat. Med. 4 (1) (Jan-Mar 1985) 87–90, https://doi.org/10.1002/sim.4780040112.