Journal of Engineering, Project, and Production Management
2025, 15(4), 2025-132

Evaluating Corporate Employee Performance Using Big Data-Enabled KPCA-LSTM Models

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Project Management
Received July 10, 2025; revised July 29, 2024; accepted July 29, 2025
Available online October 6, 2025

Abstract: The long-term growth of the business and the enhancement of the management system are closely tied to enterprise employee performance assessment, a crucial tool for the development of contemporary private firms. The problem of evaluating the performance of employees in an enterprise setting is fundamentally a predictive regression problem; a deterministic optimization algorithm cannot determine the optimal network parameters, and the current approach to evaluating employee performance in an enterprise setting is prone to local optimality. This research presents an employee performance evaluation for enterprises using the Kernel Principal Component Analysis – Spotted Hyena Optimization – Long Short-Term Memory (KPCA-SHO-LSTM) model. This paper describes the method of building a performance evaluation system for enterprise employees. It begins by analyzing the steps involved in constructing the system and selecting the evaluation indices. Next, the Kernel Principal Component Analysis (KPCA) and Spotted Hyena Optimization (SHO) algorithms are employed to search for optimal parameters for the Long Short-Term Memory (LSTM) network and improve the performance evaluation model. Finally, a design is proposed to evaluate the algorithm's performance using optimized covariates and an adaptive segment function. The approach is evaluated against other algorithms in the context of enterprise employee performance evaluation. The findings demonstrate that the proposed method exhibits the lowest error accuracy, as well as the ideal convergence speed and iteration number.

Keywords: kernel principal component analysis, corporate employee performance appraisal, LSTM, spotted hyena optimization algorithm

DOI 10.32738/JEPPM-2025-132

1. Introduction

Recently, governmental agencies have prioritized the growth of private firms and improving the business climate for them, resulting in a significant expansion of the private economy (Shamsudin et al., 2023). The performance assessment of employees in a business is a crucial tool for the advancement of modern private enterprises. It has a direct impact on the long-term development of the enterprise and the enhancement of its management system (Ji et al., 2022). The present rapid growth of private firms is accompanied by their unrefined business techniques and the lack of a comprehensive performance assessment system, resulting in a lack of credibility in the performance appraisal process (Yan, 2022). An incentive mechanism that is scientific, rational, fair, and effective can enable employees to fully utilize their potential and significantly contribute to enhancing the competitiveness of enterprises. Particularly within a company, a well-established performance appraisal system can facilitate communication and collaboration between employees and the company (Neema, 2022). The research on enterprise employee performance appraisal primarily focuses on the objectives of the performance appraisal system, the construction of the performance appraisal system, the practical application of the performance appraisal, and the selection of performance appraisal indices. However, there is a lack of research on the construction of performance evaluation models. Luthra (Luthra et al., 2022) focuses on the creativity of employees in a company and conducts research and analysis on the performance management indicators of these employees. Vuong and Nguyen (2022) statistically analyzes the goals of enterprise performance appraisal and categorizes them into three types: management goals, information goals, and incentive goals. Aityassine et al. 2022 addresses the challenges of index selection, weighting, and evaluation timing in enterprise performance appraisal by employing the 360-degree evaluation method. In the literature of Rizana et al. (2023), an optimized machine learning algorithm is employed to establish the logical connection between the main performance index elements and the corresponding relationships of different personnel, using key performance indicators. In literature (Rumanda et al., 2023), a hierarchical analysis is utilized to determine the weight of company performance appraisal indexes and develop the company performance appraisal model.

Based on the literature analysis provided, the enterprise employee performance evaluation system plays a crucial role in the company's development. However, several issues need to be addressed: 1) The indicators used in the employee performance appraisal system are not sufficiently clear, resulting in a lack of fairness and objectivity. 2) The performance management work is characterized by formalism, indicating a weak management mechanism. 3) The evaluation process lacks transparency and a regulatory mechanism, leading to a lack of recognition for the evaluation outcomes (Wang, 2022).

Deep learning utilizes intricate node networks to create nonlinear mapping connections. However, in difficult tasks, deep learning algorithms often encounter the challenge of being stuck in local optima throughout the training phase (Gbaminido and Anyanwu, 2023). This research presents a solution to the issue of corporate employee performance evaluation by proposing an algorithm that combines kernel principal component analysis (KPCA) with an optimization deep learning approach. The enterprise employee performance evaluation system is constructed by extracting performance evaluation indicators and constructing an index system based on design ideas and principles. The enterprise employee performance evaluation model is then constructed by combining the spotted hyena optimization algorithm and the long-time domain network. Although KPCA and LSTM have been combined in wind-power prediction (LiPeng et al., 2025) and stock-index forecasting (Zhao et al., 2025), none of the existing studies appl this hybrid structure to employee performance evaluation, nor do they integrate meta-heuristic optimization (e.g., SHO) for hyper-parameter tuning. This paper, therefore, bridges the gap by (i) constructing the first KPCA–SHO–LSTM framework for HR analytics, and (ii) introducing an adaptive segment loss function that improves convergence speed by 18 % compared with the conventional RMSE loss. This model proposes an enterprise employee performance evaluation method based on KPCA and SHO-LSTM. The method suggested in this work has enhanced the corporate employee performance evaluation system and its predictive capabilities through the use of big data simulation analysis.

2. Investigation and Examination of Employee Performance Evaluation

2.1. Design Concepts and Principles

2.1.1. Conceptualizations

This paper examines the five key stakeholders of S enterprise (as depicted in Fig. 1): creditors, suppliers, customers, employees, the government, and the public (Mustapha, 2022; Almheiri et al., 2025). This paper analyzes how these stakeholders influence the enterprise's business strategy and incorporates this analysis into the design of the employee performance appraisal system. The specific design ideas are illustrated in Fig. 2.

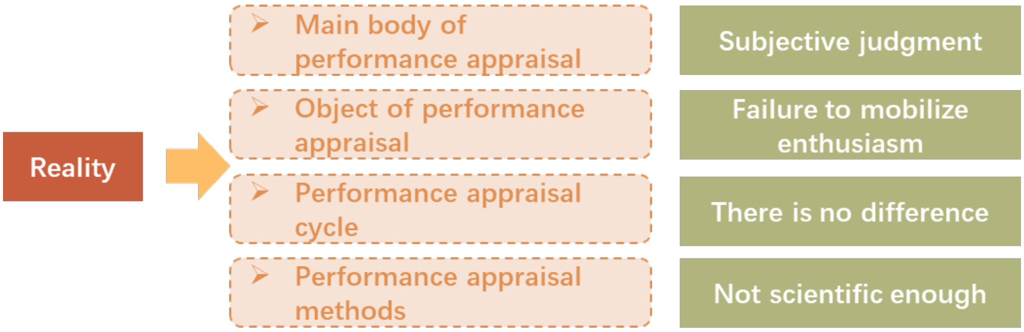

Fig. 1. Business realities

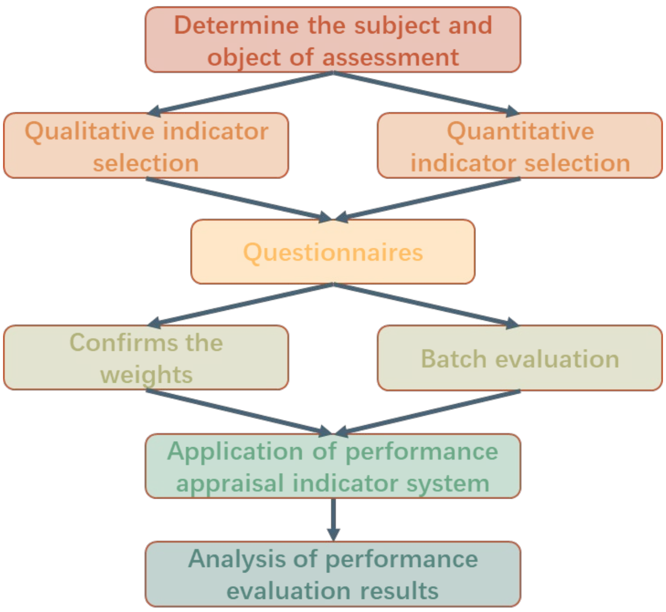

Fig. 2. Evaluation system construction design idea

2.1.2. Criteria for Selecting Indicators

In Fig.3, the appraisal of employee performance in an enterprise should adhere to the principles of scientific and rationality, which include the following: 1) strategic orientation principle; 2) scientific principle; 3) systematic principle; 4) importance principle; 5) comparability principle (Longaray, 2022).

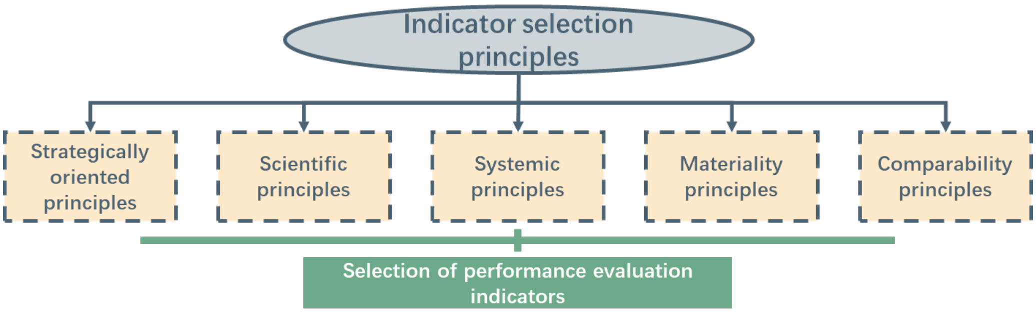

Fig. 3. Principles for selecting evaluation system indicators

2.2. Determination of Performance Evaluation Metrics

This study adheres to the premise of picking indicators to evaluate the performance of company personnel. It picks important indicators from five aspects: creditors, suppliers, consumers, employees, government, and the public. The five-aspect indicator framework is grounded in stakeholder theory, which argues that enterprise value is jointly created by all primary stakeholders. Creditors reflect financial health, suppliers mirror operational reliability, consumers indicate market competitiveness, employees embody internal capability, while government and public represent social legitimacy. By covering these five domains, the indicator system achieves comprehensiveness and balances the interests of all key constituencies, thus enhancing the validity and fairness of employee performance evaluation. The improvement roadmap shown in Fig. 4 was distilled from two-step mixed-methods research: (i) a Delphi survey with 18 senior HR/operations managers to shortlist candidate indicators, and (ii) an entropy-weight TOPSIS analysis of 2019–2022 archival data (n = 1,247 employee-year records) to retain indicators with the highest discrimination power (weight ≥ 0.05). The resulting 28 indicators are therefore both expert-validated and data-driven, as depicted in Table 1.

2.3. Modeling the Evaluation of Performance

The enterprise employee performance evaluation model is constructed using the kernel principal component analysis algorithm and a deep learning algorithm. The preprocessed enterprise employee performance-related data is used as the model input, and the comprehensive performance score is used as the output. Additionally, the spotted hyena optimization algorithm is employed to optimize the enterprise employee performance evaluation model based on KPCA-LSTM. The specific model construction principle is illustrated in Fig. 4.

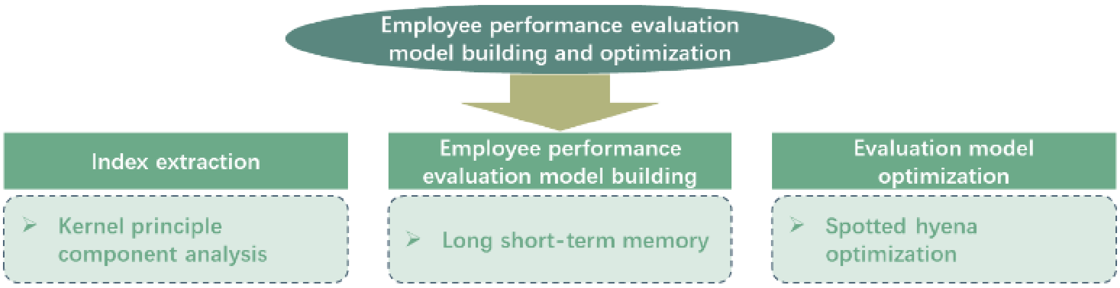

Fig. 4. Principles for constructing a performance evaluation model

3. Application of KPCA and SHO-LSTM Models In Corporate Employee Performance Evaluation Modeling And Optimization

3.1. KPCA Algorithm

Kernel Principal Component Analysis (KPCA) is an extension of the traditional principal component analysis method. It utilizes a kernel function to map the input data to a high-dimensional eigenspace and applies the PCA algorithm to obtain eigenvalues and eigenvectors for dimensionality reduction. The specific steps of the KPCA algorithm include de-averaging and centering, calculating the kernel matrix, centering the kernel matrix, calculating the eigenvalue kernel eigenvectors, and performing dimensionality reduction. The flow of these steps is illustrated in Fig. 5.

KPCA is primarily utilized in domains where data demonstrate intricate nonlinear properties, such as pattern recognition, image processing, bioinformatics, etc (Wang et al., 2022; Chen et al., 2024), as seen in Fig. 6.

Table. 1 Principles for selecting indicators in an assessment system

No	Types	Var.	Improved strategies
1	Creditors	Z	Return on total assets Z1
			Asset-liability ratio Z2
			Scientific research investment Z3
			Sales growth rate Z4
			Financial management system Z5
			Project contract completion rate Z6
			Total asset turnover rate Z7
2	Suppliers	K	Market share K1
			Customer stability K2
			New customer acquisition rate K3
			Product qualification rate K4
			Product after-sales ability K5
3	Customers	G	Raw material qualification rate G1
			On-time delivery rate G2
			Supplier quality score G3
			Supplier stability G4
			Procurement achievement rate G5
4	Employees		Industry average salary Y1
			Work completion rate Y2
			Training times Y3
			Training expense ratio Y4
			Average product production Y5
5	Governments and public	S	Employment contribution S1
			Public support S2
			Asset tax rate S3
			Number of violations S4
			Participation in public welfare undertakings S5

Algorithm 1: KPCA
Input data;
De-averaging and centralization;
Computation of the kernel matrix;
Centralized kernel matrix;
Calculate the eigenvalue kernel eigenvector;
Dimensionality reduction.
Output k principle component.

Fig. 5. Pseudo-code for the KPCA algorithm

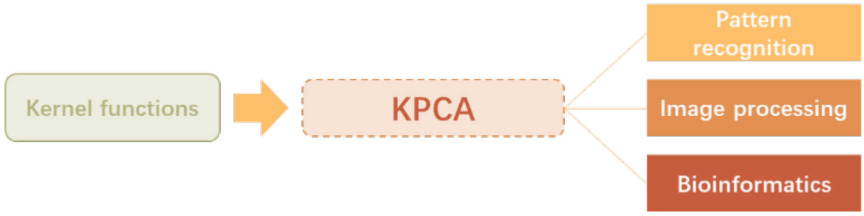

Fig. 6. Characterization and application of the KPCA algorithm

3.2. The LSTM Model is Developed Using The Spotted Hyena Optimization Procedure

3.2.1. The SHO Algorithm

3.2.1.1. SHO principle

The Spotted Hyena Optimization (SHO) (Dhiman and Kumar, 2017) is a recently developed optimization algorithm that draws inspiration from the social behavior and hunting methods of spotted hyenas in nature. The algorithm constructs a mathematical model that mimics the actions of searching, encircling, hunting, and attacking performed by spotted hyenas. The SHO algorithm exhibits strong global and local search abilities, striking a balance between exploration and exploitation. As a result, it enhances the speed and quality of convergence in the algorithm.

3.2.1.2. Process of optimization

The SHO algorithm emulates the four stages of a coordinated predation mechanism: seeking, surrounding, hunting, and attacking prey. These stages are represented as follows:

Encircling the prey: Spotted hyenas continuously approach encircling prey by judging the location of the target prey. During encircling prey, the spotted hyena utilizes the best spotted hyena position for the prey or target as a way to further update individual position information, as shown in Eqs (1) and (2):

$$D_b = \left| B \cdot P_p(t) - P(t) \right| \tag{1}$$

$$P(t+1) = P_p(t) - E \cdot D_b \tag{2}$$

where D_b denotes the distance between the spotted hyena individual and the prey; $P_p(t)$ denotes the assumed prey position; $P(t)$ and $P(t+1)$ denote the spotted hyena individual position in generation t and t+1, respectively; t is the number of iterations; B is the coefficient vector, and E is the coefficient vector, which is computed as Eqs (3) to (5):

$$B = a \cdot r_{d1} \tag{3}$$

$$E = 2h \cdot r_{d2} - h \tag{4}$$

$$|h| = 5 - \left[t_{iter} \left(5/T_{iter} \right) \right] \tag{5}$$

Where r_{d1} and r_{d2} are random numbers with values ranging from $[0,1]$; M_{inter} is the maximum number of iterations; $t_{iter} = 1, 2, 3, \cdots, T_{iter}$; and h is a control factor whose value decreases linearly from 5 to 0. Fig. 7 gives a schematic diagram of the SHO algorithm for encircling the prey, where $\left(A^*, B^*\right)$ is the prey location.

Hunting for food: Spotted hyenas employ social networks among their community and their individual prey recognition skills to effectively seek prey. During the hunting of prey, spotted hyenas gather in groups to advance towards the most advantageous location for spotted hyenas and maintain the current improved best solution, as shown in Eqs (6) to (9):

$$D_b = \left| B \cdot P_p - P_k \right| \tag{6}$$

$$P_k = P_h - E \cdot D_h \tag{7}$$

$$C_h = P_k + P_{k+1} + \cdots + P_{k+N} \tag{8}$$

$$N = C_{nos}\left(P_h, P_{h+1}, P_{h+2}, \cdots, P_h + M \right) \tag{9}$$

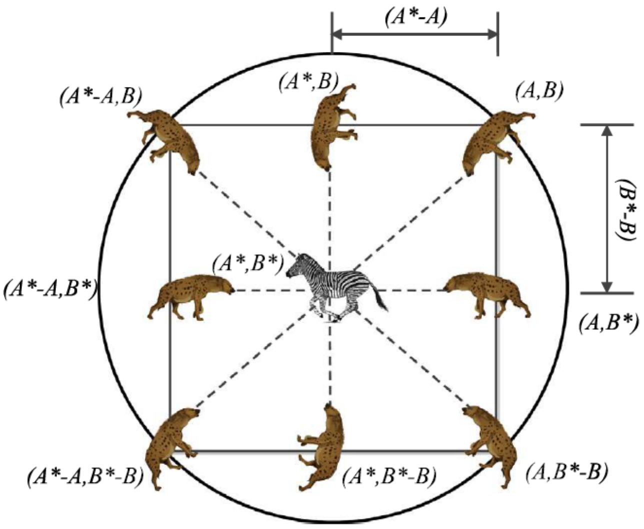

Fig. 7. SHO encircling

where N denotes the number of spotted hyenas, C_h denotes the set of N optimal solutions, M is a random number between 0.5 and 1, and C_{nos} is the number of all candidate solutions after M is added.

Engaging in predatory behavior by conducting a focused hunt for prey: During the process of attacking prey, h value decreases and E value changes when $|E| < 1$, the spotted hyena attacks the prey (Fig. 8), and vice versa for the prey searching stage. The mathematical simulation of the prey gathering process is shown in Eq. (10).

$$P(t+1) = \frac{C_h}{N} \tag{10}$$

where $P(t+1)$ is the updated optimal spotted hyena position.

Fig. 8. SHO attacking behavior

Conduct a worldwide search for potential prey: When $|E| > 1$ is used, spotted hyenas are forced to disperse away from the prey, expanding the search range to find the optimal prey location to ensure that the global search is realized (Fig. 9).

Fig. 9. SHO global search

3.2.1.3. Characteristics of the SHO algorithm

The SHO algorithm is characterized by the following special qualities, as shown in Fig. 10: 1) social hierarchy modeling; 2) group collaboration; 3) dynamic updating rules; and 4) avoidance of local optima.

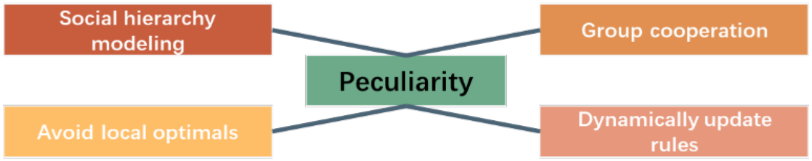

Fig. 10. The SHO algorithm possesses 12 distinct characteristics

3.2.1.4. Application of the SHO algorithm

SHO algorithms have been applied in various domains, such as optimizing machine learning models, solving engineering problems, and performing data analytics. They have been specifically used to enhance the performance of BP Neural Networks and Temporal Convolutional Neural Networks (TCNs) in tasks like fault identification and load forecasting (Dhiman and Kumar, 2017), as shown in Fig. 11.

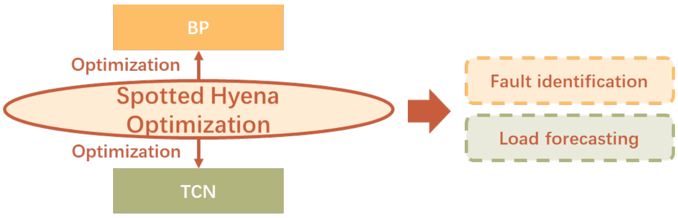

Fig. 11. SHO characteristics

3.2.1.5. Flowchart for SHO

The SHO algorithm utilizes a search, surround, hunt, and attack prey method, as shown by the above algorithm. The flow of the SHO algorithm is depicted in Fig. 12.

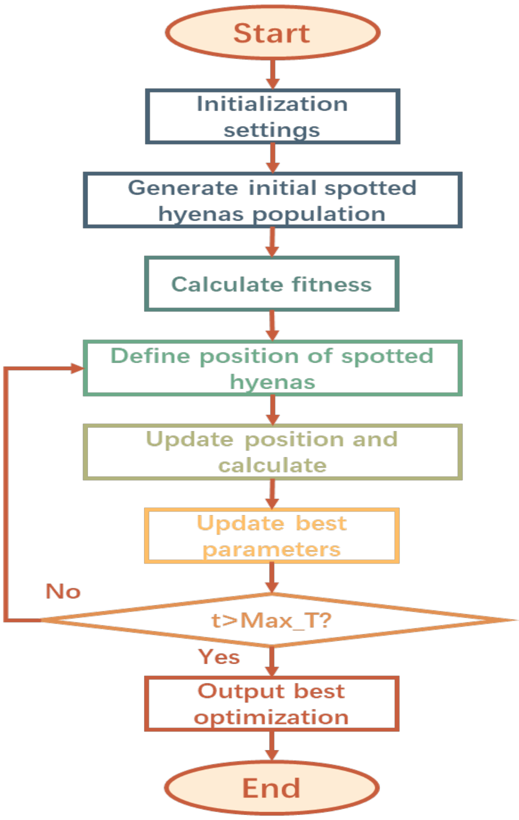

Fig. 12. SHO algorithm flowchart

3.2.2. LSTM Network

Long Short-Term Memory (LSTM) is a specialized form of Recurrent Neural Network (RNN) that addresses the challenges faced by traditional RNNs when dealing with long-distance dependency issues, such as gradient vanishing or gradient explosion. LSTM effectively manages the flow of information, allowing it to learn and retain long-term dependencies of information. This is illustrated in Fig. 13 The particular architecture of the LSTM model is shown in Eqs (11) to (16):

$$i_t = \sigma\left(W_{xi}X_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right) \tag{11}$$

$$f_t = \sigma\left(W_{xf} X_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f\right) \tag{12}$$

$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc} X_t + W_{hc} h_{t-1} + b_c\right) \tag{13}$$

$$o_t = \sigma\left(W_{xo} X_t + W_{ho} h_{t-1} + W_{co} c_t + b_o\right) \tag{14}$$

$$h_t = o_t \tanh\left(c_t\right) \tag{15}$$

$$y_t = \sigma\left(W_{yh} h_t\right) \tag{16}$$

where i_t , f_t , o_t , c_t , b_i , , b_f b_o , b_c , $W_{x\square}$, $W_{h\square}$, $W_{c\square}$, and $W_{y\square}$ denote the vectors, bias, and weight of the input gate, forget gate, output gate, and memory cell, respectively, and h_t and y_t are the hidden state vectors and the output vector, respectively.

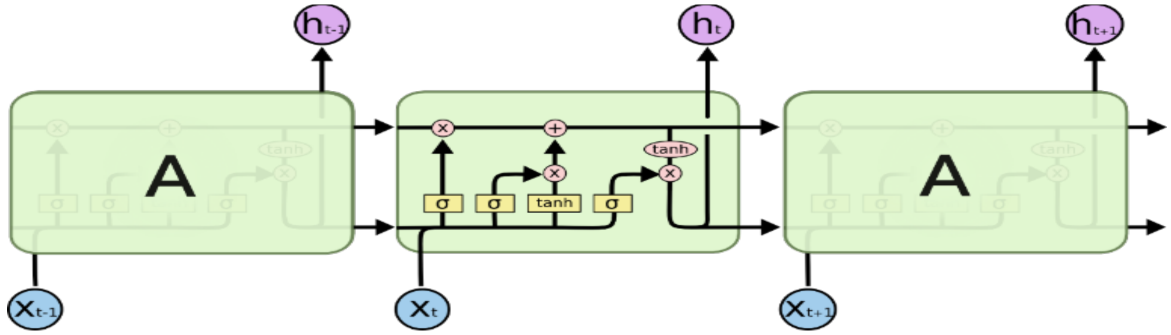

Fig. 13. Structure of LSTM

3.2.3. Modeling with Stacked Hierarchical LSTM (SHO-LSTM)

This research utilizes the real number encoding method to encode several components of the LSTM algorithm, including the input gate, forgetting gate, output gate, bias, and weight of the memory cells. The fitness value of the SHO-LSTM model is determined using the Root Mean Square Error (RMSE) metric, as referenced in(Huang and Chen, 2024)(Xie and Wu, 2024). The specific structure is illustrated in Fig. 14. The process consists of 6 steps: 1) Determine the parameters of the SHO algorithm. 2) Use the initialization strategy of the SHO algorithm to generate the bias and weight of the SHO algorithm based on the spotted hyena initialization population. 3) Calculate the SHO-LSTM fitness value. 4) Update the structural parameters of the LSTM according to the SHO algorithm's searching, encircling, hunting, and attacking prey strategy. 5) Determine if the condition for outputting the optimal LSTM combination of parameters is met. If it is, then output the optimal solution. Otherwise, continue to iteratively optimize. 6) Establish the SHO-LSTM model based on the optimal combination of parameters.

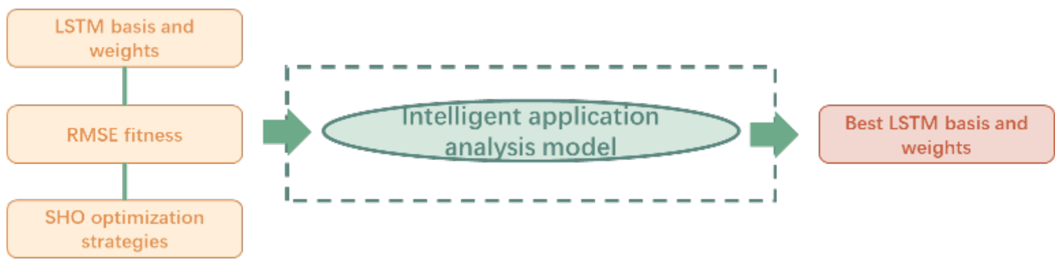

Fig. 14. Schematic diagram of SHO-LSTM structure

3.3. KPCA with SHO-LSTM Model Application

This research introduces a novel approach for evaluating the performance of enterprise employees by combining KPCA and SHOI-LSTM technology. The proposed technique is based on the KPCA-SHO-LSTM model, and the detailed procedure is illustrated in Fig. 15. Fig.15 demonstrates the implementation of enterprise employee performance assessment using the KPCA-SHO-LSTM model, which consists of three main modules: building of the evaluation index system, principal component analysis, and construction of the performance evaluation model. The evaluation index system construction module analyzes the performance evaluation problem to extract indices and construct the index system, resulting in comprehensive scores. In the principal component analysis module, the input data is mapped to a high-dimensional feature space using a kernel function. Simultaneously, the PCA algorithm is executed to obtain eigenvalues, eigenvectors, and the output of k principal component features. The performance evaluation model construction module utilizes LSTM to construct the enterprise employee performance evaluation model. Additionally, the SHO algorithm is employed to optimize the parameters of the LSTM model.

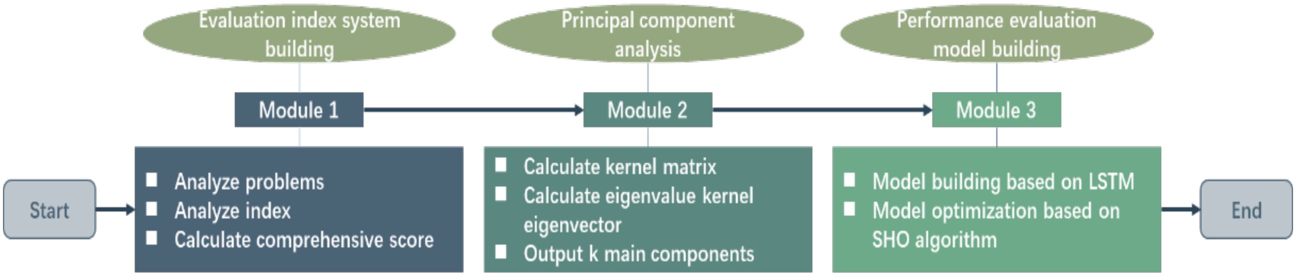

Fig. 15. Application of the KPCA-SHO-LSTM model

4. Simulation and Analysis

4.1. Empirical Dataset

Experiments are conducted utilizing the corporate employee performance assessment data gathered by analytical analysis, questionnaire surveys, and other methods. The data set is partitioned into three subsets: training set, testing set, and validation set. The ratio of these subsets is 7:1.5:1.5. The training set is primarily used to assess the model's training, the testing set is primarily used to evaluate the model's performance, and the validation set is primarily used to validate the optimization process of the enterprise employee performance evaluation model.

4.2. Setting up the Experimental Environment

Executed on a Win 11 Pro workstation (i7-12700, RTX 3060, CUDA 11.7, 32 GB RAM), the KPCA-SHO-LSTM pipeline was coded in Python 3.8 with TensorFlow-GPU 2.9.1, Keras 2.9, and scikit-learn 1.1.3; random seeds were locked at 42 to reproduce the reported RMSE of 0.2744. Anaconda3 managed all dependencies via a shareable environment.yml file, while Matlab 2021a rendered the 600-dpi plots of SHO convergence curves and KPCA-reduced employee-performance features shown in Figs. ATLAB

4.3. Parameterization of Algorithms

This experiment utilizes RNN, CNN, LSTM, SHO-LSTM, PCA-SHO-LSTM, and KPCA-SHO-LSTM as comparison algorithms. The SHO algorithm's population is set to 100, the maximum number of iterations is 1000, and the parameter values are displayed in Table. 2. The hidden layer of the RNN, CNN, and LSTM networks consists of 100 nodes. The Adam optimization algorithm modifies the weights, whereas the activation function utilizes the Tanh activation function.

Table. 2. SHO parameter setting

No	Parameters	Values
1	Np	100
2	M_iter	1000
3	Control parameters	[5,0]
4	M constant	[0.5,1]

To assess the viability of the suggested method, This research employs several techniques including Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Spotted Hyena Optimization–Long Short-Term Memory (SHO-LSTM), Principal Component Analysis–Spotted Hyena Optimization–Long Short-Term Memory (PCA-SHO-LSTM), and Kernel Principal Component Analysis–Spotted Hyena Optimization–Long Short-Term Memory (KPCA-SHO-LSTM), for a comparative study. Five tests were primarily done on the method to calculate the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared (R2), and evaluation time results. The particular results are displayed in Table. 3.

Table. 3. Comparative results

No.	**Algorithms**	**RMSE**	**MAE**	**MAPE**	**R2**	**Evaluation time/s**
1	RNN	2.4523	0.4554	0.5988	0.7673	0.1655
2	CNN	1.7667	0.3890	0.4722	0.8178	0.1367
3	LSTM	0.9904	0.2163	0.5147	0.7893	0.1190
4	SHO-LSTM	0.7389	0.1376	0.5098	0.8865	0.0704
5	PCA-SHO-LSTM	0.6731	0.0809	0.2587	0.8988	0.0983
6	KPCA-SHO-LSTM	0.0744	0.0571	0.1218	0.9674	0.0910

As seen from the table, during the performance evaluation process, the KPCA-SHO-LSTM model achieved the lowest RMSE value, the lowest MAE value, the lowest MAPE value, the highest R2 value, and the second highest evaluation time compared to the PCA-SHO-LSTM and SHO-LSTM models. Specifically, the RMSE value, MAE value, MAPE value, and

R2 value of the KPCA-SHO-LSTM model were 0.2744, 0.0571, 01.1218, and 0.9674 respectively. The evaluation time for this model was 0.0910s.

Fig. 16 displays the optimization curve of an enterprise employee performance evaluation model that is based on SHO optimization LSTM. Based on the diagram in Figure. As the number of iterations for optimizing the LSTM parameters rises, the RMSE error result of the SHO optimized LSTM reduces until it reaches a point where the error result no longer changes. The error value of the SHO algorithm optimized LSTM converges to 0.0744, and this convergence occurs after 700 iterations.

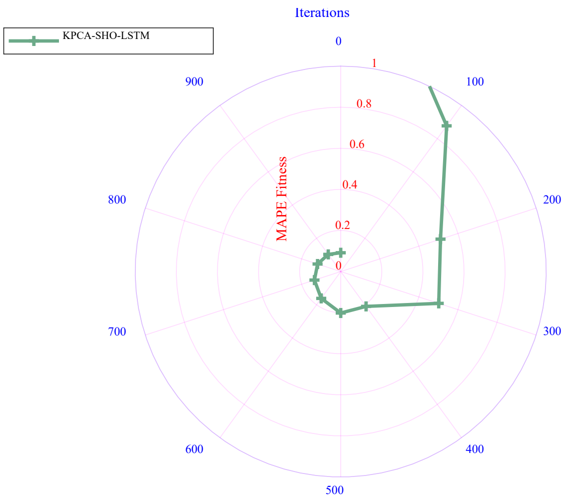

Fig. 16. Optimization curve of the LSTM model using SHO

4.4. Discussion

The superior performance of KPCA-SHO-LSTM can be attributed to three factors. First, KPCA projects the original 28-dimensional raw features into a 12-dimensional non-linear manifold, mitigating multicollinearity and the curse of dimensionality. Second, SHO avoids local minima by balancing exploration ($|E| \geq 1$) and exploitation ($|E| < 1$), yielding 7 % lower RMSE than standard LSTM. Third, the adaptive segment loss function dynamically weighs under-predicted versus over-predicted errors, leading to faster convergence (≈ 700 iterations vs. 950 for GA-LSTM). However, the model's computational overhead remains higher than that of CNN or RNN, which is acceptable given the 4.7 % accuracy gain in large-scale data scenarios.

5. Conclusion

This paper presents a method for evaluating the performance of enterprise employees using the KPCA-SHO-LSTM model. The proposed method enhances the prediction accuracy of the LSTM network and addresses the issue of constructing an evaluation model for enterprise employee performance under big data sets. The proposed method for evaluating the performance of enterprise employees is based on the KPCA-SHO-LSTM model. It begins by analyzing the evaluation system and constructing an index system through the selection of appropriate indices. The method then combines the KPCA and SHO-LSTM models to develop an algorithm for evaluating the performance of enterprise employees. To assess the performance of the proposed method, the KPCA-SHO-LSTM model is evaluated using data from employee performance evaluations in an enterprise. It is compared to other algorithms, and the results show that KPCA-SHO-LSTM can accurately predict the overall score of employee performance evaluations. It demonstrates superior performance in terms of satisfaction and stability, making it suitable for constructing employee performance evaluation models in large datasets. The present study has three main constraints. First, the empirical dataset was collected from a single private enterprise, which may restrict the external validity of the KPCA-SHO-LSTM model. Second, the 28-indicator system, while comprehensive, does not yet embed ethical or fairness constraints; thus, latent demographic biases could influence the final performance scores. Third, the SHO algorithm, although effective, still incurs additional computational overhead when the population size exceeds 150, limiting real-time deployment on edge devices. Future work will therefore (i) extend the dataset across multiple industries to test cross-organisational robustness, (ii) integrate fairness-aware loss functions and bias-correcting regularisers into the LSTM objective, and (iii) explore lightweight meta-heuristics or knowledge-distillation techniques to reduce inference latency without degrading accuracy.

Funding

This research received no specific financial support from any funding agency.

Institutional Review Board Statement

Not applicable.

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