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Quantitative Performance Evaluation Technology Based on Sparse Oblique Trees Algorithm in Mobile Internet

Abstract: - The quantitative performance evaluation is a method for evaluating an employee based on measurable factors directly related to their job. Many professionals in the modern workforce are no longer able to easily and consistently access desktop computers due to their increasingly itinerant lifestyle. Employees must be able to access contemporary employee performance management programs via mobile internet for them to be completely inclusive. Problems with the performance evaluation include the subjective one-sidedness of the evaluation indicators and the challenging measurement of the indicators. To address this drawback, the methodology used in this research was provided in order to classify employee data more precisely. The data is gathered from 227 enterprises in South Korea. At the pre-processing stage, the adaptive robust cubature kalman filtering is used to pre-process the data. The employee discipline, employee attitude, employee effort are successfully classified using sparse oblique trees algorithm (SOTA).To increase the SOTA, the neural network's weight parameter is optimized using the Sea Lion optimization (SLO).The proposed QPET-SOTA-SLO applied in MATLAB/Simulink platform. The proposed method was calculated using performance measures like accuracy, precision, sensitivity, computation time, and recall. Higher accuracy of 16.65%, 18.85%, and 17.89%, as well as higher sensitivity of 16.34%, 12.23%, and 18.54%, are achieved by the suggested QPET-SOTA-SLO approach. In comparison to the current approach, there are 14.89%, 16.89%, and 18.23% as well as 82.37%, 94.47%, and 87.76% less computing time.

Keywords: Adaptive Robust Cubature Kalman Filtering, Sparse Oblique Trees Algorithm, Sea Lion Optimization, Employee Discipline, Employee Attitude, Employee Effort.

I. INTRODUCTION

A competitive advantage is one of the main things that modern businesses are looking for. They make an effort to do this by offering premium products or services. Performance evaluation and quality improvement therefore appear to be essential [1]. One of the duties of managers is to keep an eye on the performance of the organization. Nonetheless, one could counter that the word "organizational performance" is broad and includes the connections and goods a company forges. In actuality, organizational effectiveness can be linked to the caliber of the organization's outputs as well as the efficacy of the mission, assignments, and organizational actions [2, 3]. Organizational performance evaluation has garnered considerable attention from both the commercial and academic sectors as one of their difficulties [4]. Performance evaluation must be used with the efficient tools and methods for managing human resources to fulfill the requirements of the workforce and the business's goal of the greatest level of performance [5]. The development of the company and the caliber of its workforce depend on an effective evaluation system that also applies its conclusions. Naturally, creating and implementing a performance review procedure can aid businesses in accomplishing their goals by improving employee effectiveness [6, 7].

Businesses are encountering many difficulties as a result of the escalating level of market rivalry. Keeping up positive working relationships is a constant challenge that businesses must deal with [8, 9]. Counterproductive conduct, an implicit and pervasive issue, is the detrimental actions of workers toward the company and its stakeholders, whether overt or covert. In [10] discovered 13 different types of counterproductive behavior, in varied degrees, in organizations. These included violent behavior, stealing, and destruction. The most difficult issue facing modern businesses is the rise in counterproductive employee behaviors as science and technology have advanced and the big data era has begun. These behaviors, such as data leakage and user information sales, have caused irreversible losses to businesses and society [11, 12]. In the field of corporate HRM, reducing counterproductive work behavior among employees has become crucial [13]. The elements impacting an organization's performance are demonstrated by the management factors. Managers establish the goals and mission of the company, make them visible, Create the values required for long-term achievement, and act and behave in a way that embodies those values. These factors could affect a company's performance and operations directly or indirectly [14, 15]. The impact of human resources on the success of organizations has also been studied and verified.

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Due to their focus on public benefit, non-profit organizations have brought their business methods to the attention of society. The public, businesses, and government agencies are now focusing on the non-profit sector's performance level. Research on the assessment of non-profit organizations' performance has also been initiated by numerous academics [16, 17]. The assessment of non-profit organizations' performance is a developing field. The particularity, openness, diversity, complexity and public welfare of the evaluation objectives are features of non-profit performance evaluations that set them apart from enterprise performance evaluations [18, 19]. Problems with the performance evaluation include the subjective one-sidedness of the evaluation indicators and the challenging measurement of the indicators.

"The following is an outline of the paper's main contributions:"

- At first, the data are collected from 227 enterprises in South Korea.
- The noise in the employee data is removed at the pre-processing stage by using an adaptive robust cubature kalman filtering.
- After that, the pre-processing data are sent to the sparse oblique trees algorithm (SOTA), which categorizes the effort, discipline, and attitude of the employees.
- To increase the SOTA, the weight parameter of the neural network is optimized using the Sea Lion optimization (SLO).
- The suggested QPET-SOTA-SLO method is implemented, and performance metrics like accuracy, sensitivity, computing time, precision ,and recall are examined.

The rest portions of this manuscript are organized as follows: segment 2 reviews the relevant literature; segment 3 clarifies the suggested strategy; Part 4 clarifies the results and discussion; and segment 5 concludes.

II. LITERATURE REVIEW

Numerous research studies on the quantitative performance evaluation technologies for employees based on different approaches and elements are accessible in the literature. A few of them are reviews that go like this:

Qian and Yin [20] have suggested that a performance evaluation techniques, ‘performance evaluation algorithm based on genetic algorithm and fuzzy comprehensive performance evaluation algorithm’ were presented, there benefits and drawbacks were contrasted and examined, and the ‘fuzzy performance evaluation algorithm based on compound elements design idea’ was proposed. It consists of seven steps: defining the assessment's aim and object; choosing the best evaluation mode and technique; building the evaluation index system; Fourth, a large amount of information needed to be gathered; fifth, the evaluation used a range of techniques, multiple perspectives, and multiple sides to gather materials so that the evaluation's conclusion had a strong enough factual foundation; and sixth, the information needed to be processed in order to create a thorough evaluation.

Pap et al. [21] have suggested that the use of cutting-edge machine learning analysis is a factor influencing business performance and employee wellbeing. ‘Considering the significance of identifying key performance points in organizations, this study uses the European Company Survey (ECS) 2019 framework to identify the most important intra- and extra-organizational components for analyzing a firm's performance’. An ANN-ICA optimized with an imperialist competitive algorithm was trained using the ECS 2019 survey data in order to predict business performance and staff well-being. The determination coefficient (R2), MAPE, MSE, RMSE, correlation coefficient (r), have all been used to evaluate the correctness of the model.

Shang et al. [22] have suggested that the present era has become the information age due to the expansion and constant growth of the Internet.. At every level, the network transaction mode has been used. At the similar time, e-commerce companies were developing as a new kind of business. E-commerce companies were less focused on traditional business models and more on networking, data technology, and convenience. ‘The current cross-border enterprise development model’ has always placed a high priority on the application and evaluation of e-commerce enterprise performance. This study combines the in-depth learning model with experimental analysis based on the cross-border e-commerce firms' performance lag calculation and analysis. •

Lin [23] have suggested that a corporate system was established based on the CS design in order to address the issues with low system throughput and inadequate performance appraisal indicators in traditional enterprise staff performance appraisal management systems’. The functional elements of the evaluation management system were examined and the system architecture for the performance appraisal system was first constructed. Additionally, a system logical architecture design was created. ‘After the influencing factors of the employee performance appraisal managing system were investigated using the evaluation constraint parameters, the enterprise employee performance management software design was accomplished by developing the quantitative regression analyses model of enterprise employee performance management'.

Peng et al. [24] have suggested that Counterproductive work behavior (ECWB) by employees has resulted in significant harm to the organization, and its recurrent nature makes it challenging for the organization to prevent. to investigate how employees and the internal influence path are affected by HPWS on both sides of the ECWB.In order to create an HPWS five-level model, it also seeks to integrate affective events theory with resource conservation. It offers businesses human resource management strategies to successfully lower and stop ECWB. This paper uses a quantitative analytic method to poll employees in 366 Chinese companies using a questionnaire.

Sahu et al. [25] have suggested that Economists and computer scientists have shown interest in the classic but challenging subject of stock market behavior forecasting. In an attempt to develop an effective prediction model, researchers have looked into linear models throughout the past few decades in addition to models based on RL, ML, DRL and deep learning (DL),.High-level patterns in financial market data can now be extracted by machine learning algorithms. 'Because of the benefits of artificial intelligence, investors were utilizing deep learning models to forecast and assess the stock and foreign exchange markets'. Deep reinforcement learning algorithms have been increasingly popular in algorithmic trading in recent years. DRL agents have been used in the development of numerous completely automated trading techniques and systems that combine trading signal generation with price prediction.

Ge et al. [26] have suggested that an Employee Incentive Structure Based on Knowledge for Innovation Performance. Inspired by the goal of the Silk Road Economic Belt, the Xinjiang Uygur Autonomous Region may reinvent the open economic system and fully utilize its unique advantages. In Shihezi, it can modernize and change industrial structures that have significant regional benefits. Investigating how knowledge-based employee incentive mechanisms affect innovation performance was the aim of the study. It was intended to innovate Shihezi enterprises' knowledge-based worker (KBW) management. Utilizing a questionnaire grounded in psychology theory, real production, and Shihezi living conditions, the KBWs of typical Shihezi firms were assessed. The Development Strategy of Western Chinese Cities was taken into consideration when designing the questionnaire, taking into account the attributes of KBWs in Shihezi City. Furthermore, to provide a thorough explanation of the connection between psychological capitals (PsyCap), employee innovation performance (EIP), and EIM, pertinent structural equation models and hypotheses were proposed.

A. Motivation

A general overview of current research indicates the significance of deep learning-based quantitative performance evaluation technology for evaluating employee performance.Problems with the performance evaluation include the subjective one-sidedness of the evaluation indicators and the challenging measurement of the indicators. Keeping up a positive working connection is a constant challenge for businesses. Numerous scholars are addressing issues related to various technologies in literature, such as deep learning (DL), imperialist competitive algorithm (ICA), and fuzzy clustering algorithm. The assessment system for employee performance has multiple elements and levels. One of the specific fuzzy comprehensive evaluation algorithms is the fuzzy clustering method. The goal of the imperialist competitive algorithm is to examine the variables influencing both employee and company well-being. Employee enterprise performance is calculated using deep learning.The technologies mentioned above have an effect on the disparity in the measurement units of the questions. Very few approach-based works have been provided in the literature to deal with this issue; these shortcomings and issues are what have inspired this study effort.

III. PROPOSED METHODOLOGY

The data collected by data from 227 enterprises in South Korea. At the pre-processing stage, the noise is eliminated using an adaptive robust cubature kalman filtering. The classification step receives the output from the pre-processing stage and uses the sparse oblique trees method to classify the employee discipline, attitude, and effort of the employee data . The sparse oblique trees approach is improved by using the sea lion optimization to optimize the neural network's weight parameter. Fig 1 shows the proposed methodology's block diagram.

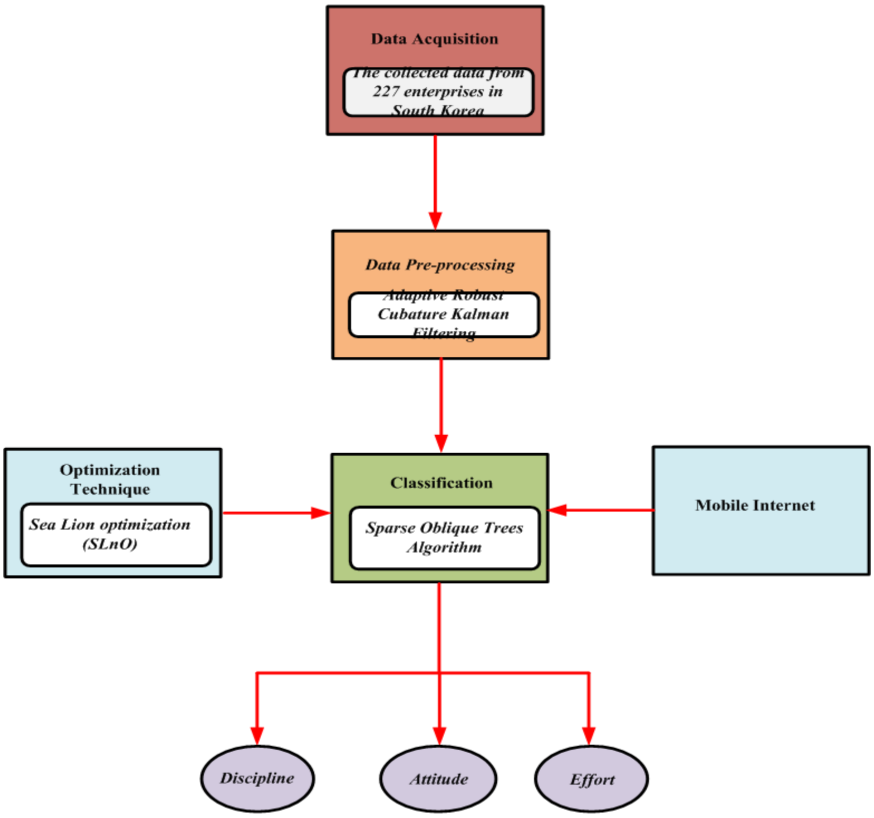

Fig 1: The proposed methodology's block diagram.

A. Data Acquisition

Salary incentives may enhance workers' workability and job attitude, which would enhance the business's operations and financial performance, according to data gathered from 227 South Korean companies [27].

B. Data Preprocessing using Adaptive Robust Cubature Kalman Filtering

In this part, adaptive robust cubature kalman filtering is proposed for pre-processing [28]. In pre-processing segment, it confiscates the reduction of the dynamics error using in the adaptive robust cubature kalman filtering before discussing the ARCKF algorithm. An ARCKF that can simultaneously filter out measurement noise and the system noise and lessen the drawbacks of observation outliers and creativity. To adapt the state estimation error covariance matrix to different circumstances, an adaptive method is created.

The associated state estimation error covariance matrix is provided to the cubature point generation, allowing for the development of cubature points that obtain the statistical characteristics. Formally, get

$$Y_{i,k-1} = \hat{y}_{k-1} + \xi_i \sqrt{\hat{Q}_{k-1}}, \qquad i = 1,\ldots\ldots,2n \tag{1}$$

Here , $Y_{i,k-1}$ is denoted as the i^{th} cubature point of $\hat{y}_{k-1}$, n is denoted as the dimension of state variables, $\sqrt{(.)}$ is denoted as the cholesky decomposition operation, ξ_i is denoted as the i^{th} column of the basic data point set.

The state transition function is used to instantiate the cubature points. Next, the corresponding state error covariance and the anticipated state can be computed as

$$Y^{*}_{i,k} = f\left(Y_{i,k-1}, u_{k-1}\right), \; i = 1, \ldots\ldots, 2n \tag{2}$$

$$\tilde{y}_k = \frac{1}{2n}\sum_{i=1}^{2n} Y^{*}_{i,k} \tag{3}$$

$$\tilde{Q}_k = \frac{1}{2n}\sum_{i=1}^{2n} Y^{*}_{i,k}\left(Y^{*}_{i,k}\right)^{T} - \tilde{y}_k \tilde{y}_k^{T} + P_{k-1} \tag{4}$$

Where, $\tilde{y}_k$ is denoted as the predicted state, $Y^*_{i,k}$ is denoted as the transformed cubature points, The associated error covariance is indicated by $\tilde{Q}_k$, and the matrix transpose operation is indicated by the superscript T.

Using the relationship between the expected state and the true state, the batch-mode regression form is constructed.

$$\tilde{y}_k = y_k - \eta_k \tag{5}$$

Where, η_k is denoted as the prediction error.

Furthermore, the following can be obtained by using the statistical linearization technique on the measurement function.

$$x_k = H_k\left(y_k - \tilde{y}_k\right) + h\left(\tilde{y}_k\right) + v_k \tag{6}$$

Where, $H_k\left(Q_{xy,k}\right)^T\left(\tilde{Q}_k\right)^{-1}$ is denoted as the statistical regression matrix.

The compact form of the above both equations are given below:

$$\tilde{y}_k = \tilde{H}_k y_k + \tilde{e}_k \tag{7}$$

where the following method can be used to generate the covariance matrix $\tilde{e}_k$:

$$\sum_k = \mathrm{E}\left[\tilde{e}_k \tilde{e}_k^T\right] = S_k S_k^T \tag{8}$$

where S_k can be computed using the Cholesky decomposition method or the UD factorization.

It is necessary to create a 2 -dimensional matrix Z with the innovation vector and the prediction state vector for the purposes of outlier detection and down-weighting.

$$Z_k = \begin{bmatrix} x_{k-1} - h\left(\tilde{y}_k - 1\right) & x_k - h\left(\tilde{y}_k\right) \\ \tilde{y}_k - 1 & \tilde{y}_k \end{bmatrix} \tag{9}$$

Where, the superscripts k and $k-1$ are denoted as the instants of time; $x_{k-1} - h\left(\tilde{y}_k - 1\right)$ and $x_k - h\left(\tilde{y}_k\right)$ are denoted as the innovation vector at the instants of time $k-1$ and k; $\tilde{y}_k - 1$ and $\tilde{y}_k$ are denoted as the prediction state.

By using the overall influence function technique, the estimate error covariance matrix can be generated and updated in the following ways to raise the robustness of the proposed system against outliers.

$$\tilde{Q}_k = \begin{cases} \tilde{Q}_k - K_k Q_{yy,k} K_k^T & if \ \max\left(PS_i\right) \le \chi^2_{2,(.0975)} \\ \mu\left(C_k^T C_k\right)^{-1}\left(C_k^T \Omega_{\varpi} C_k\right)\left(C_k^T C_k\right)^{-1}, & otherwise \end{cases} \tag{10}$$

Where, $\tilde{Q}_k$ is denoted as the state prediction error's covariance matrix at any given time; $\chi^2_{2,(.0975)}$ is denoted as the value of $\chi^2_{2,(.)}$, $\chi^2_{2,(.)}$ is denoted as the distribution of chi-square with two degrees of freedom $Q_{yy,k}$, is denoted as the predicted measurement's covariance matrix, and The Kalman gain, represented by the symbol K_k, is determined by

$$Q_{yy,k} = \frac{1}{2n}\sum X_{i,k} X_{i,k}^T - \tilde{x}_k \tilde{x}_k^T + R_k \tag{11}$$

$$K_k = Q_{xy,k} Q_{yy,k}^{-1} \tag{12}$$

Finally, the filtering method is updating the better covariance matrix and this cubature filters are used to estimate the errors. Then data are transferred into SOTA for classification.

C. Classification Using Sparse Oblique Trees Algorithm (SOTA)

Let us consider a trained deep net $x = g(y)$ that is used to classify an input instance $y \in M^G$ into k classes. The vector y in this case consists of k softmax values that approximate the class distribution given y [29]. Express the net $g(y) = h(G(y))$ as the combination of a feature-extraction layer G (neuron outputs at $z = G(y) \in M^G$), which is the deep net features, and a classifier layer $x = h(z)$, which is made up of the remaining net1. The raw inputs y (here G is the identity) and the softmax outputs or class label (here h is the identity) are examples of specific cases of features in this; nevertheless, features at an intermediate layer are typically of greater importance. Every neuron in that layer can be compared to a feature detector that stores an attribute or idea from the input pattern y. This information can be used to support or refute one or more classes when combined with the concepts of other neurons.

Let's say you have a dataset containing the labels of the input instances, $\{(y_n, x_n)\}_{n=1}^{N} \subset M^{G} \times \{1,\ldots,k\}$ (often the one used to train the net). Next:

1. Utilizing TAO, train a sparse oblique tree $x = L(z)$ on the $\{(G(y_n), x_n)\}_{n=1}^{N} \subset M^{g} \times \{1,\ldots,k\}$ training set. Select a final tree after examining the interpretability-accuracy trade-off throughout a suitable range of the sparsity hyperparameter $\lambda \in [0,\infty]$. This will typically be a sparsest tree with nearly the maximum precision of validation.
2. Examine the tree to uncover intriguing deep net patterns.

A tree that is as simple as feasible and accurately replicates the deep net is the aim. To achieve this, train the tree using the similar training set as the net, utilizing the ground-truth feature set instead of the latter's features.

The neural net $x = g(x) = h(G(y))$ is made up of the classifier part $x = h(z)$ and the feature extraction part $z = g(y)$. This translates, for instance, to the first four (convolutional and subsampling) and last two (fully-connected) layers of the LeNet5 neural net shown in the diagram. The activations (outputs) of g neurons make up the "neural net feature" vector z, which is a feature that the neural net derived from the initial features y (data values, for LeNet5). To replicate the classifier portion $x = h(z)$, a sparse oblique tree is used. The tree is trained with neural net features z as input and the matching ground-truth labels as output.

Step 2 is purposely vague. The tree probably has a plethora of information on the importance of the features and how they impact the categorization, from the stage of a particular input instance to a more global one.

Finally, the SOTA processing that organizes the information based on the work disciplines attitude and effort of the employees. The optimization procedures needed to determine the best variables to confirm an exact detection are typically not provided by SOTA. Therefore, in order for the optimization process to optimize SOTA, the weight parameter is crucial.

D. Optimization Technique using Sea Lion Optimization

The Sea Lion optimization (SLO) method's inspiration is initially covered in this section [30]. Next, the SLO mathematical model is given.

Step 1: Initialization

Set the input parameters to their initial values. In this case, the input parameters are the SOTA weight parameters, indicated by g.

Step 2: Random Generation

The input parameter in a matrix described by is generated randomly.

$$e = \begin{bmatrix} Y_{11} & Y_{12} & Y_{13} \\ Y_{21} & Y_{22} & Y_{23} \\ Y_{31} & Y_{32} & Y_{33} \end{bmatrix} \tag{13}$$

Here Y represents the system's parameters and e stands for random generation.

Step 3: Calculation of Fitness Value

The outcome is derived from the random response and initialized assessments. In evaluating the fitness function, the effects of weight parameter optimization g are considered. Equation (14) is used to calculate it.

$$fitness\ function = Optimizing\,[g] \tag{14}$$

Here, g denotes the better node representation.

Step 4: Detecting and Tracking Phase

The size, form, and location of prey are all discerned by the sea lions using their whiskers. The orientation of the whiskers helps sea lions perceive and locate prey when they are pointing in the ocean's waves in the opposite direction. The whiskers did not vibrate as much as they did when they were oriented in the same direction as they are now.

Sea lions are able to locate prey and signal to other participants of their subgroup to join them in pursuing and hunting the prey. For the sake of this hunting mechanism, this sea lion is regarded as the leader, and other participants adjust their locations in relation to the intended prey. The target victim is thought by the SLO algorithm to be the best available solution at the moment, or nearly so. The mathematical representation of this behaviour is made using Eq. (15).

$$\vec{D} = \left| \overrightarrow{2b}.\overrightarrow{p(t)} - \overrightarrow{sl(t)} \right| \tag{15}$$

where $p(t)$ and $\overrightarrow{sl(t)}$ stand for the target victim's and the sea lion 's respective position vectors, and $\vec{D}$ indicates the distance between the two; The present iteration is indicated by the symbol t, and the random vector b is multiplied by to expand the seek space and aid search agents in locating the optimal or nearly optimal solution.

The sea lion approaches the intended victim in order to be closest for the subsequent cycle. Equation (16) provides a mathematical representation of this behavior.

$$\overrightarrow{sl(t+1)} = \overrightarrow{p(t)} - \vec{D}.\overline{B} \tag{16}$$

While the next iteration is denoted by $(t+1)$, and $\overline{B}$ decreases linearly from 2 to 0 during the iterations because this diminishing forces the sea lion leader to approach and encircle the current target.

Step 5: Vocalization Phase

Amphibians include sea lions. Put differently, sea lions are both aquatic and terrestrial animals. In water, their sounds travel at a speed of four times that of air. When pursuing and hunting in groups, sea lions use a variety of vocalizations to communicate with one another. They also call other members who remain on the coast using their sound. Sea lions pursue and imprison their prey in order to get them as close to the ocean's surface as possible. They also have tiny ears that can hear sounds both above and below the water. As a findings, a sea lion will alert other members to surround and attack its victim when it spots it. This behaviour is modelled mathematically as in Eq. (17), (18) and (19).

$$\overrightarrow{sp_{leader}} = \left| \left(\overrightarrow{u_1} (1 + \vec{u}_1) / \overrightarrow{u_2} \right) \right| \tag{17}$$

$$\overrightarrow{u_1} = \sin\theta \tag{18}$$

$$\overrightarrow{u_2} = \sin\phi \tag{19}$$

Whereas $\overrightarrow{u_1}$ and $\overrightarrow{u_2}$ stand for the sound speeds in H_2 O and the air, correspondingly, sp_{leader} denotes the sound speed of the sea lion leader. When a sea lion calls out to other members who are at the surface, its voice is reflected into the air and refracted into the similar medium for members who are submerged. Consequently, ($\sin\theta$) is used to represent the first situation, and ($\sin\phi$) is used to represent the second.

Step 6: Exploration Phase

Sea lions hunt by using their whiskers at random and swimming in zigzag patterns to locate prey in the wild. As a result, $\vec{B}$ is used in this investigation with random values. If $\vec{B}$ is more than one or less than negative one, sea lions are compelled to retreat from both the target victim and the leader of the sea lions.

Step 7: Exploration Phase

The ability for sea lions to locate their intended meal and circle around them. The best search agent, or leader, finds the victim and alerts the another members to their location, directing the hunt strategy. The target prey is typically thought of as the best potential answer at the moment. Nonetheless, it is possible to define a new search agent that surrounds and finds better prey.

Two stages are established as follows in order to mathematically simulate sea lions' methods of hunting:

The behavior of the decreasing encircling approach at the initial phase is dependent on the value of $\vec{B}$ in Eq. (20). More specifically, during the duration of the iterations, $\vec{B}$ is reduced linearly from 2 to 0. As a result of this decline, the sea lion pack leader approaches and encircles the prey. As a result, the sea lion's (search agent's) arrival location can be found anywhere in between the agent's prime position and the location of the best agent at the moment.

In the 2nd stage, sea lions update their circle of sight as they pursue fish bait balls and begin their search from the edges. For this reason, Eq. (29) is proposed.

$$\vec{sl}(t+1) = \left|\vec{p}(t) - \vec{sl}(t)\right| . \cos(2\pi m) + \vec{p}(t) \tag{20}$$

Here m is a arbitrary count in [-1, 1], $|\ |$ signifies the absolute value, and $\left|\vec{p}(t) - \vec{sl}(t)\right|$ reflects the separation between the search agent and the perfect solution. The sea lion swims in a circle around the prey to start following it when it is on the bait ball's edge. Because of this, $\cos(2\pi m)$ is employed to mathematically signify this performance.

Step 8: Update the Best solution

In the phase of exploitation, the sea lions modify their postures by employing the most efficient search agent. However, during the exploration phase, the searchers move around in response to a randomly selected sea lion. Stated differently, the SLO technique performs a worldwide search agent and finds the worldwide optimal solution when $\vec{B}$ is greater than 1. In this regard, Eqs. (21) and (22) are proposed .

$$\vec{D} = \left|\vec{2b}.\vec{sl}_{rnd}(t) - \overline{sl(t)}\right| \tag{21}$$

$$\vec{sl}(t+1) = \left|.\vec{sl}_{rnd}(t) - \vec{D}.\vec{B}\right| \tag{22}$$

Here , $\vec{sl}_{rnd}(t)$ indicates to random sea lion that is selected from the current population.

Step 9: Termination

Examine the stopping criteria, and if the best answer is found, the procedure terminates; otherwise, move on to step 3.

IV. RESULT AND DISCUSSION

These part discusses the experimental outcomes of the QPET-SOTA-SLO method for quantitative performance evaluation, which is based on the Deep Learning technique. The simulations are done in MATLAB/Simulink. MATLAB is used to simulate the suggested approach under various performance criteria. Results of QPET-SOTA-SLO were analyzed using QPET-FCA, QPET-ICA, and QPET-DL, among other existing methodologies.

A. Performance metrics

A comparative analyses of the performance metrics, including precision, sensitivity, and computing time, is also presented. Accurate evaluation of the performance measures requires the confusion matrix. Accurately calculating the confusion matrix requires knowledge of the false positive (FP) true positive (TP), and false negative (FN) true negative (TN) values.

1) Accuracy

It is defined as the overall count of occurrences inside the dataset. The outcome is a matrix that describes the model's performance for every class. Equation so establishes it equation (23),

$$Accuracy(acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{23}$$

2) Sensitivity

Sensitivity can also refer to true positive rate or recall. Equation (24), based on the sensitivity, calculates

$$Sensitivity(sen) = \frac{TP}{TP + FN} \tag{24}$$

3) Precision

The accuracy, which is determined by equation (25), is referred to as true positive predictive principles.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{25}$$

4) Recall value

Equation (26) represents recall value.,

$$\operatorname{Re} call = \frac{pt}{(TP + FN)} \tag{26}$$

B. Performance Analysis

Fig 2 to 6 shows the simulation outcomes of QPET-SOTA-SLO. Then the outcomes are analysed with existing QPET-FCA, QPET-ICA, and QPET-DL. Accuracy value comparison between the proposed and existing technique is depicts in Fig 2. The performance of the proposed technique results in accuracy that are 50.52%, 20.72%, 35.92% higher for the classification of discipline, 20.42%, 35.52%, 23.52% higher for the classification of attitude and 21.42%, 30.72%, 18.41% higher for the classification of effort, when evaluated to the existing QPET-FCA, QPET-ICA, and QPET-DL models respectively.

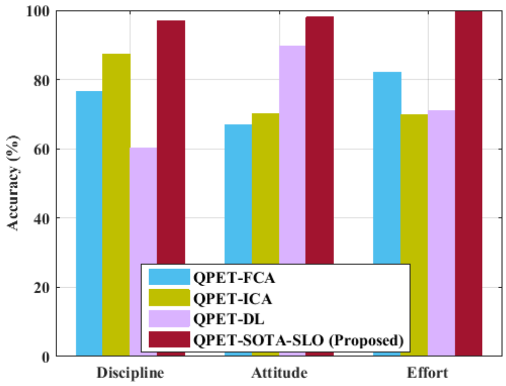

Fig 2: Accuracy value comparison between the proposed and existing technique.

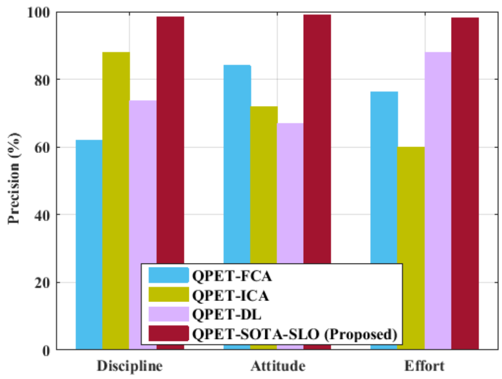

Fig 3: Analyses of precision value with proposed and existing method.

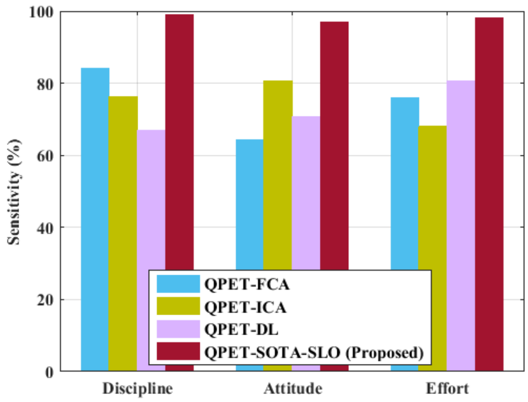

Fig 4: Sensitivity value performance using the proposed and existing technique.

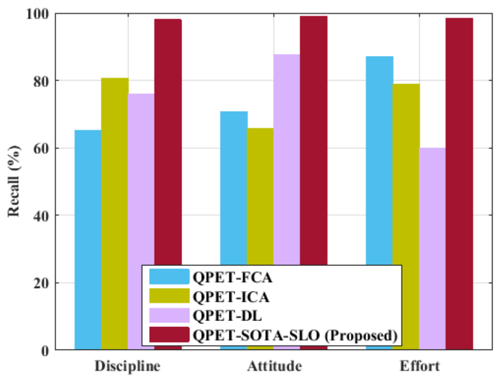

Fig 5: Recall value performance using the proposed and existing method .

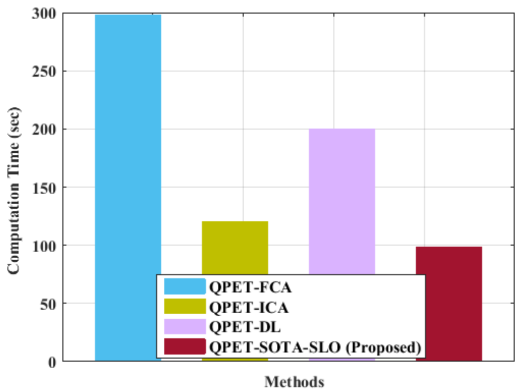

Fig 6: Computational time analysis using the proposed and existing technique.

The Analyses of precision value with proposed and existing system is depicts in Fig 3. The performance of the proposed technique results in precision that are 30.52%, 21.72%, 35.92%, higher for the classification of discipline, 21.42%, 33.52%, 23.52% higher for the classification of attitude and 21.42%, 30.72%, 18.42% higher for the classification of effort when evaluated to the existing QPET-FCA, QPET-ICA, and QPET-DL models respectively. Sensitivity value performance using the proposed and existing method is depicts in Fig 4. The performance of the proposed technique results in sensitivity that are 30.52%, 21.72%, 35.92%, higher for the classification of discipline, 21.42%, 33.52%, 23.52% higher for the classification of attitude and 21.42%, 30.72%, 18.41% higher for the classification of effort when evaluated to the existing QPET-FCA, QPET-ICA, and QPET-DL models respectively. Recall value performance using the proposed and existing method is depicts in Fig 5. The performance of the proposed technique results in recall that are 23.52%, 22.72%, 31.92% higher for the classification of discipline, 22.42%, 31.52%, 22.52% higher for the classification of attitude and 22.42%, 29.72%, 17.41% higher for the classification of effort when evaluated to the existing QPET-FCA, QPET-ICA, and QPET-DL models respectively. Computational time analysis using the proposed and existing technique is depicts in Fig 6. The proposed QPET-SOTA-SLO is assessed to the QPET-FCA, QPET-ICA, and QPET-DL existing methods. Comparing the proposed QPET-SOTA-SLO approach to the existing QPET-FCA, QPET-ICA, and QPET-DL methods, respectively, the former yields computational time savings of 5.31%, 10.11%, and 10.22%.

V. CONCLUSION

Data collection via the 227 firms in South Korea is a crucial initial step. The pre-processing stage involves processing the employee data using adaptive robust cubature kalman filtering. The pre-processing result is sent to the classification, which uses a sparse oblique trees algorithm to efficiently classify the employee data in terms of effort, discipline, and attitude. To improve SOTA, which accurately categorizes employee effort, attitude, and discipline, the Sea Lion optimization is developed. The proposed system is examined using the MATLAB platform and contrasted with other methods that are already in use. A variety of scenarios, including those involving accuracy, precision, sensitivity, calculation time, and recall, are examined with the proposed approach. The final step of the system uses the SOTA classifier, which has increased its accuracy to 98% due to its precise identification of the recommended optimum region expanding technique. This shows that the system is capable of accurately identifying employee discipline, attitude, and effort of employee data.

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