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# Application of Natural Language Processing Technology in Student Evaluation and Feedback in Teaching Quality Assurance System

***Abstract:* -** As the on-going reform in higher education teaching deepens and expands, there has been a significant focus on researching educational quality. Enhancing teaching quality is crucial for improving education, with teacher evaluation serving as a vital instrument in achieving this goal. In this manuscript proposes an Application of Natural Language Processing Technology in Student Evaluation and Feedback in Teaching Quality Assurance System (NLTSEFTQ-MORA-RNN) . Initially, the data is collected from the 2 separate universities data set. Then, the collected data is fed to Pre-processing segment. In pre-processing stage, Multimodal Hierarchical Graph Collaborative Filtering (MHGCF) is used to clean the data. Then pre-processed output is given to Mixed-Order Relation-Aware Recurrent Neural Networks (MORARNN)that classifies the teaching qualification such as Leadership Evaluation, Expert Evaluation, Peer Evaluation and Student Evaluation. The weight parameters of MORARNN are optimized using Fennec Fox Optimization Algorithm (FOA). The proposed NLTSEFTQ-MORA-RNN method is implemented and the performance metrics such as Accuracy, precision, sensitivity, specificity, F1-score, and computational time are evaluated. By then, the performance of the proposed technique is executed in the Python platform. The performance of the proposed NLTSEFTQ-MORA-RNN approach attains28.5%, 27.5% and 28% higher accuracy, 25.06%, 25.33% and 22.98% higher Precision and 27.12%, 21.33% and 24.98% higher sensitivity compared with existing methods such as an improved genetic algorithm and neural network-based evaluation model of classroom teaching quality in colleges and universities (ECTQ-GA-BPNN), Artificial intelligence for assessment and feedback to enhance student success in higher education(AIFSHE-ANN)and Sentiment analysis of students' feedback with NLP and deep learning: A systematic mapping study (SASF-NLP-DL). By comparing other three existing methods, the proposed NLTSEFTQ-MORA-RNN method gives high accuracy respectively.

***Keywords:*** Multimodal Hierarchical Graph Collaborative Filtering, Mixed-Order Relation-Aware Recurrent Neural Networks, Fennec Fox Optimization Algorithm, Teaching Quality, Students

## I. INTRODUCTION

In the dynamic landscape of learning, the pursuit of excellence in teaching remains paramount for fostering an enriching and effective learning environment [1]. Central to this endeavour is the practice of Student Evaluation and Feedback in Teaching Quality. This process stands as a cornerstone in the continual improvement of educational practices [2], serving to bridge the gap between educators and students in a symbiotic relationship aimed at enhancing the overall educational experience [3]. As educational institutions strive to adapt to evolving pedagogical methods and student needs, the importance of student evaluation and feedback mechanisms becomes increasingly evident [4]. By providing students with a platform to voice their opinions, concerns, and suggestions regarding teaching methods, curriculum design, and classroom dynamics, educators gain invaluable insights into their teaching effectiveness, thus enabling them to tailor their methods to improved meet the diverse requirements of their pupils [5].

However, despite its significance, the process of student evaluation and feedback in teaching quality is not without its drawbacks and challenges [6]. Issues such as bias in evaluation, lack of standardized evaluation criteria, and insufficient mechanisms for actionable feedback can hinder the effectiveness of this practice [7]. Furthermore, there may be disparities in the perceptions of teaching quality between students and educators, leading to potential discrepancies in evaluation outcomes. Nevertheless, the importance of addressing these challenges cannot be overstated, as the continual improvement of teaching quality directly impacts the overall learning experience and academic outcomes of students [8, 9].

To overwhelmed these tests and ensure the effectiveness of student evaluation and feedback in teaching quality, several strategies can be implemented [10]. First and foremost, there is a need for the development and implementation of standardized evaluation criteria that are objective, fair, and comprehensive [11]. Additionally,

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providing training and guidance for both students and educators on the importance of constructive feedback and effective evaluation methods can help improve the quality of feedback provided [12]. Moreover, leveraging technology to streamline the evaluation process and facilitate real-time feedback can enhance the timeliness and effectiveness of student feedback mechanisms [13].

Through the resolution of these issues and the application of optimal methodologies, academic establishments may fully harness the potential of student assessment and feedback to propel ongoing enhancements in teaching quality and, in turn, augment the entire educational experience for learners [14]. Various research works have previously existed in the literatures which are based on the Student Evaluation and Feedback in Teaching Quality deep learning methodologies. Some of them are reviewed here

Zhang et al. [15] have introduced a Teacher evaluation was a key instrument in the back propagation (BP) neural network's strategy to advance education quality in learning. On the other hand, because of their shortcomings, traditional methods of evaluating the caliber of instruction presented difficulties. The standard of instruction provided in college and university classrooms, which was founded on enhanced neural networks and genetic algorithms. The main concept was to use adaptive mutation evolutionary algorithms to fine-tune the BP neural network's initial weights and thresholds. The outcomes of the assessment of teaching quality were improved by increasing the neural network's prediction accuracy and convergence speed. The combination of enhanced genetic algorithms (GA) and neural networks improved the speed and accuracy of evaluating the quality of instruction; yet, mass adoption may be challenging due to the complexity and resource needs.

Hooda et al. [16] have developed A valid critique and qualitative assessment have a positive impact on students' knowledge in a higher education setting. Prior to the rise of online education, the assessment component of learning and teaching in HEIs was not seen to be the primary focus. However, with the increased use of online learning, it has been noted that this paradigm has changed to emphasize evaluating student activities that improve learning outcomes. In order to enhance student learning outcomes through assessment and feedback methods, this research attempted to present an exploratory and comparative review of the potential applications of AI. Providing an overview of the most widely used AI and machine learning methods to raise student performance is the main objective of this study.While integrating AI-driven assessment methods improves learning outcomes in higher education by increasing feedback validity and reliability, an over-reliance on these methods may ignore qualitative factors, which could restrict our ability to evaluate educational progress holistically.

Kastrati et al. [17] have introduced aApplication of sentiment analysis was growing but remained difficult, particularly in the education sector where handling and processing students' thoughts was a difficult task due to the nature of students' language and the vast volume of data..a methodical mapping project to organize the existing published data. The mapping revealed that the sector was expanding quickly in spite of the obstacles that had been found, particularly with regard to the most recent trend the application of DL. Research maturity in education is fostered by systematic mapping studies, which offer organized insights into sentiment analysis applications. However, a narrow focus on standardized solutions and emotional expression recognition may obstruct the field's overall growth

Vaclavik et al. [18] have developedA master's candidate at one of the Czech universities assesses how well the instructional and learning approaches work. Research in this area focused on learning outcomes, teaching forms and techniques, and the use of ICT after a quantitative survey revealed the need for a more in-depth analysis of the topic in a larger context. The main approach to research was focus groups, while the qualitative study employed in-depth interviews to collect data. Data processing and analysis were done using coding methods. The benefits are outlined in the context of ICT integration into the classroom, which makes sense and enhances students' learning. Effective learning outcomes and student engagement may be hampered by the differences between the instructional strategies used by instructors and those that students prefer.

Tsiakmaki et al.[19] have developed a method in machine learning (ML) that seeks to improve the prediction performance of a learning model for a separate but related problem by utilizing the information extracted from one problem. This goal is being pursued by the present study, which looks at how effectively transfer learning from deep neural networks functions to predict students' performance in higher education.This study represents a significant advancement in the field of educational data mining as there hasn't been much research done on the creation of prediction models using transfer learning techniques. As a result, a huge amount of experimentations were carried out using data from five required courses from two undergraduate programs. By utilizing knowledge from related courses, transfer learning improves predictive accuracy in educational data mining; nevertheless, its restricted study may prevent realization of its full potential.

Wenming [20] has introduced teaching evaluation is made more difficult by using a standard evaluation approach, which also has a long turnaround time and low efficacy, all of which have a negative impact on school efficiency. The goal of this study is to enhance the quality of English instruction using machine learning technology by combining the Gaussian process to improve the algorithm, using mixed Gaussian to investigate the distribution features of data, and enhancing the standard relevance vector machine model. Furthermore, a control experiment was created for this study in order to evaluate the effectiveness of the model that was presented. The comparison shows that this study model performs well when comparing traditional models and online models in terms of how well they teach English. Demonstrating superior performance in English teaching quality evaluation compared to traditional methods yet lacks comprehensive discussion on potential challenges in real-world implementation.

The primary contribution of this study is summed up as follows:

- In this paper work, Student Evaluation and Feedback in Teaching Quality Assurance System NLTSEFTQ-MORA-RNNis proposed
- The input data is collected from the 2 separate universities
- Leadership Evaluation, Expert Evaluation, Peer Evaluation, and Student Evaluation are among the teaching qualification classifications that MORARNN uses.
- The proposed FOA algorithm aims to enhance the performance of the MORARNN classifier.
- The presentation metrics were compared with current approaches such as SASF-NLP-DL, AIFSHE-ANN, ECTQ-GA-BPNN, and so on.

The rest of the paper is organized as follows: Part 2 provides an overview of the literature review, Part 3 explains the suggested approach, Part 4 discusses the findings, and Part 5 wraps up the work.

## II. PROPOSED METHODOLOGY

In this sector, Utilizing Application of Natural Language Processing Technology in Student Evaluation and Feedback in Teaching Quality Assurance System using Mixed-Order Relation-Aware Recurrent Neural Networks (NLTSEFTQ-MORA-RNN) is deliberated. Figure 1 display the block diagram of suggested NLTSEFTQ-MORA-RNN. It covers the stages of as Multimodal Hierarchical Graph Collaborative Filtering, Mixed-Order Relation-Aware Recurrent Neural Networks, and Fennec Fox Optimization Algorithm. Thus details explanation about every step given below.

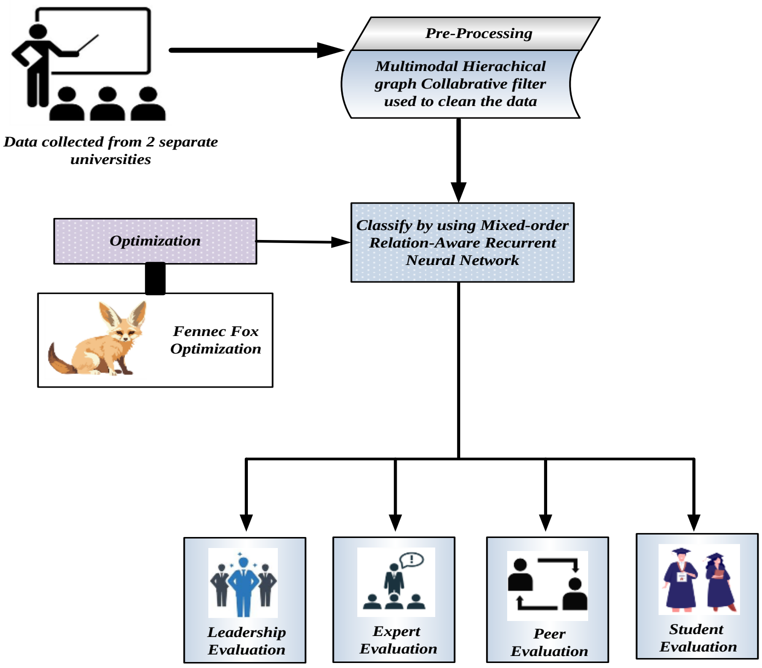


Fig 1: Block Diagram of suggested NLTSEFTQ-MORA-RNN method

*A. Data Collection*

A dataset comprising two distinct sets of information from separate universities, labelled as Data1 and Data2, has been compiled for analysis. Four components make up the assessment of teaching quality: student, peer, expert, and leader evaluations. The following techniques can be used to collect data for teaching quality evaluations: (1) Assessment of Leadership. Analyze the instructor's instruction and the students' learning by attending random lectures. (2) Professional Assessment. The expert group conducts inspection courses, while the Academic Affairs Office and each college choose which courses to evaluate. (3) Peer Review. In order to enhance the teaching techniques and methods of the examined instructors and their teaching competence, arrange for experienced teachers to evaluate their peers and to adopt the listening, evaluating, and discussing methods of lectures.(4) Assessment of Students. Students assess their own class instructors' instruction each semester. The examination of a teacher's quality of instruction is often scheduled before each semester's final exams and in the middle of the semester.

*B. Pre-Processing Using Multimodal Hierarchical Graph Collaborative Filtering (MHGCF)*

In this section, the emphasis lies on Multimodal Hierarchical Graph Collaborative Filtering (MHGCF) [21]. The pre-processing phase involves cleansing the data gathered from university datasets. MHGCF stands out in recommendation systems by harnessing multimodal data and hierarchical representation learning, enabling more precise and personalized recommendations while adeptly managing sparse data. To enhance the dataset, MHGCF employs a series of data cleansing techniques. Specifically, MHGCF utilizes a Graph Convolutional Network (GCN) module to facilitate data cleansing, which propagates user embedding’s along the interaction graph. Notably, this process initially excludes the integration of multimodal information. Equation (1) elucidates how MHGCF formulates their embedding generation to reduce dimensionality at the graph convolution layer for items on the graph and the corresponding users.

$$o_{t_1}^{(d)} = \sum_{h \in M_{t_1} \cup h_1} \frac{|M_k|^{\alpha}}{|M_{t_1}|0.5\|M_k|^{0.5}} \cdot o_h^{(d-1)} \tag{1}$$

Here, $o_{t_1}^{(d)}$ represent the user embedding, $d-1$ represent the layer, $o_{t_1}^{(d-1)}$ represent the embedding at layer, $|M_t|$ & $|M_k|$ denotes the size, $h$ denotes the item, $\alpha$ represent the co-efficient and $\frac{|M_k|^{\alpha}}{|M_{t_1}|0.5\|M_k|^{0.5}}$ It embodies the prevailing norm or consensus among the public. Since are the For the k-th graph convolution concerning the target entity element, all that is necessary is to consider the aggregate of its neighbouring elements, as specified in equation (2).

$$p_{D_1}^{(k)} = \sum_{h \in M_{D_1} D_1} \frac{|M_h|^{\alpha}}{|M_h|^{0.5}|M_{D_1}|^{0.5}} \cdot p_h^{(k-1)} \tag{2}$$

Here, $p_{D_1}^{(k)}$ represent the user embedding, $k-1$ represent the layer, $p_h^{(k-1)}$ represent the embedding at layer, $|M_h|$ & $|M_{D_1}|$ denotes the size, $h$ denotes the component, $\alpha$ represent the co-efficient. Preference-independent noise often exists in multimodal deep features, which propagates to adjacent elements during graph convolution, affecting their representations. To mitigate this issue, a more adaptable Graph Convolutional Network (GCN) module for multimodal deep characteristics can be constructed across the graph. As depicted in equation (3), MHGCF specifically formulates the generation of representations for the target user and item to reduce dimensionality within the modality.

$$G_{l,h_1}^{(1)} = \frac{|M_{f_1}|^{\alpha} V_l G_{l,h_1}^{(0)}}{|M_{f_1}|} + \sum_{t \in M_{h_1}} \frac{|M_{f_1}|^{\alpha} h_{l,t}^{(0)}}{|M_{f_1}|^{0.5}|M_t|^{0.5}} \tag{3}$$

Here, $G_{l,h_1}^{(1)}$ represent the user embedding, $|M_{f_1}|$ & $|M_t|$ denotes the size, $V_l$ represent the weight transformation matrix, $h$ denotes the item, $\alpha$ represent the co-efficient, $l$ represent the modality, $t_1$ denotes the target user and $h_1$ denotes the component. For a particular user component, MHGCF uses the element representations to compute the reduce the dimension. Thus, equation (4) illustrates it.

$$K_1 = \sum_{(t,h,i)\in N} -km\sigma\left(\left(o_t^{(K)}\right)^S \cdot o_h^{(K)} - \left(o_t^{(K)}\right)^S \cdot o_i^{(K)}\right) + \lambda\left(\|O\|_2^2\right) \quad (4)$$

Here, $(t,h,i)\in N$ represent the training data, $K_1$ objective function of initialized embedding matrix $O$, $t$ denotes the user, $\sigma(.)$ represent the sigmoid function and $o_t^{(K)}$ & $o_h^{(K)}$ represent the target item at k-th layer. For reduce the dimension, the MHGCF combines all of the initialized embedding matrix's goal functions. Thus, equation (5) illustrates it.

$$N = N_1 + N_2 + N_3 \quad (5)$$

Here, $N$ represent the objective function, $N_1$ objective function of initialized embedding matrix $O$, $N_2$ objective function of initialized embedding matrix $P$ and $N_3$ objective function of initialized embedding matrix $G$ .After completing the pre –processing, the pre-processed data are fed to MORARNN

*C. Classify the Teaching Quality using Mixed-Order Relation-Aware Recurrent Neural Networks (MORARNN)*

In this section, classify the teaching quality using MORARNN [22] is discussed. MORARNN is used for various teaching qualification assessments, including Administration Evaluation, Specialist Evaluation, Peer Evaluation, and A pupil Evaluation. MORARNN stems from its capability to model complex relationships in sequential data while maintaining memory efficiency. Its advantage lies in its ability to capture both temporary and continuing dependencies within the data, enhancing predictive accuracy and robustness in various tasks. This could involve assessing the teacher's ability to lead a classroom or educational institution. It might include qualities like communication skills, organization, decision-making, and the ability to motivate and inspire others. To classifying the neural relation is given as equation (6).

$$S_t = \partial\left(\sigma_s\left(y_t, D_{t-1}\right) + C_s\right) \quad (6)$$

Here, $S_t$ denotes the relation aware model network; $\partial$ denotes the constant of detection; $\sigma_s$ denotes the non-shared mixed classification; $y_t$ denotes the current observation; $D_{t-1}$ denotes the previous state of the detection and $C_s$ denotes the input layer. Since the purpose of detection is to classify the original sequence in advance, the Mixed-Order Relation-Aware layers are designed to supply MORARNN with the classification of various layers as input.

Evaluation could focus on the teacher's subject matter expertise. It might consider factors such as depth of knowledge, ability to convey complex concepts in an understandable manner, staying current with developments in the field, and contributions to their academic discipline. This various class input data is given in equation (7)

$$k_t = soft\max\left(\delta\left(Q_t\right)\right) \quad (7)$$

Here, $k_t$ denotes the various classes input; $soft\max$ denotes the activation of input function; $\delta$ denotes the positive input defect data and $Q_t$ denotes the various layer. Grading of teaching quality is negatively impacted by the large error accumulation effect caused by the extremely complex synovial thickening of the original sequence. Thus it is given in equation (8)

$$V_t = \partial\left(\sigma_v\left(y_t, C_{t-1}\right) + f_v\right) \quad (8)$$

Here, $V_t$ denotes the sequence of quality; $\partial$ denotes the constant of detection; $\sigma_s$ denotes the non-shared mixed classification; $y_t$ denotes the current observation; $C_{t-1}$ denotes the previous state of the detection and $f_v$ denotes the input layer.

Peer evaluation involves feedback from other educators or colleagues. This could include assessments of teaching methods, collaboration skills, professionalism, and contributions to the educational communityusing given equation (9)

$$F_t = Aggregate_{m2H}\left(g, q_t\right) \quad (9)$$

Here, $F_t$ is denotes the squashing activation vector; $Aggregate_{m2H}$ is denotes the aggregation of node detection; $g$ denotes the classification function and $q_1$ is denotes the transition classification.

MORRNNs enable the identification of hidden trends indicative of malignancy by integrating data from several orders of relations within sequential data and classifying the Student evaluation involves feedback from the learners themselves. This could encompass aspects such as clarity of instruction, approachability, responsiveness to student needs, effectiveness of teaching methods, and overall impact on student learning outcomesare given in equation (10)

$$N(\Theta)=\frac{1}{\varepsilon PG'}\sum_{t=1}^{\varepsilon}\sum_{i=1}^{P}\sum_{j=1}^{G'}\left|\hat{z}_{tij}-z_{tij}\right| \tag{10}$$

Here, $N(\Theta)$ is denotes the trainable parameter of the detection; $\varepsilon$ is denotes the detection function; $P$ is denotes the time sequence of the input data; $G'$ is denotes the data display in the MORARNN; $\hat{z}_{tij}$ is denotes the fusion operation of each images and $z_{tij}$ denotes the grading of detection classification. Using the MORARNN method, teaching quality is classified based on evaluations gathered from student feedback. These evaluations are then categorized into different types, including Administration Evaluation, Specialist Evaluation, Peer Evaluation, and The pupil Evaluation.Here, FFOA is employed to optimize the MORARNN. Here, FFOA is employed for tuning the weight and bias parameter of MORARNN.

*D. Optimization Fennec Fox Optimization Algorithm*

The proposed Fennec Fox Optimization Algorithm (FFOA) [23] is utilized to enhance weights parameters $k_t$ *and* $Q_t$ of proposed MORARNN. The parameter $k_t$ *and* $Q_t$ is implemented for increasing the accuracy and reducing RMSE. The Fennec Fox Optimization Algorithm (FFOA) stands out as a promising approach for optimizing complex systems, drawing inspiration from the adept hunting techniques of the desert-dwelling fennec fox. Its application in assessing teaching quality based on student feedback holds considerable merit due to several key advantages. FFOA is prized for its efficiency, swiftly navigating through vast datasets of student evaluations to identify optimal solutions within a short timeframe. Furthermore, its innate ability to balance exploration and exploitation mirrors the nuanced nature of teaching quality evaluation, where a comprehensive understanding requires both uncovering new insights and leveraging existing knowledge. By harnessing FFOA, educators and institutions can streamline the process of analysing student feedback, thereby facilitating the enhancement of teaching methodologies and ultimately fostering a more enriching learning experience. The entire step method is then presented in below,

***Step1:*** Initialization

Initial population of FFOA is, initially generated by randomness. Then the initialization is derived in equation (11).

$$L=\begin{bmatrix} l_{1,1} & \cdots & l_{1,j} & \cdots & l_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ l_{i,1} & \cdots & l_{i,j} & \cdots & l_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ l_{N,1} & \cdots & l_{N,j} & \cdots & l_{N,m} \end{bmatrix}_{N\times m} \tag{11}$$

Where, $l$ denotes the total population of Fennec foxin the tracks; $m$ denotes the number of FFOA while attacking towards its prey and $N$ represents the distance between the prey and FFOA.

***Step2:*** Random generation

Parameters generated at random for input. The selection of ideal fitness values was based on a clear hyperparameter condition.

***Step 3:*** Fitness Function

The system's fitness is determined by the objective function. To regulate the fitness function,

$$Fitness\,Function = optimizing\ [k_t \text{ and } Q_t] \tag{12}$$

Where, $k_t$ is used for increasing the Accuracy and $Q_t$ is used for decreasing the RMSE.

***Step 4:*** Phase: 1 digging to Look for Prey under the Sand for optimizing $k_t$

Since the behavior of fennec foxes involves a local search, imitating it can improve the FFOA's ability to find a solution that approaches the global optima. In order to mimic a fennec fox's digging behavior, Similar to a fox searching for food in its natural habitat, the algorithm combines the phases of exploration and exploitation. While exploitation concentrates on stepping up the search around specific places, exploration focuses on people searching the search space to find prospective regions. The fennec fox can find a better option in this region by doing a local search. The update of FFOA members is replicated theoretically using (13). The fennec fox is a lone nighttime hunter that uses its long ears to find food hidden beneath the sand.

$$y_{j,i}^{S1} = y_{j,i} + (2.r - 1).P_{j,i} + E^h \tag{13}$$

Where, $y_{j,i}^{S1}$ denotes new proposed status of fennec fox; $P_{j,i}$ denotes neighbourhood radius; $y_{j,i}$ is the dimension of area; $r$ denote random number. FFOA utilizes adaptive mechanisms such as mutation and crossover operators to enhance exploration and maintain diversity within the population; and it given as equation (14),

$$P_{j,i} = \beta \cdot \left(1 - \frac{t}{T}\right). + E^h \cdot y_{j,i} \tag{14}$$

Where, $t$ denotes iteration counter; $T$ denotes total number of iteration; $\beta$ denotes constant number and Figure 2 shows the corresponding flowchart.

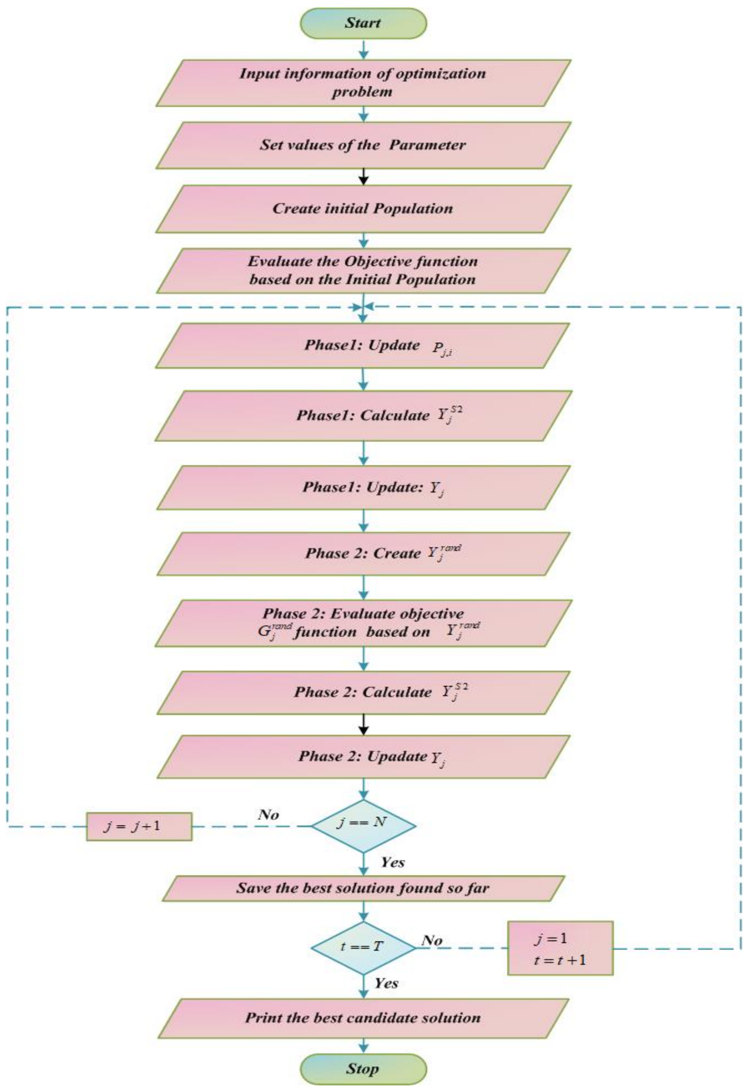


Figure2: Flow Chart of FFOA for Optimizing MSRGCN

***Step 4:*** Phase: 2 Escapes strategy from the predators' attack for optimizing $Q_t$

Wild predators like striped hyenas, caracals, and Pharaoh eagle-owls can attack fennec foxes. However, because of its amazing speed and abrupt direction change, it manages to elude predators. This fennec fox escape strategy serves as the foundation for the worldwide scanning of the search space. When this escape strategy is replicated, the proposed FFOA has greater exploring power. The second part of the FFOA populace update is carried out through mathematical simulation. By avoiding becoming mired in the optimally local areas, it facilitates the identification of the optimal global area. Consequently, the random location of each candidate solution in the search space can be understood as a model of how the fennec fox would behave in trying to escape (15)

$$y_{j,i}^{S2} = \begin{cases} y_{j,i} + r \cdot (y_{j,i}^{rand} - L \cdot y_{j,i} + \beta_{(j)}^{h}), & G_j^{rand} < G_j; \\ y_{j,i} + r \cdot (y_{j,i} - y_{j,i}^{rand}) & , else \end{cases} \tag{15}$$

Where, $G_j^{rand}$ denotes objective function value; $L$ denotes arbitrary count from set $\{1,2\}$. The algorithm usually uses fine-tuning mechanisms or local search approaches to refine the solutions around the identified potential regions during exploitation. These strategies might include gradient-based approaches, hill-climbing algorithms, or other heuristic strategies customized for the particular optimization issue at hand; and it given as equation (16),

$$Y_j = \begin{cases} Y_j^{S2} & G_j^{S2} < G_j \\ Y_j + \beta_{(j)}^{h} & else \end{cases} \tag{16}$$

Where, $Y_j^{S2}$ denotes new suggested status; $Y_j$ denotes fennec fox. . The method seeks to converge towards the global optimum and iteratively enhance the quality of the solutions by utilizing the information gained during exploration.

***Step 5:*** Termination Criteria

The weight parameter value of generator $E^h$ *and* $\beta_{(j)}^{h}$ Multi-Scale Residual Graph Convolution Network(MSRGCN) is optimized by utilizing Fennec Fox Optimization Algorithm (FFOA)and it will repeat step 3 until it obtains its halting criteria $L = L + 1$.Then NLTSEFTQ-MORA-RNN effectively predict groundwater level with low RMSE and MAE

## III. RESULT AND DISCUSSION

Investigational outcomes of NLTSEFTQ-MORA-RNN are conversed. The simulation is implemented in python using real time data collected from 2 separate universities. NLTSEFTQ-MORA-RNN model is teaching quality predicting using various performance metrics like Accuracy, Computational time, F1-score, Mean Square Error, Precision, Recall, True positive rate, and Specificity are analysed. The results of the proposed NLTSEFTQ-MORA-RNNprocedure are linked to those existing methods such as ECTQ-GA-BPNN [15], AIFSHE-ANN [16] and SASF-NLP-DL [17].

### *A. Performance Measures*

This is a crucial step for determining the exploration of optimization algorithm. Performance measures to evaluate to access performance such as such as Accuracy, Computational time, F1-score, Mean Square Error, Precision, Recall, True positive rate, and Specificity are analysed.

It is determined to scale the performance parameters using the confusion matrix.

- True Positive $(TP)$ : Teaching quality, prediction are both positive
- True Negative $(TN)$ : Teaching quality are both negative
- False Positive $(FP)$ : Teaching quality, prediction is positive
- False Negative $(FN)$ : Teaching quality, prediction is negative

*1) Accuracy*

Accuracy describes classification rate that are correctly classified. The formula is derived in equation (17).

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{17}$$

Here, $TP$ denotes True Positive; $TN$ denotes True Negative; $FP$ denotes False Positive and $FN$ denotes False Negative.

*2) Mean Absolute Error (MAE)*

MAE metric is one of many that are used to assess a machine learning model's performance. Each data point's prediction error is calculated separately, and the error is then converted to a non-negative value. It is given in equation (18),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

(18)

As an example, the letters $MAE$ stand for mean absolute error, $n$ for number of data points, $y_i$ for actual value, and $\hat{y}_i$ for forecasted value.

*3) Recall*

Sensitivity is a performance metric commonly used in convergence application. That's provided in equation (19).

$$\mathrm{R}ecall = \frac{TN}{(FP + TN)} \quad (19)$$

*4) Specificity*

It estimates the proportion of negative instances and expressed in equation (20)

$$Specificity = \frac{TP}{FN + TP} \quad (20)$$

*5) Precision*

It estimates positive result count while detection of infested soybean laves. Then the formula is derived in equation (21).

$$\mathrm{Pr}ecision = \frac{TP}{(TP + FP)} \quad (21)$$

*6) Correlation coefficient (R)*

The R measures the strength and direction of a linear connection between two continuous variables. It estimates the extent to which two variables tend to change simultaneously. R is expressed in equation (22)

$$R = \frac{n\sum_{i=1}^{n}(x_i\hat{x}_i) - \left(\sum_{i=1}^{n}x_i\right)\left(\sum_{i=1}^{n}\hat{x}_i\right)}{\sqrt{n\sum_{i=1}^{n}x_i^2 - \left(\sum_{i=1}^{n}x_i\right)^2}\sqrt{n\sum_{i=1}^{n}\hat{x}_i^2\left(\sum_{i=1}^{n}\hat{x}_i\right)^2}} \quad (22)$$

Where $n$ denotes the entire amount of observations, indicates the sum of overall observation, $x_i$ represents the individual data point, $\hat{x}_i$ represents the mean value.

*7) AUC*

The AUC score evaluates the model's overall performance. A perfect classifier receives a score of 1.0, while a arbitrary classifier receives a value of 0.5. A higher AUC score denotes larger model performance. This is calculated by equation (23)

$$AUC = \frac{1}{2}\left(\frac{TP}{TP + FP} + \frac{TN}{TN + FP}\right) \quad (23)$$

*8) F1-score*

The F1-score evaluation parameter is examined and the performance equation is given. Then the formula is derived in equation (24).

$$F1 - Score = 2 \times \frac{recall \times precision}{recall + precision} \quad (24)$$

*B. Performance analysis*

The NLTSEFTQ-MORA-RNN approach's simulation results are shown in figure 3 to 10. The suggested NLTSEFTQ-MORA-RNNapproach is compared to existing ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DLmodels.

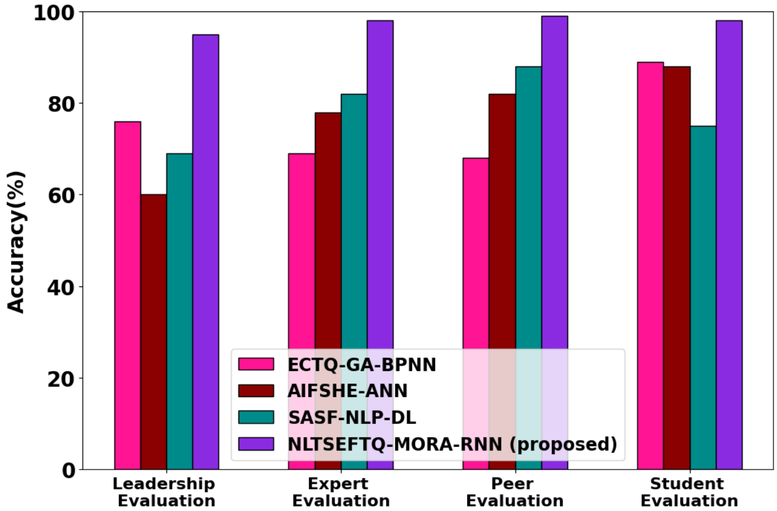


Figure3: Performance analysis of Accuracy

Figure 3 depicts that Performance analysis of Accuracy. The accuracy of the proposed method based on an improved proposed NLTSEFTQ-MORA-RNN method for evaluating classroom teaching quality.The proposed model significantly improved the prediction accuracy and convergence speed of the neural network, offering a more practical and accurate method for assessing teaching quality in higher education settings. Overall, the combination of proposed NLTSEFTQ-MORA-RNN method in the evaluation model contributed to higher accuracy in assessing classroom teaching quality, offering a more effective tool for educational management and teacher evaluation in colleges and universities. The performance of the proposed PSPTI-RBAGCN-NOA approach attains28.5%, 27.5% and 28% higher accuracy.

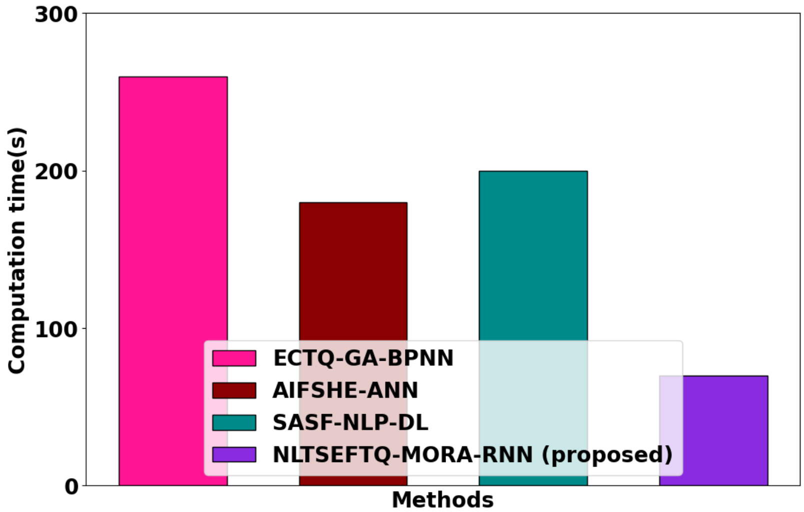


Figure 4: Performance analysis of Computational Time

Performance analysis of Computational Time shows in fig 4.Student Evaluation and Feedback in Teaching Quality, computational time plays a crucial role in various facets of the research procedure. The proposed NLTSEFTQ-MORA-RNN method attains 18.3%, 19.4%, and 20.4% lower Computational time as compared to the existing methods ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DLmodels correspondingly.

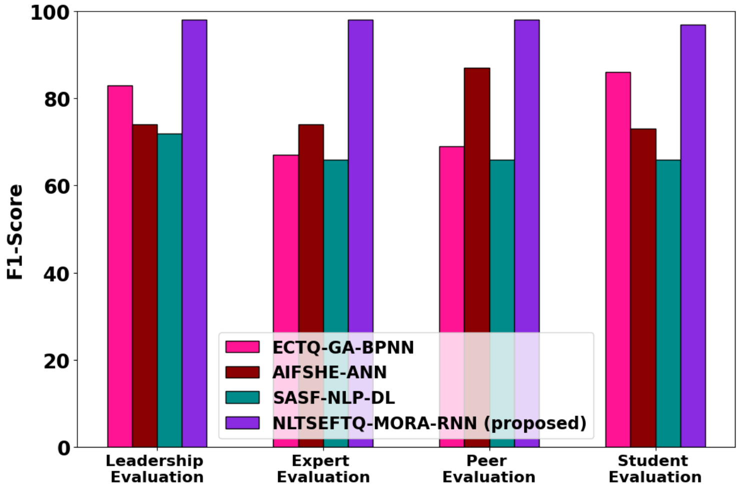


Figure 5: Examining the performance of the F1-Score

Examining the performance of the F1-Score is shown in fig 5. The F1-score represents the balanced combination of precision and recall. It offers a well-balanced approach that considers both precision and recall, making it especially valuable for handling datasets with imbalances. A high F1-score suggests a model with strong performance, demonstrating both precision and recall.The proposed NLTSEFTQ-MORA-RNN method attains 23.4%, 30.4% and 28.3% higher F1-score for leadership evolution 29.4%, 28.4% and 31.4% higher F1-score for expert evaluation ; 28.3%, 27.4% and 31.0% higher F1-score Peer evaluation ; 27.4%, 28.3%, and 29.3% higher F1-score for student evaluation as compared to the existing methods ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively.

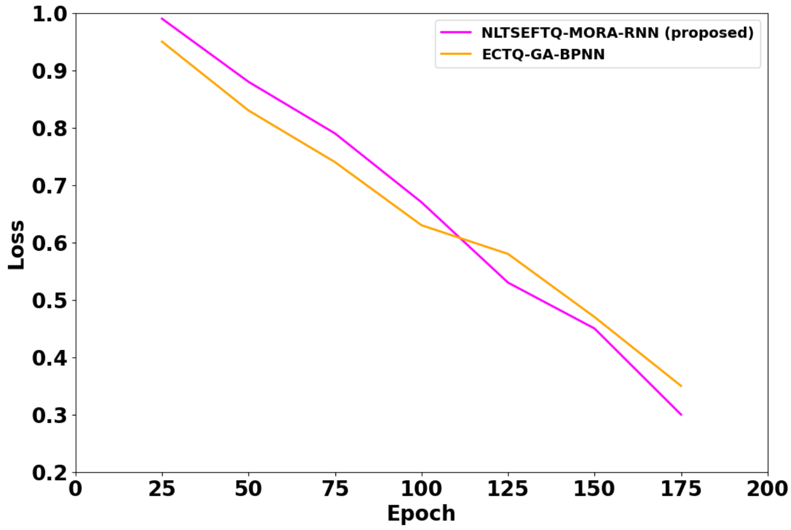


Figure 6: Performance analysis of loss

Performance analysis of loss is shown in fig 6.To analyse a loss graph typically associated with neural network training, you would need access to the training data, model architecture, and training process details. Loss graphs are commonly used to visualize the decrease in loss over epochs or iterations throughout the training of a neural network. The require assistance with creating or interpreting a loss graph for a proposed method please provide more specific details or data related to the model's training process. The proposed method loss value is initially started from 1.0 at 25 epoch then they slightly reduced to reach 0.3 at 25 to 175 epochs the proposed method loss value is lower than other exiting methods.

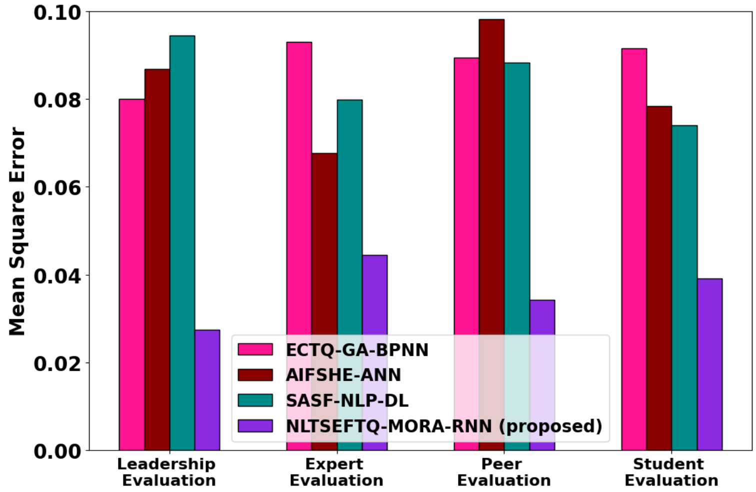

Figure 7: Analyzing the performance of Mean Square Error (MSE)

Analyzing the performance of Mean Square Error (MSE) is shown in fig 7. MSE is a statistical measure commonly employed to evaluate the accuracy of a predictive model or the quality of an estimator.In the context of Student Evaluation and Feedback in Teaching Quality, MSE can be utilized to evaluate how well a predictive model, perhaps built on student feedback data, is performing in estimating teaching quality. The proposed NLTSEFTQ-MORA-RNN method attains 29.4%, 30.2% and 31.4% lower Error rate for leadership evolution 26.4%, 28.4%, and 27.3% lower Error rate for expert evaluation; 29.3%, 22.4% and 27.1% lower Error rate for Peer evaluation; 25.4%, 27.3% and 25.3% lower Error rate for student evaluation as linked to the current methods ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively.

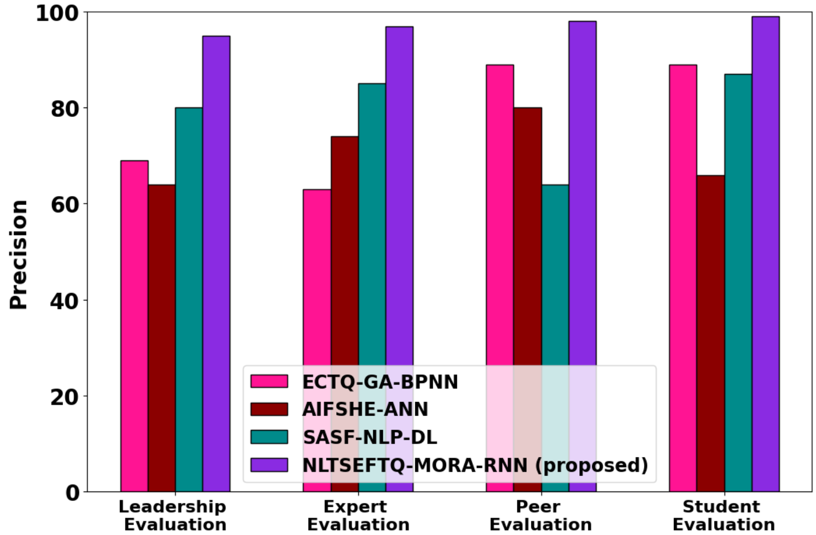

Figure 8: Performance analysis of precision

Performance analysis of precision is shown in fig 8. Precision could be related to the accuracy and reliability of predictive models built to estimate teaching quality based on feedback data. Precision here refers to the capability of the model to make exact predictions consistently. The proposed NLTSEFTQ-MORA-RNN method attains 29.3%, 30.4% and 28.4% higher precision for leadership evolution; 22.7%, 25.3% and 27.3% higher precision for expert evaluation28.2%, 294.3% and 25.1% higher precision for Peer evaluation; 22.3%, 23.3% and 28.4% higher precision for student evaluation as compared to the existing methods ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively.

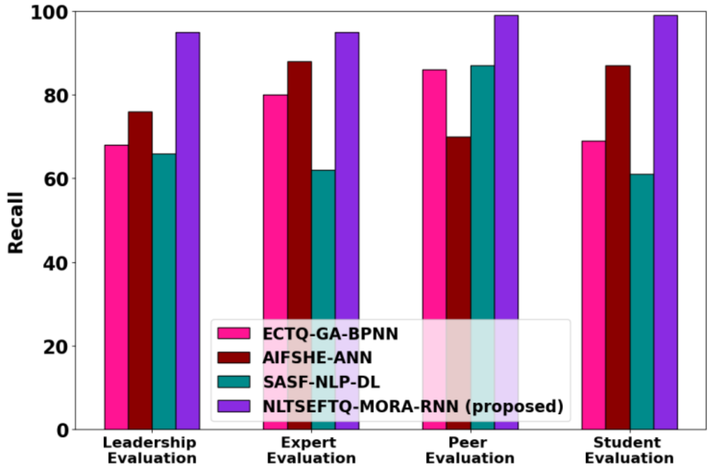


Figure 9: Performance analysis of Recall

Performance analysis of Recall is shown in fig 9: When considering teaching quality evaluation, recall refers to the percentage of relevant feedback or evaluation points that are captured by the evaluation process. The proposed NLTSEFTQ-MORA-RNN method attains 28.3%, 27.4% and 25.4% higher recall for leadership evolution; 22.7%, 25.3% and 28.3% higher recall for expert evaluation24.3%, 25.3% and 26.1% higher recall for Peer evaluation; 25.3%, 27.3% and 28.4% higher recall for student evaluation as compared to the existing methods ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively.

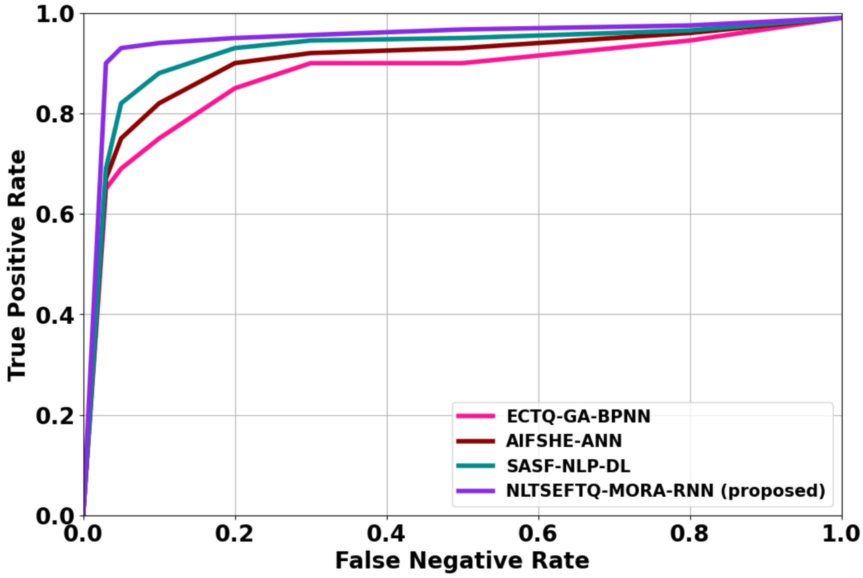


Figure 10: Analyzing the performance of the True Positive Rate

Analyzing the performance of the True Positive Rate is shown in fig 10. Student Evaluation and Feedback in Teaching Quality, the analysis of Area under the Curve (AUC) typically involves Receiver Operating Characteristic (ROC). AUC used as a criterion for selecting the best-performing model among several candidate models. In this context the proposed NLTSEFTQ-MORA-RNN technique reaches in the range of21.36%, 22.42% and 19.27% higher AUC for leadership evolution 27.26%, 20.41% and 23.26% higher AUC for expert evaluation22.36%, 35.42% and 28.27% higher AUC for peer evaluation 27.26%, 20.41% and 23.26% higher AUC student evaluation22.36%, 25.42% and 18.27%compared to existing techniques such as ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively.

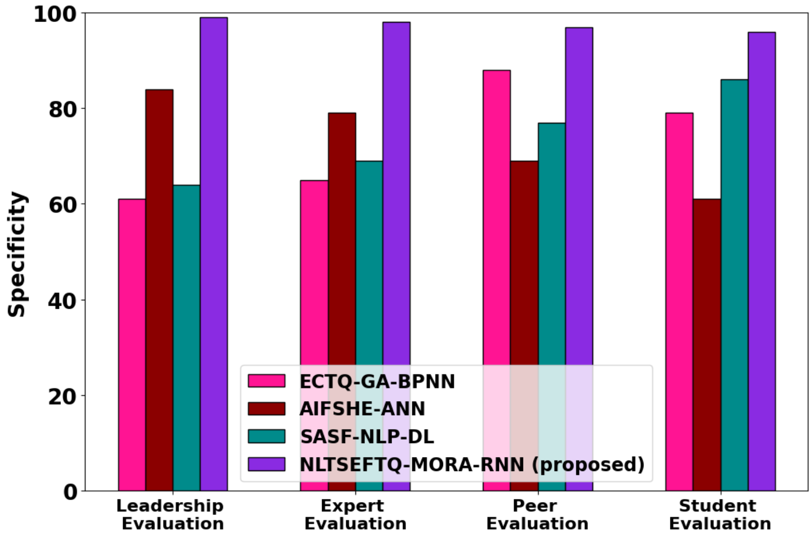

Figure 11: Performance analysis of Specificity

The specificity metric evaluates how accurately the evaluation process identifies instances of low-quality teaching among all the negative feedback received shown in Fig 11. The model's ability to accurately identify instances of low-quality teaching among all instances that truly belong to this category is measured by specificity. In this context the proposed NLTSEFTQ-MORA-RNN technique reaches in the range of20.36%, 24.42% and 21.27% higher Specificity for leadership evolution 25.26%, 22.41% and 28.26% higher Specificity for expert evaluation26.36%, 25.42% and 27.27% higher Specificity for peer evaluation 28.26%, 21.41% and 22.26% higher Specificity student evaluation 21.36%, 23.42% and 19.27%compared to existing techniques such as ECTQ-GA-BPNN, AIFSHE-ANN and SASF-NLP-DL respectively

*C. Discussion*

The comparison between the proposed NLTSEFTQ-MORA-RNN method and existing approaches underscores its significant advancements in evaluating teaching quality through student feedback. The NLTSEFTQ-MORA-RNN method demonstrates substantial enhancements across various performance metrics compared to existing techniques. Specifically, it achieves notably higher accuracy, precision, sensitivity, and specificity. This suggests its effectiveness in accurately assessing teaching quality based on diverse evaluation criteria such as leadership, expertise, peer perception, and student feedback. The MORARNN represents a novel approach to handling student evaluation data. By leveraging MHGCF in the pre-processing stage and MORARNN for classification, The proposed method efficiently processes and analyzes the input data, resulting in enhanced classification accuracy.The optimization of MORARNN's weight parameters using the Fennec Fox Optimization Algorithm further enhances the model's performance, resulting in more precise and reliable evaluations of teaching quality. This innovative methodology not only elevates the accuracy of teacher evaluations but also streamlines the process, potentially reducing the time and effort required for manual assessment.

## IV. CONCLUSION

In conclusion, the NLTSEFTQ-MORA-RNN approach, implemented in Python, demonstrates significant enhancements in both computational efficiency and accuracy compared to existing methods. Specifically, it showcases 25.03%, 22.53%, and 20.05% reductions in computation time, along with 28.5%, 27.5%, and 28% improvements in accuracy when compared to ECTQ-GA-BPNN, AIFSHE-ANN, and SASF-NLP-DL, correspondingly. These results underscore the effectiveness and promise of the suggested approach in predicting student evaluation and feedback in teaching quality. Moreover, the study delved into the concept of enhancing classification through a more nuanced understanding of teaching quality. By leveraging Natural Language Processing technology and advanced neural network architectures, the proposed method effectively captures and analyzes multifaceted data, leading to more accurate assessments. Overall, the findings suggest that the proposed method holds promise for proceeding the field of training quality valuation in higher education institutions, contributing to continuous improvement and enhancement of educational outcomes. Its combination of improved accuracy and reduced computational burden positions it as a valuable tool for educators and administrators seeking to optimize teaching quality assurance systems.

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