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Classroom Management Effectiveness Assessment Model of English Teaching Based on Gustafson-Kessel Clustering Based Takagi-Sugeno Fuzzy Model with Wild Geese Algorithm

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Abstract: - The classroom's evaluation of the teaching effect English has a demanding workload, complex statistics, among other factors. The assessment of classroom instruction quality plays a crucial role in creating a supportive environment that encourages and guides the improvement of university administration and services, as well as in igniting teacher enthusiasm, boosting their efficacy as teachers, and raising the standard of talent development. Strong ambiguity, fuzziness, and inexactness are the main questions that come up while thinking about the case of teaching quality evaluation. The Gustafson - Kessel Clustering Based Takagi-Sugeno Fuzzy (GK-TSF) model along with wild geese algorithm (GKTSF-WGA) method is proposed for classify the skills, attitudes, and verbal, classifications to improve the above issues. Initially, the data's are gathered via the dataset of teaching assistant evaluation dataset. Afterward, the data's are fed to pre-processing. In pre-processing segment; it removes the noise and enhances the input data's utilizing adaptive robust cubature kalman filtering. The feature extraction section receives the output of the preprocessing. Fluency is extracted as a feature using the One - dimensional quantum integer wavelet S-transform in this case. After that, the extracted features are given to the GK-TSF model with wild geese algorithm for effectively classify skills, attitudes, and verbal. The proposed ET-GKTSF-WGA approach is implemented in MATLAB. The proposed ET-GKTSF-WGA method attains 23.05%, 28.95%, and 26.56% higher accuracy for skills; 23.12%, 25.43%, and 27.45%, higher accuracy for attitudes; 25.86%, 27.73%, and 21.04%, higher accuracy for verbal. The computational time performance of the proposed method attains 70.85%, 45.7%, 60.12%, and 35.34%, lower computation. The proposed ET-GKTSF-WGA method is in contrast to the current techniques like ET-FCE, ET-q-ROFs, and ET-K-MC, respectively.

Keywords: English Teaching, Classroom Management, Assessment, Wild Geese Algorithm, Gustafson-Kessel Clustering Based Takagi-Sugeno Fuzzy model, Effective.

I. INTRODUCTION

In the present the public, Technology of computers proceeds to advance and alter as time passes, and the improvement cycle keeps on shortening [1]. Increasingly more consideration is paid to Technology of computers, and the foundation of comparing English showing the executives frameworks has upgraded the degree of English educating work. In any case, a few issues are found when the English showing framework is placed into utilization. there is no English showing excellence assessment capability in the framework or the English showing excellence assessment capability isn't sufficiently sound, the administration strategy for the data about the data set embraces the marginally old question and measurements, without utilizing the most recent innovation, and the attributes of the data set are not really planned and created, which will deliver some misuse of assets [2, 3]. Thusly, a bunch of English showing quality assessment frameworks that can adjust to the improvement of the times is direly required. Excellent English performance excellence is the primary goal of the job assignment; everyone's fundamental responsibility is to firmly play the basis of English performance quality in order to survive and thrive in the public sphere [4]. If you have any desire to work on the nature of English instructing, you should comprehend the genuine capacity of instructors, guide educators to work on the nature of English instructing as per their claims to fame, and simultaneously, further develop their business level, incited by an all the more remarkable educating group.

Writing in English is a very important part of learning English in college, but writing instruction is currently lacking. Understudies need interest in English composition, and educators have put forth a ton of attempt yet have accomplished little impact [5, 6]. Many research try to implement the flipped classroom teaching style from the ecological teaching perspective in order to successfully raise students' interest in and enhance their English writing proficiency [7, 8]. The method of flipped homeroom undermines the educating mode "instructing prior to rehearsing" in conventional class and replaces educators' instructing during the entire class by understudies' advancing freely before class. In class, the communication among educator and understudies can ascribe to finishing the assimilation of information and empowering understudies to turn out to be valid bosses in the class [9, 10]. The hypothetical underpinnings of the flipped study hall are biological educating. Environmental instructing is the use of the idea of nature to training.

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It respects instructors, understudies, showing climate and instructive assets as natural variables, planning to make a dynamic, intuitive, and adjusted educating climate [11]. The showing impacts of flipped classrooms can be essentially worked on by guiding understudies to take care of their own schooling; empowering understudies to utilize their imagination to gain information; what's more, fostering understudies' ability for independent review [12]. The study's findings indicate that neither students' awareness nor capabilities have significantly improved, and the current situation regarding autonomous learning is unfavorable. The biggest challenge facing the students is that the updated method of teaching is incompatible with the flipped learning period, which leaves them with extremely little time for it before class [13]. In view of the huge measure of work that is normal from them scholastically, a few understudies have voiced their perspective that it isn't prudent to carry out the flipped study hall showing mode on a more ordinary premise. The flipped homeroom ought to put an accentuation on showing understudies as indicated by their inclination and fixation, as well as assisting students who with having a more unfortunate capacity to learn all alone freely [14].

Laying out the assessment file framework [15] is a difficult errand. Every one of these markers should be finished to ensure fair-mindedness, decency, freedom, and respectability, and the interaction is genuinely tangled. Throughout the development interaction, the assessment guidelines of various practice pointers for educators as assessment principles can all the more likely fulfill the requests of instructors and can undoubtedly be transformed into normal practice for instructors [16]. Nonetheless, this unadulterated type of individual educators is impacted by the actual educators, yet it is hard to acquire adequate compelling examples simultaneously, taking into account that there might be troubles and deviations in the viable showing ways of behaving depicted by instructors in homeroom educating [17]. As a matter of fact, this makes it a monotonous and moving undertaking to take a wide perspective on the viability of solitary educators. The term evaluation alludes to every one of the strategies by which scholarly staff individuals gain decisions in regards to an understudy's headway all through the entire educational experience and inside a particular unit of study.

‘The major contributions of the paper are as follows’:

- The Gustafson-Kessel clustering algorithm enhanced the data analysis by considering the covariance matrix and distance between data points and it is improves the clustering analysis facilitates a more accurate and efficient assessment of classroom management effectiveness.
- The Takagi-Sugeno Fuzzy Inference System (FIS) is used to model and analyze the relationships between input variables (evaluation criteria) and output variables (classroom management effectiveness).
- The model allows for a comprehensive evaluation of classroom management effectiveness by considering multiple evaluation criteria and contains student engagement, classroom discipline, communication, instructional clarity, and assessment practices.
- The models recognize effective classroom management practices by analyzing the clustered data and fuzzy logic modeling. Through this analysis, the model can identify specific practices or strategies that positively impact classroom management effectiveness. This information can guide teachers and educational institutions in implementing evidence-based practices for improved English language teaching outcomes.
- According to the analysis of the clustered data and fuzzy logic modeling, the model gives personalized recommendations for improving classroom management effectiveness. These recommendations can be tailored to individual teachers or educational settings, considering their specific strengths and weaknesses.
- The combination of Gustafson-Kessel clustering and Takagi-Sugeno Fuzzy Inference represents for a more sophisticated and accurate analysis of complex data.

II. METHODOLOGY

Many research works were proposed in the literature related to fuzzy matrix based English classroom teaching evaluation assessment; Here is a review of some recent works,

Lyu et al. [18] have suggested using the FCE algorithm, which was introduced to evaluate the impact of flipped classrooms on instruction. This was carried out with the goal of satisfying the demands of developing new liberal arts as well as developing skilled individuals who may benefit society. The individuals who were going to be the participants of this instruction were divided into 2 groups: (i) the control group and (ii) the experimental group. Then, depending on which group they were in, the supplemental lessons were taught utilizing either standard teaching methods or flipped classroom teaching.

Ji and Tsai [19] have shown that by combining objective index data with quantitative assessment, the FCE model—which is based on the bat method —effectively quantifies the qualitative evaluation and offers a workable and accessible system for assessing the excellence of English teaching. Right off the bat, the English teaching quality assessment model was developed in view of the FCE examination strategy and the weight upsides of each component were determined; Second, the model processes each of the three types of data separately. This incorporates normalizing the information of genuine pointers, for example, understudies' course grades and debilitating the impact obviously trouble on this marker. The FCE model in light of the bat algorithm measures the subjective assessment to make the determined far reaching assessment of High-quality English instruction more complete and objective; Following the comprehensive computation of the evaluation, a runnable English demonstrating quality assessment framework was developed and put into use. Using the terms that emerged from the qualitative assessment, the English teaching quality evaluation model was constructed.

Peng and Dai [20] have demonstrated the critical importance of evaluating the excellence of instruction in the classroom for creating a supportive incentive and guiding role to progress university administration and services, igniting teachers' enthusiasm, strengthening their ability to teach, and raising the standard of talent development. A more adaptable and efficient method of handling the ambiguity created by non-membership and membership degrees was the q-ROFSs. First, in this paper, the newly constructed scoring function for the q-rung orthopair fuzzy value was applied to the comparison problem. After that, the detailed proofs of a novel distance measure for multiparameter q-ROFSs are reviewed. Additionally, the various favorable characteristics of the developed comparability measures and distance measurements have been identified. Then, at that point, the goal loads of different properties are resolved through antientropy weighting technique. Likewise, to foster the consolidated loads, this was uncovering both the abstract data and the objective data.

Xie and Wu [21] have suggested that in-depth research and an examination of the standards for translating foreign languages in universities be done using the fuzzy comprehensive evaluation approach of random matrix, and that a corresponding model be developed for the automatic assessment of university education 's translation proficiency. The geometric properties of the deep neural network's loss plane were investigated using the second-order optimization method's Hessian matrix. It was shown that Wishart matrix typicality in random matrix theory, the sample covariance matrix, may be formed as the Hessian matrix. 'By examining the Hessian matrix and utilizing the research on the asymptotic distribution features of Random matrix theory's Wishart matrix, the standard conditional number distribution, the eigenvalue extreme value distribution, and the limiting spectral distribution of the matrix were determined.. The analysis recognizes that there was a great deal of ambiguity in the evaluation of foreign language translation in higher education and creates an evaluation model based on the fuzzy comprehensive judgment method, providing a research plan for future evaluations of foreign language translation in higher education'. Finally, an evaluation method for translating foreign languages taught in colleges and universities was developed and put into operation.

Zhang [22] have been employed to enhance the impact of English performance evaluation within the framework of elegant teaching, and this has grown to be a crucial component of smart English instruction. The standard English language education assessment system has issues with low stationary state maintenance time, extended envelope jitter time, and high system sensitivity due to interference elements, human factors, or external variables. Thus, this paper creates a method for evaluating the effectiveness of English learning using K-means clustering, or K-MC. Teachers, administrators, and students were each given distinct responsibilities and permissions when the system database was constructed using SQL Server 2005 database management software. ActiveX was used in the creation of the system's functional modules, with a focus on functional module scoring. 'A student-based model for assessing the efficacy of English learning was developed using BP neural network training and the K-means clustering method in order to solve the consistent estimate of the success of the English learning assessment and optimize the English learning effectiveness evaluation model'. This model will help students learn English effectively.

Zhen [23] have concentrated on the issue of imprecise big data information categorization in traditional methodologies, leading to the invention of a massive data fuzzy clustering of K-means and information fusion approach for evaluating English teaching abilities. The author initially applies the K-means clustering concept to assess the initial error data that was gathered, including policy relevance level, investment in educational facilities, and instructor level. The final fusion value is then determined by comparing the node measurement data and the weighted average after she removes any data that the algorithm deems untrustworthy and utilizes the modified fuzzy logic method's weighting factor based on the remaining valid data. The author then accomplishes the integration and clustering of the parameters in the English Teaching Ability Index, puts together the corresponding resource allocation plan for English instruction, and realizes the Evaluation of English language teaching proficiency by combining the K-means clustering method with big data information fusion. Lastly, the information fusion analysis ability of this technique of evaluating English teaching skill is superior, improving both the competence of applying teaching resources and the accuracy of the evaluation of teaching capacity.

Gu [24] have created an enhanced BP neural network, and the arbitrary matrix structure was employed to assess the teaching indicators, normalize the indicators, and construct the model for the instructor teaching quality rating system. The training data set was fed into the model through experimental design in order to train it. To develop the model's prediction accuracy and convergence speed during training, momentum term, ,the learning rate, and other parameters were varied in an increase and decrease ratio. As measures of the model's performance comparison, mean square error, iteration times, training duration, and prediction accuracy were used.

III. PROPOSED METHODOLOGY

In this section, classroom English teaching for evaluation assessment using GK-TSF model along with wild geese algorithm (GKTSF-WGA) is discussed. The block diagram of the proposed GKTSF-WGA English teaching evaluation is represented in Fig1. It covers four steps, namely Data collecting, pre-processing, feature extraction and English teaching categorization. Consequently, a thorough explanation of each step is provided below.

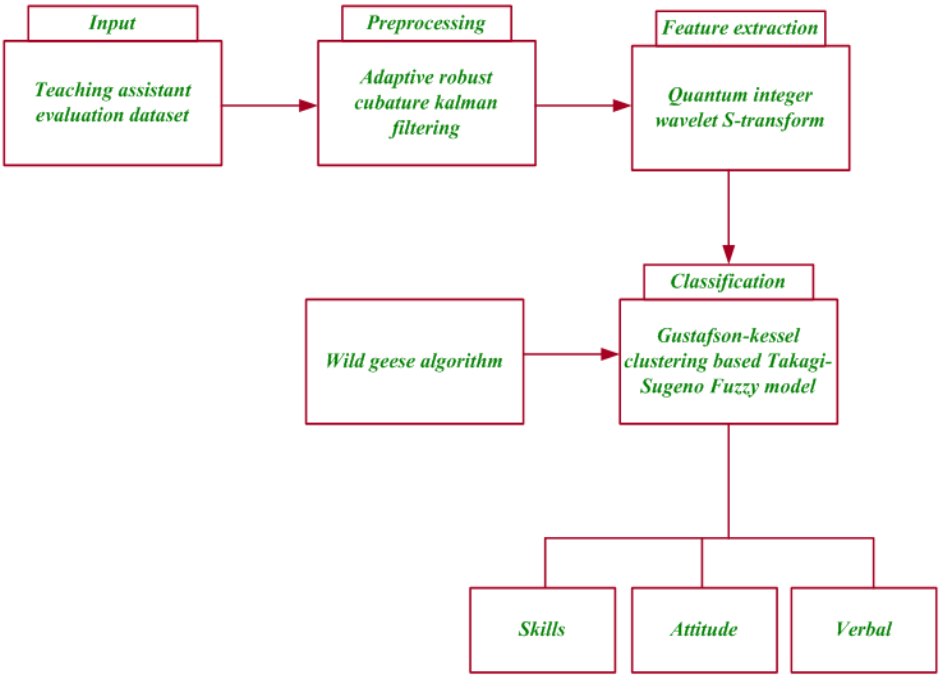

Fig 1: Block schematic illustrating the proposed strategy

A. Data Acquisition

The dataset was gathered from the evaluation dataset for teaching assistants [25]. The University of Wisconsin-Madison's Statistics Department collected the data from evaluations of 151 TA assignments over the course of two summer semesters and three regular semesters. The training as well as testing data are split into 75%, 25% for comparison with other comparable investigations.

B. Data Pre-processing with Adaptive Robust Cubature Kalman Filtering

In this part, adaptive robust cubature kalman filtering is proposed for preprocessing [26]. 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 negative effects of innovation and observation outliers. The error covariance matrix for state estimation can be modified in a flexible way depending on the circumstances.

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

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

Here , $Y_{i,k-1}$ is denoted as the ith cubature point of $\hat{y}_{k-1}$, ξ_i is denoted as the ith column of the basic data point set , n is denoted as the dimension of state variables, $\sqrt{(.)}$ is denoted as the cholesky decomposition operation. The function for state transition is used to instantiate the cubature points.

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

$$x_k = H_k(y_k - \tilde{y}_k) + h(\tilde{y}_k) + v_k \tag{2}$$

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

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

$$\tilde{y}_k = \tilde{H}_k y_k + \tilde{e}_k \tag{3}$$

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

$$\sum_k = \mathrm{E}\left[\tilde{e}_k \tilde{e}_k^T\right] = S_k S_k^T \tag{4}$$

where the UD factorization or the Cholesky decomposition method can be used to get S_k . Finally, the filtering method is updating the better covariance matrix and this cubature filters are used to estimate the errors. The feature extraction stage is then applied to the preprocessed data.

C. Feature Extraction using One-Dimensional Quantum Integer Wavelet S-Transform

After preprocessing, the different types of features are extracted using the One-dimensional QIST [27]. This technique has been utilized to extract features from input data's. The quantum elements needed to define the S-transform of a quantum integer wave. First, the ground states of data, a quantum block representation is proposed. Block representation allows storing datapairs; it is given in equation (5),

$$|A\rangle = \frac{1}{\sqrt{M}} \sum_{j=0}^{M-1} |e(2j)\rangle |j\rangle |e(2j+1)\rangle, \quad M = 2^{m-1} \tag{5}$$

Where, $|j\rangle$ is the corresponding position, The value of the component linked to a certain place is shown by $e(.)$. 2^{m-1} is the even/odd pairs. Equation (6) represents the integer quantum sum between two binary integers, x and y .

$$V_{add}|x, y, r\rangle = |x, y, r\rangle \tag{6}$$

When the qubits x , y are being added by the quantum addition operator V_{add} and r indicates the full sum. The full quantum subtraction is given in equation (7)

$$V_{sub}|x, y, z\rangle = |x, y - x, z\rangle \tag{7}$$

Here , z is the borrow bit and V_{sub} is the quantum subtract operator. The quantum division operation of a binary count is expressed in equation (8)

$$V_D|x\rangle = V_D|x_{m-1} \ldots\ldots x_1 x_0\rangle \tag{8}$$

Where, V_D is denoted as the garbage qubit. The division operation is involved in the transformation. Assume an integer value x , In equation (9) the transformation function is expressed.

$$V_T|x\rangle = |\lfloor x \rfloor\rangle \leftrightarrow x \in Z \tag{9}$$

Where, V_T is denoted as the transformation operator. Finally, the input data is extracted using QIST model. Then the English fluency speaking features as pronunciation, words, speaking type, etc., are extracted which is given into fuzzy model to effectively classify the English teaching effects.

D. Classification using Gustafson-Kessel Clustering Based Takagi-Sugeno Fuzzy (GK-TSF) model

The fuzzy partition matrix is produced by applying the fuzzy clustering method over the entire input-output space. Since the FCM clustering method is one of the most well-liked of its kind, other clustering method based on TS Fuzzy models can be found. The GK Algorithm is the redesigned version of the FCM algorithm [28]. Cluster covariance values of every class are updated by the norm inducing distance metric. Whereas the FCM produces a hyper-spherical shape, the GK clustering algorithm yields an elliptical shape. The GK algorithm's objective function is provided by,

$$J_{GK}(D;U,\theta,v,M_i)=\sum_{i=1}^{C}\sum_{k=1}^{N}\mu_{ik}{}^{m}G_{ik}^{2} \tag{10}$$

Subject to, $\sum_{i}^{C}\mu_{ik}=1$

Where, the distance metric is $G_{ik}^{2}=\left[Z_k-v^i\right]^T M_i\left[Z_k-v^i\right]$, In the input-output product space, A symmetric positive definite matrix called M_i indicates the ith cluster's volume size and The prototype for a cluster is $v^i\in R^{(n+1)}$. The above equation is a constrained teaching evaluation. In order to transform it into an unconstrained optimization form, apply the Lagrangian multipliers.

$$L(U,\lambda,\theta,v)=J_{GK}(D;U,\theta,v,M_i)-\sum_{i=1}^{C}\beta_i\left(|M_i|-\rho\right)-\sum_{k=1}^{N}\lambda_k\left(\sum_{i=1}^{C}\mu_{ik}-1\right) \tag{11}$$

For minimization of the above equation with respect to the μ_{ik}, assuming $G_{ik}^{2}\succ 0$, The following is the final expression:

$$\mu_{ik}=\frac{1}{\sum_{q=1}^{C}\left(\frac{G_{ik}^{2}}{G_{qik}^{2}}\right)^{1/m-1}} \tag{12}$$

Similarly, the English teaching equation's derivative with regard to the (v^i) is used to get the cluster center (v^i).

$$\frac{\partial L(\ldots)}{\partial v^i}=\sum_{k=1}^{N}\mu_{ik}{}^{m}\left[x_k-v^i=0\right] \tag{13}$$

$$\Rightarrow v^i=\frac{\sum_{k=1}^{N}\mu_{ik}{}^{m}Z_k}{\sum_{k=1}^{N}\mu_{ik}{}^{m}} \tag{14}$$

Taking partial derivative of the unconstrained teaching form is with respect to the (M^i)

$$\frac{\partial L(\ldots)}{\partial M^i}=\sum_{k=1}^{N}\mu_{ik}{}^{m}\left[Z_k-v^i\right]\left[Z_k-v^i\right]^T-\beta_i|M_i|M_i^{-1}=0 \tag{15}$$

$$M_i^{-1}=\frac{\sum_{k=1}^{N}\mu_{ik}{}^{m}\left[Z_k-v^i\right]\left[Z_k-v^i\right]^T}{\beta_i|M_i|} =\sqrt[n]{\left(\frac{1}{\rho|F_i|}\right)}F_i \tag{16}$$

Here , F_i is denoted as the covariance matrix, ρ denoted as the constant.

$$F_i=\frac{\sum_{k=1}^{N}\mu_{ik}{}^{m}\left[Z_k-v^i\right]\left[Z_k-v^i\right]^T}{\sum_{k=1}^{N}\mu_{ik}{}^{m}} \tag{17}$$

In here, update U^l the distance metric G_{ik}^{2}

$$U^{l} = \begin{cases} \dfrac{1}{\sum_{q=1}^{C} \left(\dfrac{G_{ik}^{2}\left(\theta^{i}\right)}{G_{qik}^{2}\left(\theta^{q}\right)} \right)^{1/m-1}}, & if G_{ik}\left(\theta^{i}\right) > 0 \\ 0, & otherwise \end{cases} \quad (18)$$

In the above updating process, $\left\| U^{l} - U^{l-1} \right\|_{2} \leq \xi$ is reached as the speaking skills, attitudes, emotions, are the classifications, then it will gives the ξ parameter to optimization for enhance the performance.

E. Optimization using Wild Geese Algorithm

Optimization using the WGA [29] to optimize the weight parameters of GK-TSF is a promising approach to enhance the model's performance.

1) Stepwise Procedure of Wild Geese Algorithm (WGA)

Numerous real-world applications have made use of population-based search algorithms with natural inspiration to address a variety of optimization problems. The WildGeese Algorithm (WGA), a straightforward and effective swarm optimizer for large-scale global optimization, is the main topic of this study. Fig.2 displays the flowchart of WGA.

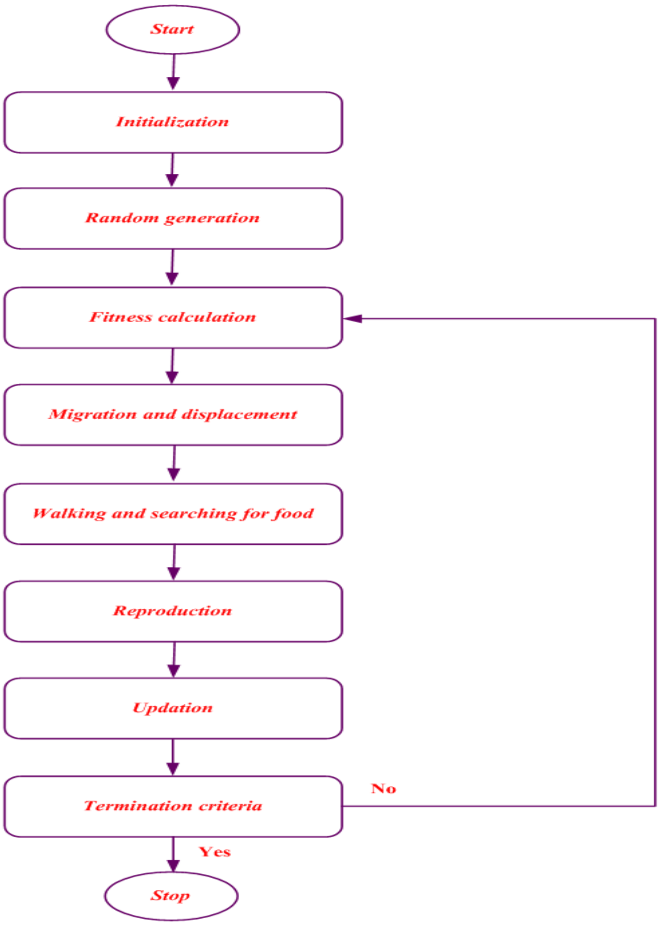

Fig 2: Flowchart of WGA

Step 1: Initialization

Initialize the input parameter as the weight parameter ξ of GK-TSF.

Step 2: Random Generation

The initialized parameters are randomly generated as given matrix form:

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,m} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,m} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,m} \end{bmatrix} \quad (19)$$

Where, X is denoted as the population, n is denoted as the initialized parameter, m is denoted as the dimension of the desirable variables.

Step 3: Fitness Function

The fitness function is used to calculate the parameter ξ

$$fitness = optimizing(\xi) \tag{20}$$

Step 4: migration and displacement velocity phase

The goal of the wild geese migration is to get to the front and adjacent individuals in the sorted population. It is a coordinated, group, ordered, and controlled movement .The following equations provide displacement and velocity based on the geese's coordinated velocity.

$$\begin{aligned} u_{i,d}^{iter+1} &= \left(s_{1,d} \times u_{i,d}^{iter+1} + s_{2,d} \times \left(u_{i+1,d}^{iter+1} - u_{i-1,d}^{iter+1}\right)\right) + s_{3,d} \times \left(q_{i,d}^{iter} - y_{i-1,d}^{iter}\right) \\ &+ s_{4,d} \times \left(q_{i+1,d}^{iter} - y_{i,d}^{iter}\right) + s_{5,d} \times \left(q_{i+2,d}^{iter} - y_{i+1,d}^{iter}\right) - s_{6,d} \times \left(q_{i-1,d}^{iter} - y_{i+2,d}^{iter}\right) \end{aligned} \tag{21}$$

Where, $y_{i,d}$, $q_{i,d}$, and $u_{i,d}$ are denoted as the dth dimension of the current position, the ith wild goose's ideal spot and its current velocity, correspondingly.

The world's best participant is also utilized as a second guidance for the flock's motions, as seen in the equation below. In order to depict each member's movement as an ordered a series, this position shift is executed in an orderly manner and coordinated with the front members.

$$y_{i,d}^{y} = q_{i,d}^{iter} + s_{7,d} \times s_{8,d} \times \left(\left(g_{d}^{iter} + q_{i+1,d}^{iter} - 2 \times q_{i,d}^{iter}\right) + u_{i,d}^{iter+1}\right) \tag{22}$$

Here , g_d is denoted as the best position among all members worldwide.

Step 5: Walking and Searching for Food by Wild Geese

This phase is represented so that the i-th wild goose $\left(q_{i,d}^{iter} \rightarrow q_{i+1,d}^{iter}\right)$ approaches its upfront member, the $(i+1)$th goose. Stated differently, the i-th goose attempts to make contact with the $(i+1)$th goose $\left(q_{i+1,}^{iter} \rightarrow q_{i,}^{iter}\right)$. The wild goose, y_i^w, uses the following equation to walk and look for food:

$$y_{i,d}^{y} = q_{i,d}^{iter} + s_{9,d} \times s_{10,d} \times \left(q_{i+1,d}^{iter} - q_{i,d}^{iter}\right) \tag{23}$$

Step 6: Reproduction and Evolution of Wild Geese

The reproductive and evolutionary stages of a wild geese's life are another. In this study, the modeling is done by combining the on foot and search for food equation y_i^w with the migration equation y_i^v .

$$y_{i,d}^{iter+1} = \begin{cases} y_{i,d}^{v} & if\ s_{11,d} \le Cs \\ y_{i,d}^{w} & otherwise \end{cases} \tag{24}$$

Step 7: Death, Migration, and Ordered Evolution

To maintain an even distribution of method performance across all test functions, the death phase is utilized. The population size will reduce linearly in this phase of the algorithm, reaching its final value of Np^{final} in the final iteration. The method begins with the utmost population number, $Np^{initial}$. The weaker individuals of the population will be eliminated by the algorithm iterations based on the following equation.

$$Np = round\left(Np^{initial} - \left(\left(Np^{initial} - Np^{final}\right) * \left(\frac{FEs}{FEs_{\max}}\right)\right)\right) \tag{25}$$

Where, FEs and $FEs_{\max}$ are denoted as the maximum number of functions for evaluations.

Step 8: Termination Criteria

Verify the ending criteria and if the ideal solution is obtain then the procedure ends or else goes to step 3. In here, skills, attitudes, and verbal, are classified as high performance.

IV. RESULT AND DISCUSSION

This part discusses the experimental results using the proposed method. A PC running Windows 7 with an Intel Core i5 2.50 GHz CPU, 8GB RAM , and the simulations is used. Then, the proposed process is simulated utilizing MATLAB under several performance metrics, such as precision, accuracy, F1-score, and computational time. The obtained results of the proposed ET-GK-TSF-WGA method are analyzed with the existing methods, like non-linear fuzzy matrix based Fuzzy comprehensive evaluation (ET-FCE) [18], ET-q-ROFs [20], and K-means clustering (ET-K-MC) [22], respectively.

A. Performance Measures

In order to choose the optimal classifier, this is an important task. Performance parameters like recall, F1-score, precision, accuracy, and computing time are analyzed to assess the performance. The confusion matrix will be used to scale the performance measures, it is decided. To scale the confusion matrix, the False Positive/ Negative and True Positive /Negative values are needed.

- True Positive (TP): Number of samples where the actual class label is exact and the predicted class label implies a positive value.
- True Negative (TN): Number of samples where the actual class label is exact and the predicted class label implies a negative value.
- False Positive (FP): The number of samples in which the real class label is unclear and the predicted class label implies a positive value.
- False Negative (FN): The number of samples in which the real class label is unclear and the predicted class label implies a negative value.

1) Accuracy

It is the ratio of count of exact prediction with total number of predictions made for a dataset. It is measured through eqn (34),

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{26}$$

2) F1-Score

F-score is a metric used to analyze the performance of proposed PCSANN technique. It is computed in eqn (35),

$$F\ score = F1score = \frac{TP}{TP + \frac{1}{2}\left[FP + FN\right]} \tag{27}$$

3) Precision

Precision is a metric which quantifies the count of correct positive prediction made. This is computed via following equation (36)

$$P = \frac{TP}{TP + FP} \tag{28}$$

4) Recall(R)

Recall is a measure that determines how accurate a forecast is based on the total number of accurate forecasts made. Equation (37) is used to measure it.,

$$R = \frac{TP}{TP + FN} \tag{29}$$

B. Performance Analysis

Figure 3 to 7 depicts the simulation results of proposed ET-GK-TSF-WGA method. Next, the proposed PLDI-DDCGAN-AVOA approach is likened with current approaches like ET-FCE, ET-q-ROFs, and ET-K-MC, correspondingly. Fig. 3 displays the performance of accuracy analyses. The proposed ET-GKTSF-WGA method attains 23.05%, 28.95%, and 26.56% higher accuracy for skills; 23.12%, 25.43%, and 27.45%, higher accuracy for attitudes; 25.86%, 27.73%, and 21.04%, higher accuracy for verbal; compared with the existing methods like ET-FCE, ET-q-ROFs, and ET-K-MC, correspondingly.Fig.4 displays the performance of F score analysis. The proposed ET-GKTSF-WGA method attains 24.19%, 27.12%, and 23.23% higher F score for skills; 27.85%, 21.98%, and 20.12%, higher F score for attitudes; 24.65%, 23.54%, and 20.19%, higher F score for verbal; compared with the existing methods such as ET-FCE, ET-q-ROFs, and ET-K-MC, respectively.

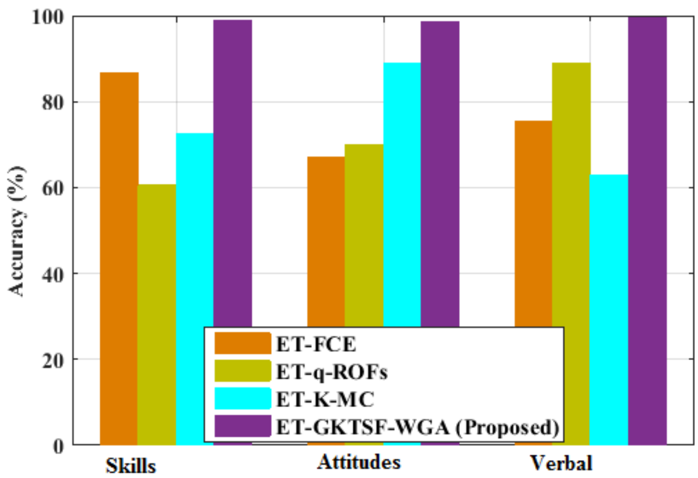

Fig 3: Performance of accuracy analyses

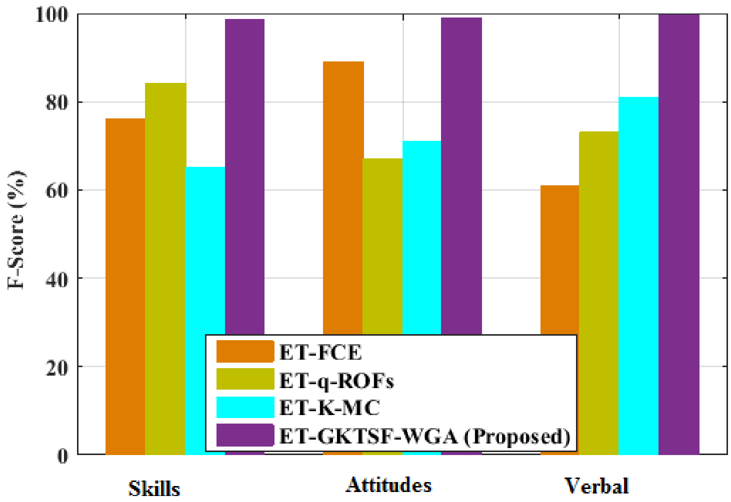

Fig 4: Performance of F score analyses

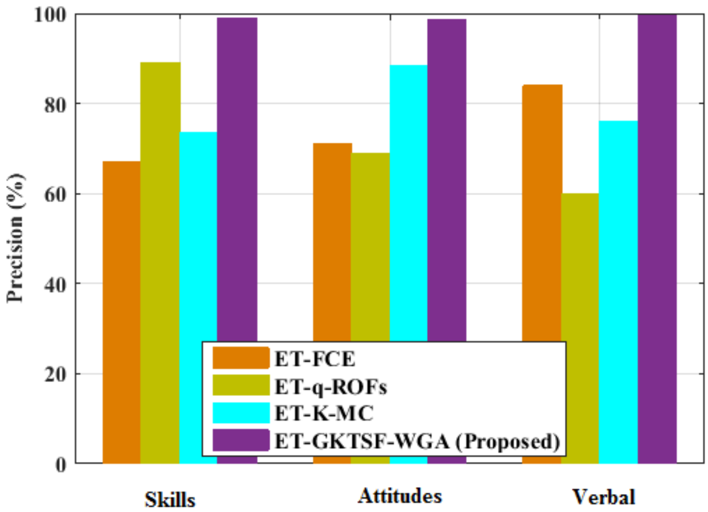

Fig 5: Performance of precision analyses

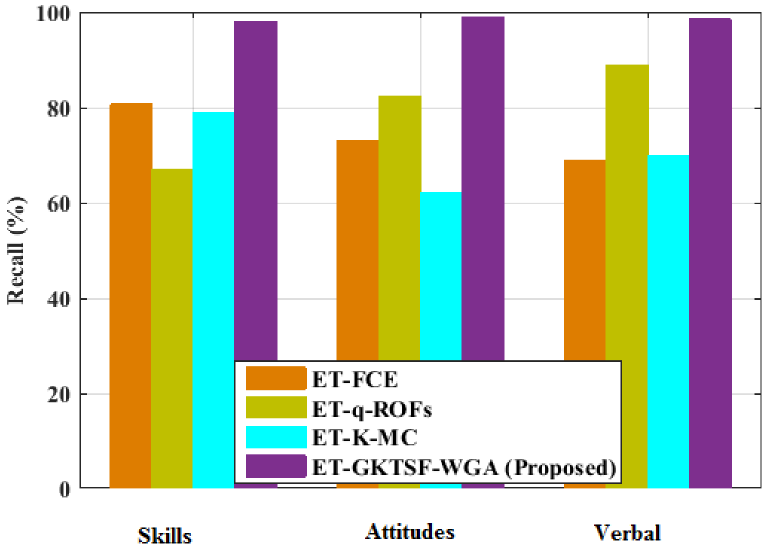

Fig 6: Performance of recall analyses

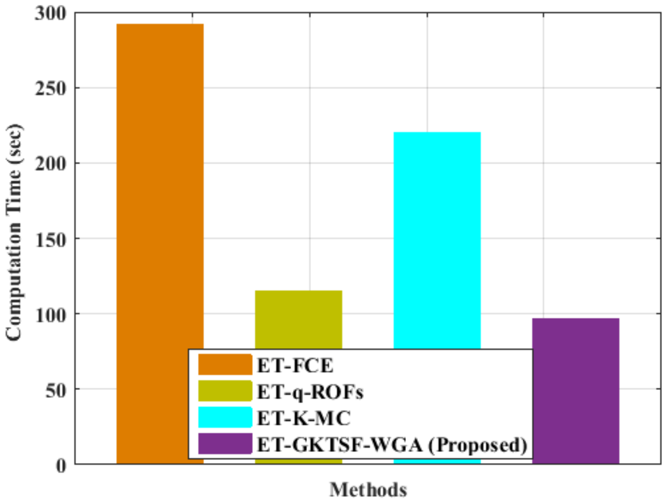

Fig 7: Performance of computational time analyses

Fig 5 shows the performance of precision analyses. The proposed ET-GKTSF-WGA method attains 28.15%, 21.89%, and 27.12% higher precision for skills; 26.9%, 25.28%, and 21.12%, higher precision for attitudes; 20.13%, 28.67%, and 23.67%, higher precision for verbal; compared with the existing methods like ET-FCE, ET-q-ROFs, and ET-K-MC, respectively. Fig 6 displays the performance of recall analyses. The proposed ET-GKTSF-WGA method attains 27.03, 20.02%, and 26.29% higher recall for skills; 25.82%, 29.87%, and 20.87%, higher recall for attitudes; 23.56%, 28.81%, and 23.71%, higher recall for verbal; compared with the existing methods such as ET-FCE, ET-q-ROFs, and ET-K-MC, correspondingly. Fig 7 shows the performance of computational time analyses. The computational time performance of the proposed method attains 70.85%, 45.7%, 60.12%, and 35.34%, lower computation. Time compared with the exiting techniques like ET-FCE, ET-q-ROFs, and ET-K-MC, respectively.

V. CONCLUSION

In this section, English teaching assessment evaluation using ET-GKTSF-WGA method was successfully implemented for classifying skills, attitudes, and verbal, of the English teaching assessment. The proposed ET-GKTSF-WGA method is executed in the MATLAB platform utilizing the dataset of English teaching assessment dataset. The performance of the ET-GKTSF-WGA method contains F-score, ,precision ,accuracy, recall and computational time. The proposed ET-GKTSF-WGA method attains 23.05%, 28.95%, and 26.56% higher accuracy for skills; 23.12%, 25.43%, and 27.45%, higher accuracy for attitudes; 25.86%, 27.73%, and 21.04%, higher accuracy for verbal; respectively. The proposed ET-GKTSF-WGA method attains 24.19%, 27.12%, and 23.23% higher F score for skills; 27.85%, 21.98%, and 20.12%, higher F score for attitudes; 24.65%, 23.54%, and 20.19%, higher F score for verbal; respectively. The proposed ET-GKTSF-WGA method attains 28.15%, 21.89%, and 27.12% higher precision for skills; 26.9%, 25.28%, and 21.12%, higher precision for attitudes; 20.13%, 28.67%, and 23.67%, higher precision for verbal, respectively. The proposed ET-GKTSF-WGA method attains 27.03, 20.02%, and 26.29% higher recall for skills; 25.82%, 29.87%, and 20.87%, higher recall for attitudes; 23.56%, 28.81%, and 23.71%, higher recall for verbal; respectively. The computational time performance of the proposed method attains 70.85%, 45.7%, 60.12%, and 35.34%, lower computation. The proposed ET-GKTSF-WGA method's performance is contrasted with that of the current approaches such as ET-FCE, ET-q-ROFs, and ET-K-MC.

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