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Construction of Personalized Learning Content Recommendation System Based on Recommendation Algorithm in English Learning

Abstract: - English is currently a valuable information transmission medium for quickly acquiring many cutting-edge technology and professional skills. Traditional English learning has very limited time and space, therefore teachers unable to present students with enough English learning information. This manuscript proposes a construction of personalized learning content Recommendation system based on recommendation algorithm in English learning (CPLRS-EL-RA).Initially, the data is collected from Movielens-1M dataset. Then, the collected data are fed to pre-processing. In pre-processing, Generalized Moment Kalman Filter (GMKF) is utilized to clean the data. Then the pre-processing output is supplied to the feature extraction using Enhanced Synchro extracting Wavelet Transform (ESWT) for extracting the students' attitude, relationship and entities. Afterward, the extracted output is fed to the recommendation algorithm. The recommendation algorithm effectively classifies each student's learning into listening, speaking, reading and writing. The Tiger Beetle Optimizer (TBO) is used to optimize the weight parameter of Recommendation Algorithm. The proposed method is activated in Python and the efficiency is estimated under metrics, like accuracy, precision, recall, sensitivity, specificity and computation time. The CPLRS-EL-RA method attains higher accuracy 22.32%, 31.25% and29.31%, higher sensitivity 27.32%,24.43%, 38.24% and higher recall 31.13%, 23.33% and 38.13%for listening analysed to the existing methods, like Personalized Recommendation System for English Teaching Resources (PRSETR-CRNN),Learner comments-based Recommendation system(LCBRS-CNN), and Hybrid recommendation system combined content(HRSC-ANN)respectively.

Keywords: Attitudes, English Learning, Entities, Learning Behaviour, Personalized Learning, Recommendation System, Recommendation Algorithm.

I. INTRODUCTION

a) Background

The rapid advancement of artificial intelligence and the digital economy has ushered in the information age [1].The time and space constraints of traditional English classroom instruction make it impossible for teachers to give students enough English language learning resources or opportunities for language application, much less one-on-one personal tutoring. Students' varying learning needs are also not satisfied [2, 3]. Existing online learning mainly separates knowledge content according to pupils' grades. They also typically combine and arrange knowledge without taking into account each student's unique learning needs. This leads to problems like giving good students insufficient learning resources, while average and poor students never learn anything [4]. Manually grading students' behavior in the classroom is the standard method, which takes a lot of time [5]. We can now employ AI technology to turn this disadvantage into a strength because of the great improvements in the field over the past several years [6]. It has become a significant issue for educational advancement, leading to the progress of an intelligent, effective, and comprehensive education analysis scheme [7]. Low learning efficiency and unsatisfactory learning outcomes are problems with traditional English language learning methods [8].The Internet of Vehicles will lessen economic losses brought on by traffic congestion, enhance travel experiences, and hasten the development of intelligent transportation and self-driving cars [9].To address the issue that while traditional English classroom education in big courses is more efficient, this is impossible to care for each pupil and satisfy the needs of individualized learning [10].

b) Challenges

The term "English listening impairment" describes the barriers that people encounter when trying to comprehend English. These difficulties and challenges may arise from a variety of causes, including congenital hearing loss, acquired disorders, an unsuitable language context, and so on. English listening impairment affects pupils' academic achievement as well as their future job development. Learners can learn at any time and from

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any location using a variety of terminal devices, providing both convenience and challenges. Creating an adaptive recommendation system has become a crucial problem due to the difficult and constantly changing learning environment with user needs. As educational approaches continue to advance and change, schools and institutions that teach English must address a multitude of challenges and demands.

During the teaching process, it is necessary to handle a number of challenges, including balancing multiple learning objectives, integrating functional linguistics theories and actual teaching activities effectively, and evaluating students' language application abilities. Students' knowledge structures and individual learning demands differ; therefore they are unable to rapidly and accurately locate their own curriculum materials. As a result, a significant amount of people, material resources, and time have been wasted. At this scenario, the recommendation scheme effectively tackles the issue.

c) Literature Review

In literature, various research works have previously existed which was based on the personalized English learning content based on recommendation system. Some of them reviewed were follows,

Afoudi et al. [11] have suggested the recommendation schemes were information filtering that presented objects to users under their tastes and behaviour, such as suggestions. In light of the aforementioned and the development of computer science, which has shown interest in big data and its application in identifying user preferences, a great deal of study has been conducted in the field of recommendation, and robust systems are now available. It offers a fresh method for creating a hybrid recommender system in the field of unsupervised learning that combines self-organizing map neural networks, collaborative filtering, and content-based approaches.

Yuanfei, [12] has utilized when confronted with multiplicity of materials, many pupils fail to immediately identify the content that important to them. With the abundance of English teaching resources accessible, it was challenging to provide pupils with trustworthy recommendations. Consequently, based on the identification of learning behaviors, offer a customized recommendation system for English language teaching materials. First, students' online classroom behavior was properly recognized using a spatiotemporal convolutional network. Next, a global attention module was included to enhance the methods capacity to learn global feature information.

Hazar et al. [13] have suggested a recommender model depending on free-text reviews submitted online by users was used to discover user requirements and interests by analyzing the variations amongst a new rating prediction and the original rating. Sentiment analysis and recommendations served as the foundation for the model's construction. To extract features and opinions from text user comments and reviews using sentiment analysis in order to calculate more accurate ratings from student reviews and comments published in English.

Huang and Zhu [14] have developed world has raced in the information age. English affects the global environment of information transmission and interaction as a lingua franca. Learning English was like having an essential tool for obtaining important data. For this reason, it was imperative to improve English instruction. The problems of teaching English in a regular classroom and online are examined, along with strategies for maintaining student interest in the material, improving their proficiency in the language, and attending to their individual needs.

Shi and Shi [15] have developed Individualized English under machine learning and the IoT have a significant impact on computer-aided training. This explains the difficulties in determining user similarity and the value of user feedback in the recommendation system. Next, a method for detecting user similarity based on emotions was presented, which improves suggestion accuracy by using users' emotional comment data to adjust the similarity between users.

To address the issue of the higher teaching efficiency of the existing standard English classroom instruction in more classes, Jin [16] has employed a technique that combines collaborative filtering algorithms with user interest modeling to present a knowledge-based learning resource recommendation technique. The technique makes it difficult to meet the needs of each individual student and cater to their personalized learning needs.It provides an algorithm based on the user interest model. Furthermore, depends on the user's historical interest model, the user interest model is created by combining user behavior information and calculating the similarity amongst the candidate products and user.

Yang [17] have utilized to Large-scale open online courses, when used in the context of big data, raise learning paths for learners; However, derivative learners had the conundrum of having access to a wealth of high-quality curriculum resources but finding it challenging to select them, leading to a confusion of information for learners. The issue of education big data was how to help students locate their specific learning resources in the vast array of MOOC resources in a timely and appropriate manner. However, when faced with limited data and a cold start, the conventional collaborative filtering recommendation system performs badly. When it comes to handling higher dimensional along nonlinear data from users of online learning, the suggestion material is repetitious and inefficient.

d) Research Gap and Motivation

Presently, information content is generally divided by students' grades; knowledge is frequently integrated and arranged without consideration for the individual needs of each student. This leads to problems like giving good students insufficient learning materials. ANN approach is unsuitable for learners, and as the volume of material kept on the Internet continues to expand at an accelerated rate, it is getting harder and harder to identify helpful learning resources. The CNN approach does not increase the identification of student actions. According to some academics, employing CRNN as a recommendation algorithm for educational materials allows them to more effectively detect and classify resource properties using numerous features. As a result, this study employs the recommendation algorithm in a recommendation system to offer recommendations for English learning instructional materials. Additional modifications have been made to the recommendation system to improve the accurateness of the resource recommendations. This study is driven by the desire to improve English language learning in the digital age by developing a more individualized and engaging online learning experience.

e) Contribution

The main contributions are summarized as follows,

- A construction of personalized learning content Recommendation system based on recommendation algorithm in English learning (CPL-RS-EL)is proposed. Initially the input data is amassed from the Movielens-1M dataset.
- Using a Generalized Moment Kalman Filter (GMKF) to clean the data at Movie-1M data in the pre-processing segment.
- The pre-processed output is then fed to feature extraction usingEnhanced Synchro extracting Wavelet Transform to extract the students’ attitude, relationship and entities. Afterward the extracted output is fed to the ensemble classifiers.
- The recommendation algorithm effectively classifies each student's learning into listening, speaking, reading and writing.
- The performance indicator like accuracy, precision, sensitivity, specificity, recall, computation time is examined.

f) Organization

Remaining paper is structured as: division 2 describes the proposed methodology, division 3 proves the result, division 4 depicts the conclusion.

II. PROPOSED METHODOLOGY

In this section, the personalized learning content recommendation system based on recommendation algorithm in English learning is proposed. This process comprises data acquisition, pre-processing, feature extraction, classification, optimization. In the proposed method, the personalized English learning, the data undergo preprocessing theGeneralized Moment Kalman Filter is used to clean the data. Then the data in the text format is converted into a vector of features using feature extraction.The Enhanced Synchro extracting Wavelet Transform is used to extract the students’ attitudes, relationships and entities. The output of extraction is passed into the ensemble classifiers. The recommendation algorithms are employed to assess the suggested methodologies. The Tiger beetle optimizer (TBO) is used to optimize the weight parameter ofrecommendation algorithm. The block diagram of proposed methodology is represented in Figure 1. The description of all step is given below,

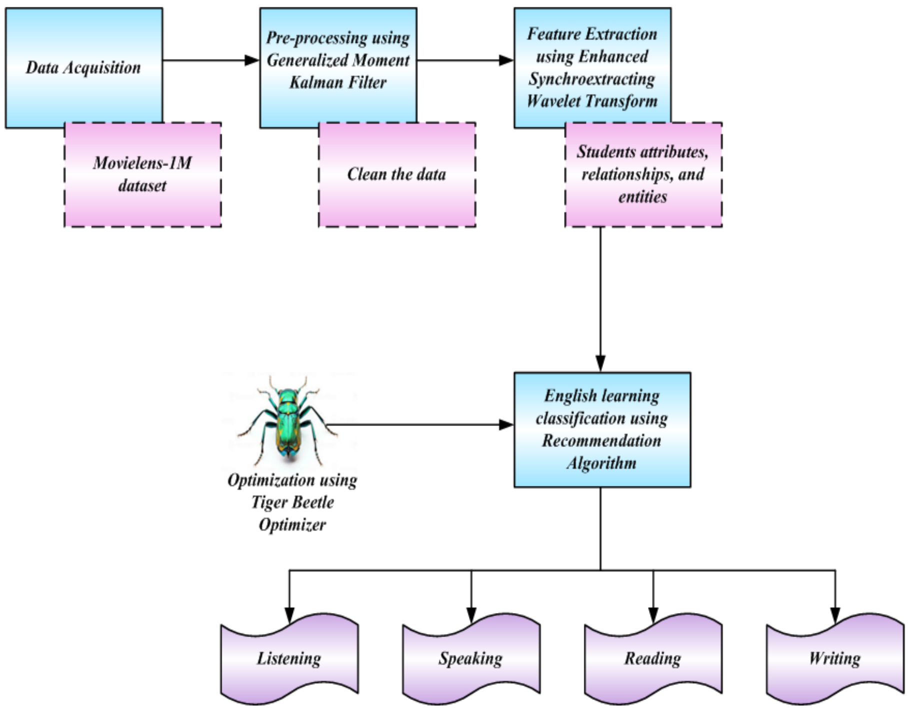

Figure 1: Proposed methodology

A. Data Acquisition

The data is enriched with additional information about movies, such as the geographical origin of movies, the producer companies, runtime, etc. The data is taken from the movielens-1M dataset [18].The dataset can be used in a wide range of recommendation tasks such as investigating bias and inequity against provider groups either based on their geographical location or their producer company. This is a well-known movie dataset in the recommendation domain provided by the Group Lens research group. Gather hidden data points from the platform's webpages first. Incorporate undetectable probes into webpages, gather information about user learning behavior, then the server handles moving the obtained log data to the storage device.

B. Pre-processing using Generalized Moment Kalman Filter (GMKF)

The data is fed into pre-processing it is done by GMKF. GMKF is used to clean the data. The GMKF operates using the same blueprint as the traditional Kalman Filter [19]. At typical KF, the estimation step utilizes (quadratic) belief at recommendation K then the control activities calculate a preceding system at time $K+1$. The prior system is then applied over time by the update process, which finally combines the capacities to make newly posterior belief. A prediction phase that employs a recommendation system over time is incorporated into GMKF. K define a preceding SOS belief at $K+1$, a recommendation system employs the preceding recommendation belief over time $K+1$. The state of the system specified by a recommendation system:

$$K = \sigma\left(\hat{X}_0, \hat{\sum}_o \right) \tag{1}$$

Where, $\hat{\sum}_o$ is the multipliers of the system, K is the time of recommendation system, X_0 is the optimal solution.

When $R=1$ in the recommendation system, the SOS belief may contain high-order moments.

The recommendation system at K times as well as combines the measurements Y_K in SOS belief. The recommendation system at K times including observation $M_{Obs}(Y_K, X_K)$.To create a recommendation system, the recommendation system elucidates a moment relaxation as well as their (dual) suggestion relaxation:

$$k=\sigma\left(\hat{X}_K^+,\hat{\sum}_K^+\right)\overset{bpue}{\leftarrow}\sigma\left(\hat{X}_K,\hat{\sum}_K^-\right)+||M_{Obs}(Y_K,X_K)||^2_{r_K^{-1}} \tag{2}$$

Where, $bpue$ is Best Polynomial Unbiased Estimator, k denotes time of recommendation system, M_{Obs} is the observation of the recommendation system.

This is identical to KF in every way, wherein the update phase is understood as an optimization issue on the measurements, belief. The only difference is that KF has quadratic terms at the optimization, also the solution is found in close format.

Recommendation system at time K and "propagates" it to time $K+1$ using system dynamics. The recommendation system at time K and observation $M_{Obs}(Y_K,X_K)$, the procedure resolves moment relaxation with its (dual) recommendation relaxation to derive SOS belief. Recommendation system at time K and input U_K at the dynamics $M_{Dyn}(X_{K+1},X_K,U_K)$, the prediction stage overwhelms moment relaxation with their (dual) recommendation relaxation to acquire are commendation system over the 2conditions $\begin{bmatrix}\hat{X}_K^-\\ \hat{X}_{K+1}^-\end{bmatrix}$.

$$k=\sigma\left(\begin{bmatrix}\hat{X}_K^-\\ \hat{X}_{K+1}^-\end{bmatrix},\hat{\sum}^-_{K:K+1}\right)\overset{bpue}{\leftarrow}\sigma\left(\hat{X}_K^+,\hat{\sum}_K^+\right)+||M_{Dyn}(X_{K+1},X_K,U_K)||^2_{q_K^{-1}} \tag{3}$$

Where, k is the time of recommendation system, $bpue$ is the ideal polynomial unbiased estimator, M_{Dyn} as dynamics of recommendation system.

Again, this is exactly the same as the classical KF, in which the system dynamics direct the transition amongst K and $K+1$ time and the predictions. The data is cleansed after being transferred, GMKF features are extracted using ESEWT. The data must be transformed into a numerical representation. Once the data has been translated to numeric representation, it is used for feature extraction. The feature extraction procedure is given below.

C. Feature Extraction by Enhanced Synchro extracting Wavelet Transform (ESWT)

Feature extraction is a critical activity in data analytic research because datasets contain a significant number of attributes. ESWT is utilized for feature extraction of the students' properties, relationships, and entities [20]. The wavelet transform is utilized to handle the teaching platform's resources, which are primarily made up of unstructured data (pictures, audios, videos, and texts), as well as the recommendation system. This is highlighted that the parent wavelet process has a significant impact on system representations via ESEWT. The data has several parent wavelets, both discrete and continuous. Because of its excellent harmonic analysis and data extraction capabilities, the Morlet wavelet is preferred as the parent wavelet process on account of its analogue to the Fourier transform. Moreover, a reasonable balance between temporal and frequency localization is achieved using the Morlet wavelet..

$$w(A,B)=\frac{1}{\sqrt{A}}\int_{-\infty}^{\infty}a(t)\cdot a_\psi\left(\frac{T-B}{A}\right)\cdot e^{i\left[\varphi(t)-\theta\left(\frac{T-B}{A}\right)\right]}dt \tag{4}$$

Consider A and B implicates scale feature and dilation feature,. $a(t)$ and $a_\psi(t)$ implies recommendation of $S(t)$, wavelet generating process $\psi_{A,B}(t)$. Consider $\varphi(t),\theta(t)$ symbolizes recommendation of $S(t)$ and $\psi_{A,B}(t)$; $\phi_{(A,B)}(t)$ implicates ph $w(A,B)$ labelled in eqn (5).

$$\phi_{(A,B)}(t)=Arg[w(A,B)]=\varphi(t)-\theta\left(\frac{T-B}{A}\right) \tag{5}$$

Let $Arg[\cdot]$ signifies phase calculation of data in square bracket. The preliminary estimate of learners is achieved by deeming t partial derivative $\phi_{(A,B)}(t)$ along B using eqn (6).

$$\frac{\partial \phi_{(A,B)}(t)}{\partial B} = \frac{1}{A}\theta'\left(\frac{T-B}{A}\right) = \frac{\omega_C}{A} = \omega(A,B) \tag{6}$$

Where, ω_C epitomizes center circular learners for parent wavelet functioning $\psi(t)$, $\omega(A,B)$ specifies computed circular learners. Every computed learners constitute a matrix, it signifies a student surface with B as the attitude, $\omega(A,B)$ as the relationship. Both ω_C and $\omega(A,B)$ have circular learners then the associated learners on Hz is addressed by separating 2π into the circular learners.

Consider $\omega(A,B)$ has multiply by K to scale the learner resultant to their coordinate expressed in eqn (7).

$$F(A,B) = \frac{K}{2\pi}\cdot\omega(A,B) \tag{7}$$

Here K denotes constant with student name. Then the extracted text features such as student's attributes, relationships, and entity features are fed to RA to classify the text feature.

D. Classification using Recommendation Algorithm (RA)

In this section, classification using RA is discussed. RA is used to classify each student's learning feedback text into listening, speaking, reading and writing. One of the most well-known algorithms for recommendation systems is the user-basis collaborative filtering approach [21]. The method's goal is to suggest classes that a relevant to the interests of student users. This approach includes 2 stages: (1) learner similarity matrix is calculated using the course or knowledge points learned through object student user,(2) other K students same as object student user that identified, and top N courses/knowledge points have mentioned to object student after similarity is weighted. However, the cold start problem is the most serious defect in the collaborative filtering method. Let there be a collection of users who utilize the recommendation system, as well as a collection of all conceivable objects to be recommended.

In addition, let U be a utility function measuring the utility of object $O \in o$ for user $C \in c$. This is $U : cXo \rightarrow w$, w is an ordered collection (e.g. non-negative integers). Then, for each user belonging C to c, a sub-collection r_C belonging to o is selected, this maximizes user usability. This means that for the arrangement $C \in c$ determine the collection of the recommended objects as follows:

$$r_C = \left\{R \in 0 : U(\alpha, R) = \max_{O \in o} U(\beta, O)\right\} \tag{8}$$

Where, α, β are weight parameters adjust the ratio of distance matrix and the similarity matrix, r_C is the collection of recommended object, and $U(\alpha, R)$ represent The utility function for a set of recommendations. In general, the aim of recommendation algorithms is finding a sub-collection r_C called the collection of recommended objects for user C.

In a specific case, a recommendation is made to the selected object M without directly considering the user C, for whom the recommendation is made. Therefore, condition (3), taking into account a change in the function of the recommendation such that $U : oXo \rightarrow w$ can be presented as follows:

Firstly, the collection of recommendations for user r_C is replaced by r_M, i.e. the collection of recommendations for the object. Secondly, for the arranged $M \in o$ determine the collection of recommended objects as follows:

$$r_M = \left\{R \in o : U(\alpha, R) = \max_{O \in o} U(\beta, O)\right\} \tag{9}$$

Where, r_M is the collection of recommended to the selected object, $U(\alpha, R)$ is the utility function on the collection of recommended selected object. Here, TBO is employed for tuning the weight α, β,

E. Optimization using Tiger Beetle Optimizer (TBO)

The TBO is used to optimize the weight parameter of recommendation algorithm. Tiger beetles are powerful and intelligent predator insects that seek their victims using trickery. The tiger beetle burrows holes in other insects' routes to trap and hunt them [22]. To develop a TBO algorithm, this work employed a tiger beetle hunting technique. The optimum position indicates the location of the prey, and each answer represents a tiger beetle. By utilizing this strategy, the tiger beetles progressively find the best answer by digging holes around them and searching for them.TBO manages the individualized English learning content suggestion system. The schematic diagram of TBO is represented in Figure 2.

Step1: Initialization

Initialize the population of TBO the weight parameter values α, β , from RA. Thus, it is expressed in equation (12)

$$P = \begin{bmatrix} tb_1^1 & tb_1^2 & \dots & tb_1^n \\ tb_2^1 & tb_2^2 & \dots & tb_2^n \\ \vdots & \vdots & \vdots & \vdots \\ tb_m^1 & tb_m^2 & \dots & tb_m^n \end{bmatrix} \tag{10}$$

Step 2: Random Generation

After setup, the input fitness function developed randomness using the TBO approach.

Step 3: Fitness Function

The result obtained via the initialization randomly. The effects of weight parameter optimization β , is applied in the fitness function calculation. This is expressed in eqn (11).

$$F = Optimizing(\alpha, \beta) \tag{11}$$

Step4: Digging Hole for Optimizing α

The exploration phase of the TBO is represented as digging hole, and position of the hole. This is achieved by introducing Equation (12), considering that the goal is to minimize the identified problem. Digging is identical to creating possible solutions (holes) where the algorithm can determine optimal or near-optimal solutions. The hole defines the grade of the solutions, navigating the algorithm towards more bright areas of the search space. This procedure improves exploration by enabling the algorithm to explore multiple areas and exploit by deepening the search in areas with high potential.

$$h(\alpha_i) = \left[1 - \exp\left(\frac{F(\alpha_i)}{F(w(t))}\right)\right].h_M \tag{12}$$

Where, $h(\alpha_i)$ denotes the number of holes bordering α , h_M represents the maximum number of holes that the TB digs into a site. The term $F(\alpha_i)$ represents the value or fitness of a TB, such as α_i the parameter h ranges from its maximum value associated with the best TB to a minimum value of zero for the worst TB. This indicates that most holes are dug near the optimal solution to investigate this region also.

A distance function is presented to mitigate the divergence in the standard deviation of the solution's allocation across the Tiger Beetle optimization iterations. The SD of the TB hole distribution for three values of p. Raising p broadens the divergence capacity of the SD to [0.8, 1].

$$\alpha(t) = \alpha_0 - \left|\frac{P}{\pi} A\tan\left(\frac{P}{\pi} t\right)\right| \tag{13}$$

Where, P is the scaffold for a coefficient controlling hole reduction and distribution, α_0 represents the initial standard deviation assigned to 1, and t is the algorithm's iteration counter.

Step 5: Hunting Insects for Optimizing β

The exploitation phase of the TBO is represented after position of hole performs its specific operation; hunting insects in prone region and mating. Each hole can catch prey based on its quality, and those in irregular regions may yield during hunting. If a tiger beetle cannot catch any prey in a certain hole, that hole is left or crushed. Some solutions iteration is destroyed due to unsuccessful hunting. For this purpose, a mechanism for the chance of survival of a solution is represented through Equation (14) in the context of a minimization problem:

$$P(\beta_i) = 1 - \frac{1}{\sum_{i=1}^{N} \frac{F(\beta_i)}{F(w(t))}} \times \frac{F(\beta_i)}{F(w(t))} \tag{14}$$

Where, $P(\beta_i)$ denotes the probability of a solution. A random number within the intermission [0, 1], indicated as R, is used to determine whether to destroy. The tiger beetles can investigate the problem space in search of appropriate mates. The idea is that β_i denotes a tiger beetle and can transfer towards the positions of β_L and β_K, which are randomly chosen from the population. Mating presents diversity in the population of solutions, assisting in exploration by yielding new solution candidates. Equation (15) expresses the direction of the β_i beetle in the direction of the two other TBs:

$$\beta_i^j = \beta_i^j + \left(\beta_K^i - \beta_l^j\right) Rand \tag{15}$$

Where, β_i^j is the position of the tiger beetle, β_l^j and β_K^i is the randomly chosen from the population. The choice of dual TBs to be tracked by β_i the TB affects the behaviour on the one hand and does not become entangled in the local optimum on the other hand.

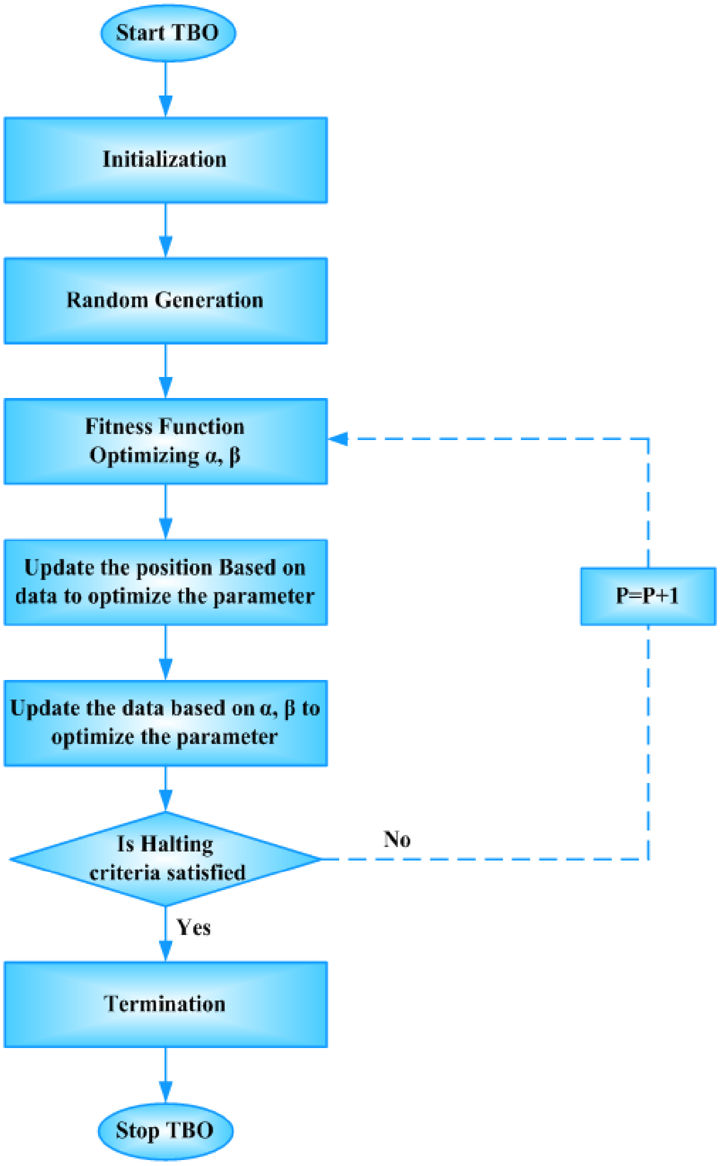

Figure 2: Flowchart of TBO optimizing RA

Step 6: Termination

The weight parameter α, β, from RA are optimized using TBO algorithm, otherwise repeat iteratively step 3 until fulfil the halting criterion $P = P + 1$. Lastly, RA classifies each student's learning into listening, speaking, reading, and writing higher accuracy, decreasing processing time and error.

III. RESULT AND DISCUSSION

The experimental results of proposed system are discussed in this segment. The CPLRS-EL-RA technique is simulated in Python under mentioned metrics. The acquired outcomes of the CPLRS-EL-RA approach are analyzed with existing PRSETR-CRNN, LCBRS-CNN and HRSC -ANN respectively.

A. Performance measures

To scrutinize the performance, the following performance metrics is examined.

1) Accuracy

Accuracy is the capacity to measure an exact value. A metric called accuracy can be used to characterize the model's performance in all classes. It is measured by equation (16),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{16}$$

TP epitomizes true positive, TN symbolizes true negative, FP signifies false positive, FN -specifies false negative.

2) Precision

Precision estimation include many positive labels had expected with high accuracy, it is given an equation (18)

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{17}$$

3) Recall

Recall is represented in equation (18)

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{18}$$

4) Sensitivity

Sensitivity is represented as in equation (19),

$$Sensitivity = \frac{TP}{TN + FN} \tag{19}$$

5) Specificity

Specificity is represented as in equation (20),

$$Specificity = \frac{TN}{TN + FP} \tag{20}$$

6) Computation Time

Computation time is represented as in equation (21),

$$Computation\,Time = \frac{Instruction\,count * CPI}{Clockrate} \tag{21}$$

B. Performance Analysis

Figure 3 to 8 portrays simulation results of CPLRS-EL-RA method. Then, the proposed CPLRS-EL-RA method is likened with existing PRSETR-CRNN, LCBRS-CNN and HRSC-ANN methods.

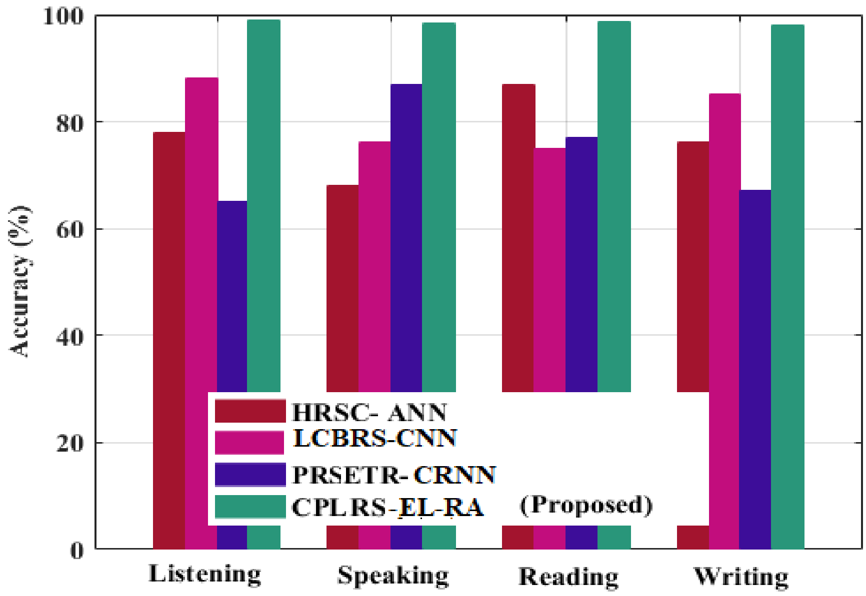

Figure 3: Accuracy analysis

Figure 3 represents accuracy analysis. The proposed CPLRS-EL-RA provides 22.32%, 31.25% and29.31% greater accuracy for listening; 22.35%, 21.28% and 19.35% greater accuracy for speaking; 20.31%, 19.23% and22.32%higher accuracy for reading; 19.22%,22.32%, and 20.23%loweraccuracy for writing when evaluated to the existing PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN models respectively.

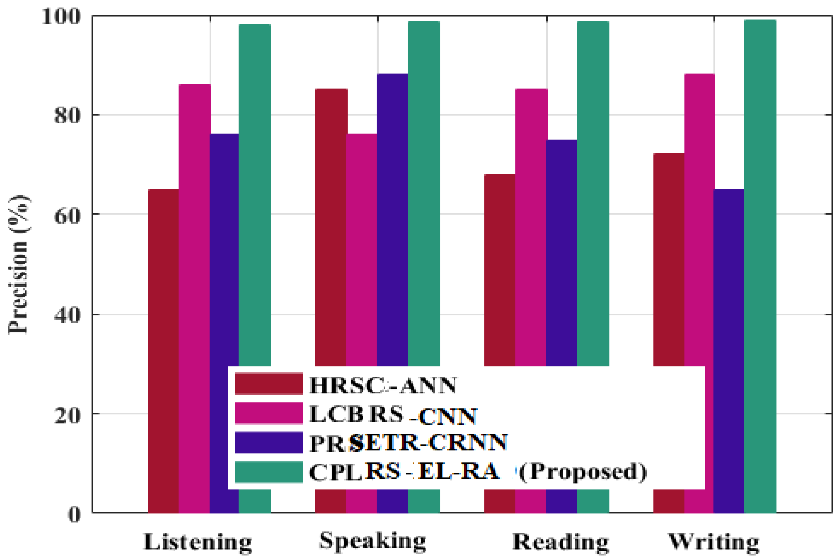

Figure 4: Precision estimation

Figure 4 represents precision estimation. The proposed CPLRS-EL-RA provides 36.22%, 38.13% and 28.17% lower precision for listening; 38.23%, 36.22% and 38.22% greater precision for speaking; 36.22% 38.13% and 29.38% higher precision for reading;28.17% 39.12%, and 38.22% higher precision for writing; when evaluated to the existing PRSETR-CRNN, LCBRS-CNN and HRSC-ANN models respectively.

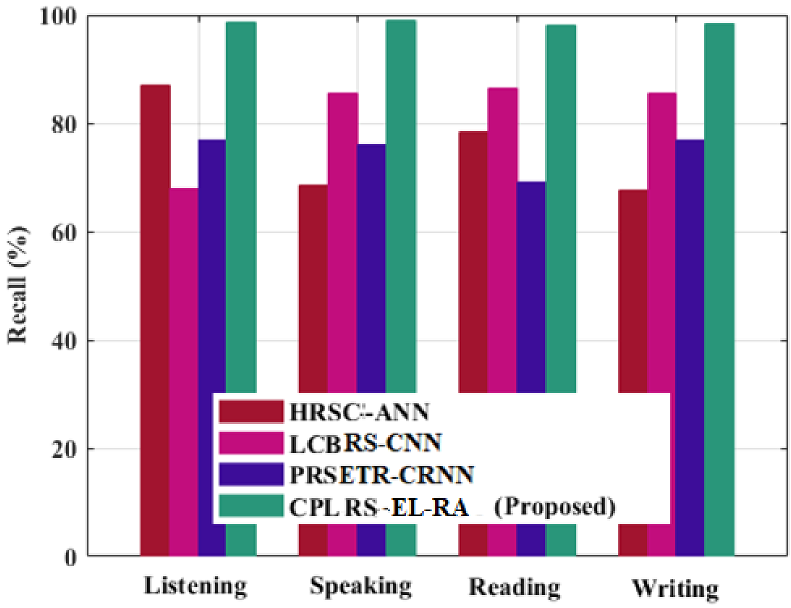

Figure 5: Recall evaluation

Figure 5 represents recall evaluation. The proposed CPLRS-EL-RA attains 31.13%, 23.33% and 38.13% greater recall for listening; 31.13%, 37.42% and 23.33% greater recall for speaking; 23.33%, 37.42%, 24.47% lower recall for reading;31.13%, 37.42%, 23.32%, higher recall for writing; when evaluated to the existing PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN models respectively.

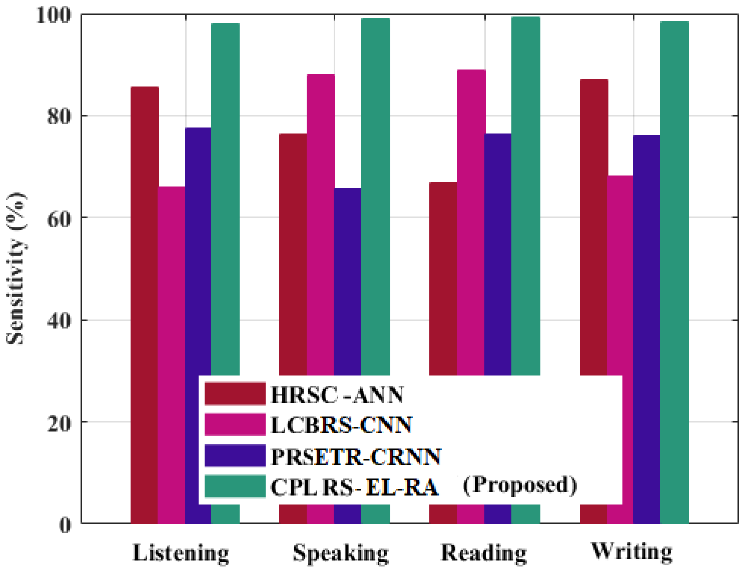

Figure 6: Sensitivity assessment

Figure 6 shows sensitivity assessment. The proposed CPLRS-EL-RA achieves 27.32%,24.43%, 38.24% lower sensitivity for listening; 24.43%, 38.28% and 27.32%, greater sensitivity for speaking; 27.32%,38.28%, and 24.43%, greater sensitivity for reading;27.35%, 25.45%, 38.24% greater sensitivity for writing; when evaluated to the existing PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN models respectively.

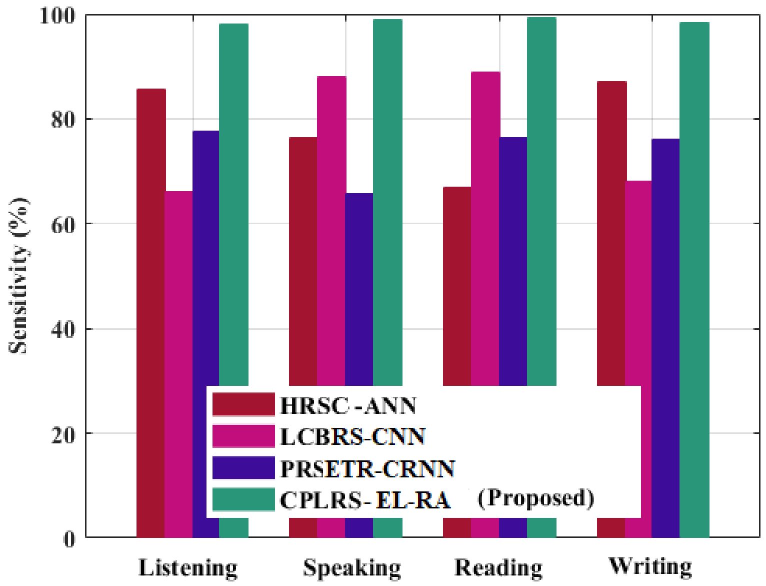

Figure 7: Performance analysis of Specificity

The specificity analysis is depicted in Figure 7. The performance of the CPLRS-EL-RA technique results in specificity that are 30.56%, 35.97%, and 21.76%, greater for listening, 21.46%, 35.97%, and 25.54% lower for speaking, 25.54%, 21.46%, and 36.15%, higher for reading, and 35.97%, 21.46%, and 24.52%,higher for writing when evaluated to the existing PRSETR-CRNN, LCBRS-CNN and HRSC-ANN models respectively.

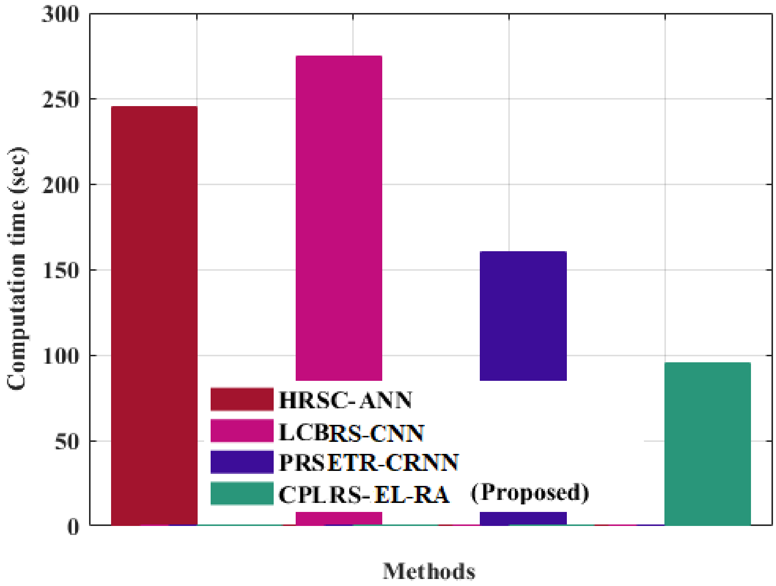

Figure 8: Performance analysis of computation time

Figure 8 portrays the performance of Computation Time. The CPLRS-EL-RA attains 32.136%, 40.32%, 38.81% less computation time than the existing PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN respectively.

C. Discussion

ACPLRS-EL-RA model for teaching of English learning from Movielens-1M data set is developed in this paper. The CPLRS-EL-RA method involves encompasses based data pre-processing Instance ofMovie-1Mdata set, the average greater outcomes were compared with average results of existing PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN respectively. The accuracy values of PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN are 22.32%, 31.25% and29.31% respectively, lesser than proposed method. Similar to this, whereas the average specificity value of comparison techniques is 83.44%, the specificity value of the suggested method is 98.93%.The proposed method CPLRS-EL-RA has high specificity and accuracy evaluation metrics than existing methods. Therefore, the comparative technique is more expensive than the proposed method. It effectively addresses the challenges associated with the socialized teaching and demonstrates superior performance compared to existing methods.

IV. CONCLUSION

In conclusion, this paper proposed a construction of personalized learning content Recommendation system based on recommendation algorithm in English learning. The Generalized Moment Kalman Filter (GMKF)is used to clean the data. Then the pre-processed output is provided to thefeature extraction usingEnhanced Synchroextracting Wavelet Transform (ESWT)for extracting the students' attitude, relationship and entities. After extraction the output is fed to the ensemble classifiers. The recommendation algorithm effectively classifies each student's learning feedback text into listening, speaking, reading and writing. The proposed CPLRS-EL-RA approach is implemented in Python utilization of questionnaire and focus group discussion guide based on survey data. The proposed approach is analysed under the mentioned metrics. Presentation of proposed CPLRS-EL-RA method covers 30.56%, 35.97%, and 21.76% higher specificity; and 32.136%, 40.32% and 38.81% lower computational time for listening analyzed to the existing methods such as PRSETR-CRNN, LCBRS-CNN, and HRSC-ANN respectively. Future work in the realm of personalized learning content Recommendation system based on recommendation algorithm in English learning could focus on several key areas. This study finding is influenced by the various activation functions, the algorithm model's number of layers, and its hidden layers. The literature study in the preceding sections shows that both the attention mechanism and the recommendation algorithm are capable of precisely forecasting the visuals. We may apply the RA model and compare it with our method. Examining a variety of learning mechanisms using several datasets to examine the results is an intriguing avenue for future research.

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