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Application of Artificial Intelligence Technology in Adaptive System for English Speaking Learning

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Abstract: - There are still issues, though, such as data bias that can result in erroneous assessments, the possibility of relying too much on technology at the expense of conventional techniques, and privacy issues brought on by data collection. Careful navigation is also required due to the limitations of AI algorithms in understanding contextual nuances and the ethical issues surrounding its use. Even though it shows promise, resolving these issues is essential to optimizing the efficacy and moral consequences of AI-based English learning. This manuscript proposes Application of Artificial Intelligence Technology in Adaptive System for English Speaking Learning (AAIT-ASESL-MORA-RNN). The input data is gleaned from the English Language Learning-Ensemble Learning dataset. Then, the data is provided to preprocessing phase. During the pre-processing phase, the Unscented Trainable Kalman Filter (UTKF) is used to identifying the missing data's. Then the preprocessed data are fed to the Mixed-Order Relation-Aware Recurrent Neural Networks (MORARNN) and predict the Error of English Speaking Learning. In general, MORARNN does not express adapting optimization strategies to determine optimal parameters using a MORARNN. The MORARNN is optimized using the Hermit Crab Optimizer (HCO). The proposed method is implemented in Python. The proficiency of the AAIT-ASESL-MORA-RNN approach is evaluated using a number of performance criteria, including accuracy, recall, precision, F1-Score. The proposed AAIT-ASESL-MORA-RNN method covers 28.36%, 23.42% and 33.27% higher precision and of 22.36%, 15.42% and 18.27% higher accuracy compared with existing AI basis English Self-Learning Effect Evaluation with Adaptive Influencing Factors Analysis (ESL-AIF-AI) Research on English Hybrid Assisted Teaching Method under Contextual Support of R-CNN (EHATS-CS-RCNN) and College English Teaching Quality Evaluation Scheme depending on Information Fusion along Optimized Radial Basis Function Neural Network (CET-QES-RBFNN) respectively.

Keywords:Hermit Crab Optimizer, Mixed-Order Relation-Aware Recurrent Neural Networks, python, Unscented Trainable Kalman Filter,

I. INTRODUCTION

Being proficient in English has become essential in today's globalized world as it facilitates communication, education, and professional opportunities. However, many learners still find it difficult to master spoken English, frequently as a result of the shortcomings of conventional language teaching techniques [1,2]. One revolutionary way to overcome these obstacles is to include artificial intelligence into adaptive systems for English language learners. These systems use artificial intelligence to provide dynamic, personalized learning experiences that are catered to the individual needs and skills of each student [3,4]. Adaptive English speaking learning systems heavily rely on artificial intelligence due to its capabilities in natural language processing (NLP) and machine learning [5,6]. These systems can evaluate spoken language and identify mistakes in vocabulary usage, syntax, and pronunciation thanks to NLP algorithms. AI can give students immediate feedback via speech recognition technology, helping them to get better [7,8]. This instant feedback loop increases learner engagement and motivation while also improving learning efficiency.Furthermore, machine learning algorithms drive recommendation engines in adaptive systems, offering individualized practice exercises, learning materials, and assessments according to learner preferences, skill level, and learning goals [9,10]. These algorithms continuously adjust and improve their recommendations by utilizing data on learner performance and behavior, guaranteeing the best possible learning route for every individual. The capacity of AI-driven adaptive systems to mimic real-world dialogue situations is one of their main advantages. Learners can participate in interactive language practice in a secure and encouraging setting by using chatbots and virtual tutors [11,12]. With the use of AI, these conversational agents may adapt their responses dynamically in response to input from learners, resulting in a realistic and engaging learning environment. Through the simulation of real-life encounters, students can improve their fluency and confidence in speaking [13,14]. Moreover, adaptive systems can now accommodate each learner's unique demands and learning preferences thanks to AI technology.

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These systems accommodate varying skill levels, interests, and objectives by offering personalized learning routes and content customisation [15,16]. Adaptive systems can offer focused support and resources catered to each learner's unique areas of improvement, whether it's pronunciation, vocabulary expansion, or grammar.While AI-driven adaptive systems offer many advantages for learning English, there are drawbacks and issues that need to be taken into account [17,18]. Ensuring equitable and transparent learning experiences requires careful management of ethical problems pertaining to algorithmic bias and data privacy. Furthermore, adoption of AI technology may be hampered for some student demographics by its accessibility in terms of hardware, internet connectivity, and digital literacy [19,20].

Even while AI techniques are beneficial for teaching English, there are downsides. Notable issues include privacy problems, potential biases, minimal human interaction, and dependence on technology. AI may potentially worsen access disparities, stifle critical thinking and innovation, and lessen the need of teachers. More difficulties arise from the emphasis on standardized learning and ethical issues. To achieve effective incorporation into English education while maintaining its quality and inclusivity, balancing AI's benefits with these shortcomings requires careful analysis, ethical examination, and constant evaluation.The use of R-CNN by English teaching assistants is fraught with difficulties, including resource requirements and implementation complexity, limited contextual understanding beyond object detection, scalability issues, reliance on visual input, maintenance complications, integration difficulties, and privacy ethics concerns. Teachers have to overcome these obstacles to guarantee successful implementation while taking into account the various learning settings and available technology. Although it has limitations, the suggested college English teaching quality evaluation system employs an information fusion and optimized RBFNN to show potential. The incomprehensibility and intricacy of RBFNNs make it difficult to comprehend how decisions are made. Generalization and performance of the model are impacted by data dependence and challenges with parameter adjustment. Adoption may be hampered by integration challenges and computational resource requirements. Furthermore, the lack of transparency in RBFNNs raises questions about justice and accountability. Collaboration is necessary to maintain transparency, dependability, and alignment with educational goals in order to overcome these obstacles.

The aim of this project was to English Speaking Learning, many models out now that successfully integrate various network data types for thorough predict the Error of English Speaking Learning. The new model should show better results by utilizing data from multiple sources at the same time. This model based on the English Language Learning-Ensemble Learning dataset with input data and Optimized Mixed-Order Relation-Aware Recurrent Neural Networks.

Important contribution of this paper as follows;

- Application of AI Technology in Adaptive System for English Speaking Learning (AAIT-ASESL-MORA-RNN) is proposed.
- For learning English, an AI-powered adaptive system provides individualized learning pathways and instant feedback.
- It improves learners' fluency and confidence in spoken English by utilizing speech recognition, natural language processing, and individualized content recommendations.
- The obtained results of proposed AAIT-ASESL-MORA-RNN algorithm is comparing to the existing ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN methods respectively.

The remaining manuscript is designed as follows: Part 2 outlines the literature survey, Part 3 illustrates the proposed method, Part 4 presents the results with discussions, and Part 5 concludes the manuscript.

II. LITERATURE SURVEY

The literature presents a number of research projects on deep learning-based of English Speaking Learning; this section evaluated some of the most recent studies.

Shu and Xu, [21] has presented Artificial intelligence-based English self-learning effect evaluation and adaptive influencing factors analysis. Given the on-going developments, typical English education was no lengthier able to satisfy the requirements of contemporary times. By means of assessing the self-governing learn of English as an effect of AI and examining the Considering variables of flexibility, the English classroom teaching impact was enhanced, and the pupils' understanding of independent Education was fostered. That was, one is the standard deviation. Generally, girls study English at a greater level than boys do.English majors are better suited for independent research on artificial intelligence in the language than non-majors were, and by building models, students can enhance their adaptability to learning AI. Adaptive learning was the key to reaching the aim of improving learners' English proficiency through transfer learning. It provides high accuracy, and it provides low precision.

Yuan, [22] has Suggested Research on English hybrid assisted teaching system utilizing contextual support of R-CNN. Applications for hybrid English teaching assistants were made using the imported model. Although there were software tool level English teaching help models accessible, they were not very user-friendly and cannot keep up with the latest technological advancements. Previous methods of providing English teaching help, such as machine learning and Boosting machine learning, were not able to include background provision. The relation amongst students, teachers, the learning environment, and learning methodologies must all be coordinated by English teachers. Modern, user-friendly construction methods and sophisticated educational Eco balancing were proposed and implemented, potentially enhancing the qualities of hybrid education and enhancing English language proficiency. It provides high F1 Score and it provides low accuracy.

Chen, [23] has presented College English teaching quality evaluation scheme utilizing information fusion along optimized RBF neural network decision approach. The primary issues involved in developing an optimal system for evaluating learning quality were examined in this research. It does this by examining the benefits and drawbacks of the earlier learning quality evaluation approaches.The system was built on information fusion, and it makes use of experimental investigation methods. Teachers can raise their teaching standards and pique college students' interest in English by introducing novel teaching strategies and improving instructional resources. The findings indicate that most college students believe that college English instruction was at a mediocre level and needs to be improved. It provides high recall, and it provides low F1 Score.

Fitria, [24] has suggested the use technology using artificial intelligence in English teaching and learning. The outcome demonstrates that AI provides an excellent environment for learning English. It may greatly customize the environment so that students can exercise their senses while simultaneously honing their English abilities based on their interests, needs for their career, and present English proficiency. AI provides a realistic simulated dialog platform similar to spoken English and enhances practical skills like writing. It increases students' practice capacity and optimizes the effects of English learning in ELT. With the progression of platforms and technology, learning English has become simpler.The technology of AI presents a chance to enhance proficiency in the English language. The availability of diverse forms of educational technology facilitates pupils' comprehension of the English language. Numerous AI-based ELT program options were available for students to use. These technologies, which were intelligent machines that think and act like people, may mimic intelligence and make decisions that are exactly like those made by humans. Examples of these technologies were Google Translate, Text to Speech (TTS), English Able, It attained higher precision, but lower recall.

Rusmiyanto, et al. [25] have presented the part of artificial intelligence (AI) in developing English language learner's communication skills. Examining the literature and research on AI-based technology application in English learning environs was the aim of this study. An introduction to artificial intelligence and its potential applications in education opens the essay. It then examines the different ways that AI could support English language learners in improving their, attending, reading, writing abilities. The results of study indicate that by offering individualized and interactive learning experiences, English language learners' communication skills could be significantly enhanced by AI.It emphasizes how AI was revolutionizing English language instruction and how it may be used to meet the various demands of language learners. If educators and policymakers are aware of the current state of research and look into the opportunities and challenges presented by AI in language learning, they can make well-informed decisions to maximize the impact of AI technology on the development of effective communication skills among English language learners. It provides high accuracy, and it provides high F1 Score.

Dong, [26] has suggested Application of artificial intelligence software depending on semantic web technology in English learning with teaching. The work splits the complete voice data into frames during speech processing in order to extract the pitch of each frame of data that corresponds to an English phrase. The autocorrelation function technique in the time domain is then used to do additional analysis in units of frames. Furthermore, this study combines the actual requirements of English learning and teaching to build system function modules, using experiment designs to assess system performance and produce data on user satisfaction. It was clear from the research findings that the system created in this work essentially meets the actual needs of teaching English and facilitating individual learning. The shortcomings of traditional English teaching and learning must be changed in the information era by using intelligent system software in English teaching and learning. It provides high precision, and it provides low F1 Score.

Zhang and Chen, [27] has presented College English smart classroom teaching mode under artificial intelligence technology (AIT) in mobile information schemes. Artificial intelligence technology has advanced quickly along with the rise of mobile information, revolutionizing every aspect of our lives. In the meantime, smart education emerged and gained a lot of attention; yet, a structured conversation about how to go with combining artificial intelligence with smart classrooms is still lacking. The primary focus was the integration of AIT into English smart classrooms, with the aim of advancing the intelligent evolution of education. A new smart classroom teaching model was created during the teaching process, and it was implemented using data from student surveys and the trial class demonstrate the high level of student satisfaction with this teaching approach. It reached high F1 Score and high recall.

III. PROPOSED METHODOLOGY

In this section, Application of Artificial Intelligence in Adaptive System for English Speaking Learning (AAIT-ASESL-MORA-RNN) is proposed. This process consists of five steps: data Acquisition, Pre-processing, classification and optimization. In the proposed were collected and pre-processing to prepare them for further analysis. The final step involves employing MORARNN for classification, with the feature vector serving as input. The Hermit Crab Optimizer (HCO) method is introduced for training the MORARNN. The block diagram of proposed AAIT-ASESL-MORA-RNN approach is represented in Fig 1. The comprehensive description of all steps given below,

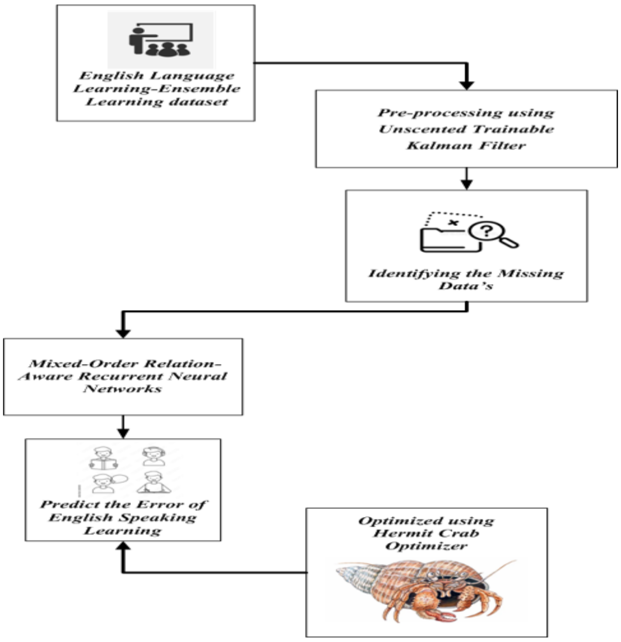

Figure 1: Block Diagram of AAIT-ASESL-MORA-RNN methods

A. Data Acquisition

The input data are amassed from English Language Learning-Ensemble Learning dataset [28], was predicting the English Speaking Learning. This competition aims to evaluate the linguistic skills of English linguistic Learners (ELLs) in grades 8 through 12. It will be easier to create proficiency models that better support all students if a dataset of Ells essays is used. Your efforts will speed up teachers' grading cycles and enable ELLs to obtain more accurate feedback on their language growth. These results may make it possible for ELLs to be assigned more suitable learning assignments that will advance their English language competency.

B. Pre-processing using Unscented Trainable Kalman Filter

In this section, pre-processing using Unscented Trainable Kalman Filter (UTKF) [29] is discussed. An UTKF method is used to pre-processing the identifying the missing data's. The Unscented Trainable Kalman Filter (UTKF) provides a revolutionary method for learning English. Its nonlinear modeling adjusts to each learner's development, fitting the intricacy of language acquisition. UTKF filters to produce correct insights by integrating varied data to create comprehensive proficiency views. With customized, data-driven pedagogy, incremental training and uncertainty quantification provide customized interventions that transform English instruction. Create, incorporate, and fine-tune a UTKF model for learning English with an emphasis on user experience, scalability, adaptability, and data gathering in equation (1),

$$y^{j} = h\left(N^{j} F\right) + c^{j} \tag{1}$$

Where, y^{j} denotes convolution layer output, N^{j} denotes weighed matrix, c^{j} denotes constant term. Are used to obtain the data of the j th node, and they can be generalized below equation (2),

$$d^{(k)} = f^{(k)} \Theta \phi\left(N^{d} y^{j} + S_{j}^{d} z^{(k-1)} + c^{d}\right) + q^{(k)} \Theta d^{(k-1)} \tag{2}$$

Where, $d^{(k)}$ denotes the state vector of k^{th} unit, k denotes the number of is unites, $q^{(k)}$ denotes the forget, ϕ denotes the hyperbolic tangent function, Removal architecture might adjust the neural network's parameters and compute the operational residual below equation (3),

$$f^{(k)} = \sigma\left(N^{f} y^{j} + S_{j}^{f} z^{(k-1)} + c^{f}\right) \tag{3}$$

Where, $f^{(k)}$ denotes the input, σ denotes the point-wise sigmoid function, Because domain knowledge sheds light on potential reasons for missing data, it is essential for understanding missing data in the below equation (4),

$$z^{(k)} = p^{(k)} \Theta \rho\left(d^{(k)}\right) \tag{4}$$

Where, ρ denotes hyperbolic tangent function, $p^{(k)}$ as output gate, Θ as associated elements multiplication of matrix, Compiling summary statistics and visually examining the data for gaps or anomalies are the first stages followed by the equation (5),

$$\hat{y}(u+1) = g(F(u)) \tag{5}$$

Where, $\hat{y}(u+1)$ denotes the prediction state, Missing value indicators are given extra consideration; these can differ according on the platform or software being utilized. finally this extracted by the equation (6),

$$\in(u+1) = t(y(u+1), \hat{y}(u+1)) \tag{6}$$

Where, $\in(u+1)$ denotes residual time $u+1; \hat{y}_{j}(u+1)$ denotes prediction state vector; Finally, UTKF has identified the missing data's. Then Pre-processed data is given to the Mixed-Order Relation-Aware Recurrent Neural Networks for predict the Error of English Speaking Learning.

C. English Speaking Learning using Mixed-Order Relation-Aware Recurrent Neural Networks (MORARNN)

In this section, MORARNN [30] is discussed. MORA-RNN is proposed for English Speaking Learning and it predicts the Error of English Speaking Learning. For English-speaking learners, Mixed-Order Relation-Aware Recurrent Neural Networks (MORANs) provide individualized experiences, flexible learning patterns, and contextual comprehension. MORANs facilitate accurate error correction, real-time feedback, and improved pronunciation learning due to their capacity to understand complex links between words and phonemes. Scalable and accessible language learning experiences across a range of devices are made possible by MORANs, which seamlessly integrate into interactive platforms. Through the analysis of individual speech patterns and the subsequent adaptation of instructional tactics, MORANs facilitate the development of effective skills, encouraging active engagement and on-going enhancement of spoken English competence in equation (7),

$$s_{u} = \partial\left(\sigma_{S}\left(Y_{u}, I_{u-1}\right) + c_{S}\right) \tag{7}$$

Here, s_{u} is denotes the relation aware model network; ∂ is denotes the constant of data; σ_{s} is denotes the non-shared mixed; Y_{u} is denotes the current observation; I_{u-1} is denotes the previous state of the Classification and c_{s} is denotes the input layer. This various input data is given in equation (8),

$$C_{u} = soft\max\left(\delta\left(q_{u}\right)\right) \tag{8}$$

Here, C_u is denotes the various data input; $soft\max$ is denotes the activation of input function; δ is denotes the positive input defect data and q_u is denotes the various layer is given in equation (9),

$$v_u = \partial\left(\sigma_v\left(Y_u, I_{u-1}\right) + c_v\right) \tag{9}$$

Here, v_u is denotes the sequence of diagnosis; ∂ is denotes the constant; σ_s is denotes the non-shared mixed; Y_u is denotes the current observation; E_{t-1} is denotes the previous state of the detection and c_v is denotes the input layer. The MORARNN makes use of the squashing vector activation function in given equation (10),

$$F_u = Aggregate_{o2i}\left(C, Q_u\right) \tag{10}$$

Here, F_u is denotes the squashing activation vector; $Aggregate_{o2i}$ is denotes the aggregation of node detection; C denotes the classification function and Q_u is denotes the transition. MORRNNs enable the identification of hidden trends indicative of malignancy by integrating data from several orders of relations within sequential are given in equation (11)

$$M(\Theta) = \frac{1}{\varepsilon O E'} \sum_{u=1}^{\varepsilon} \sum_{j=1}^{O} \sum_{k=1}^{E'} \left|\hat{z}_{ujk} - z_{ujk}\right| \tag{11}$$

Here, $M(\Theta)$ is denotes the trainable parameter of the detection; ε is denotes the detection function; O is denotes the time sequence of the input data; E' is denotes the display in the MORARNN; $\hat{z}_{ujk}$ is denotes the fusion operation of each data and z_{ujk} denotes the real value. Finally, MORARNN identifying the missing data, HCO increase the MORARNN optimum parameters ∂ and σ_v. Also, tuning the weight with bias parameter of MORARNN.

D. Optimized using Hermit Crab Optimizer (HCO)

The optimization using Hermit Crab Optimizer (HCO) [31] is discussed. The MFPIDNN weight parameter ∂ *and* σ_v is optimized by HCO. By balancing strategy exploration and exploitation, dynamically adapting to learners' profiles, efficiently allocating resources, exposing learners to a variety of linguistic contexts, promoting problem-solving skills, and fostering collaborative environments, the Hermit Crab Optimizer (HCO) offers benefits for English language learners. HCO ensures a comprehensive and efficient method of learning spoken English by allowing students to adapt and flourish in the always shifting field of language acquisition, much like hermit crabs changing their shells.Implementing the Hermit Crab Optimizer (HCO) in English-speaking learning aims to improve proficiency by striking a balance between strategy exploitation and exploration, dynamically adapting to learners' needs, efficiently allocating resources, exposing learners to a variety of linguistic contexts, encouraging collaboration, and boosting problem-solving abilities. The ultimate goal is to give students a flexible and efficient framework for learning spoken English so they can interact with others in a variety of authentic contexts with competence and confidence.

Step 1: Initialization

The optimization process in HCO starts with English Speaking Learning in the Hermit Crab in this phase determines the optimal area based on this behaviour is defined as the following equation (12),

$$Q(j) = \begin{bmatrix} y_1^{1j} & \cdots & y_e^{1j} \\ \vdots & \ddots & \vdots \\ y_1^{oj} & \cdots & y_E^{Oj} \end{bmatrix}_{O\times E} = \begin{bmatrix} \vec{Y}_1(j) \\ \vdots \\ \vec{Y}_O(j) \end{bmatrix}_{O\times 1} \tag{12}$$

Let O denotes number of search agents, E denotes the total encoded values for a search agent, Y symbolizes search agent positioning o in dimension e.

Step 2: Random Generation

After initialization, weight parameters are formed randomly generated. The best fitness are selected contingent explicit hyper parameter circumstances.

Step 3: Fitness Function

Fitness function creates random solution from initialized values. It calculated using optimizing parameter. Thus it is shown in equation (13),

$$FitnessFunction = optimizing[\partial\ ,\ \sigma_v] \tag{13}$$

Where, ∂ represents the increasing accuracy, σ_v denotes the represents the lowering computational time.

Step 4: Exploration Phase for optimizing $[\partial]$

At this stage, the exploration phase of the HCO is examined. HCO's inquisitive behavior is described. As was previously established, in their lone quest for shells, hermit crabs are tempted to emulate potent chemical cues in its environment. Taking into account the diffusion of smell molecules, an operator should be created to replicate this behavior. Thus, define the single search operator as follows equation (14),

$$\vec{Y}_o(j+1) = \frac{1}{F}\sum_{f=1}^{F}\left(\vec{Y}'_f(j) + \gamma_f \left|\delta_1 \vec{Y}'_f(j) - \partial(j)\right|\right) \tag{14}$$

Where, γ_f denotes the specific distraction rate. $\vec{Y}_o(j+1)$ and $\vec{Y}_o(j)$ denotes the state of o^{th} two successive iterations of a successful search agent, $\vec{Y}'_f(j)$ is the location that the most prominent, alluring odour sources are thought to be in the ecosystem.

Step 5: Exploitation phase for optimizing $[\sigma_v]$

Exploitation is main criteria for any metaheuristic optimization algorithms, the variable which has a random value between 0 and 1.These sources of dominating odors are the most lucrative and successful search agents. When a hermit crab finds a shell while searching alone, they encourage other hermit crabs that have successfully exchanged shells to approach them; in contrast, hermit crabs that have not found a shell trade shells using vacancy chains, ignoring those that have as follows equation (15),

$$\vec{Y}'_f(j) = \vec{Y}_f(L_e) + \beta L_f(\sigma_v) K_{1\times E},\ 1 \le f \le F \tag{15}$$

Where, β a random number in range, $\vec{Y}_f(j)$ displays the location of the main source of odor in the ecosystem, $L_f(j)$ the furthest distance that order source molecules can travel f disperse throughout the area as hermit crabs approach odour sources over time.

Step 6: Termination Condition

Weight parameter ∂ *and* σ_v of generator from Mixed-Order Relation-Aware Recurrent Neural Networksis enhanced by HCO, will repeat step 3 iteratively until fulfil the halting criterion $Q(j) = Q(j)+1$. Then MORARNN has managed the English Speaking Learning by assessment with higher accuracy. Flowchart of HCO for optimizing MORARNN parameter is shown in figure 2.

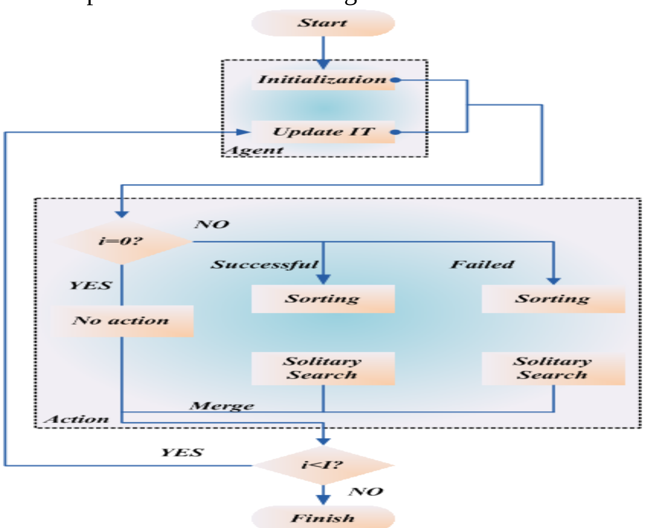

Figure 2: Flowchart of HCO for optimizing MORA-RNN parameter

IV. RESULT AND DISCUSSION

English Speaking Learning is one of the experimental results of the proposed AAIT-ASESL-MORA-RNN approach. In Implementation work was carried Python and evaluated by using metrics like, accuracy, recall, precision, and F1-Scoreare analysed. The results of the AAIT-ASESL-MORA-RNN methodology are compared to the existing ESL-AIF-AI [21], EHATS-CS-RCNN [22] and CET-QES-RBFNN [23].

A. Performance Measures

Performance measures include accuracy, recall, precision, and F1-Score.

1) Accuracy

Accuracy is the capability to scale an accurate value. This is quantified through the following eqn (16)

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

2) Recall

A machine learning model's recall quantifies its ability to identify positive examples. It gauges the probability of obtaining a favourable outcome. That's provided in equation (17)

$$\mathrm{Re}call = \frac{TP}{(TP+FN)} \tag{17}$$

3) Precision

Precision, or how well a machine learning model generates positive predictions, is one indicator of the algorithm's efficacy. The following stated equation (18) is used to measure it.

$$\mathrm{Pr}ecision = \frac{TP}{(TP+FP)} \tag{18}$$

B. Performance Analysis

The simulation results of the AAIT-ASESL-MORA-RNN technique are shown in Figure 3 to 6. The proposed AAIT-ASESL-MORA-RNN techniques linked to the ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN techniques, respectively.

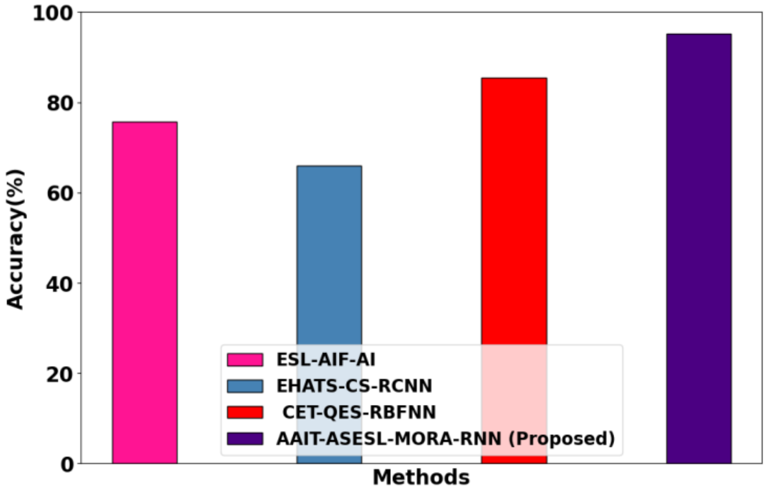

Figure 3: Accuracy analysis

Figure 3 shows accuracy analysis. Improved precision guarantees a more trustworthy assessment of language difficulties encountered by students, enabling customized feedback and focused interventions to advance speaking ability. AAIT-ASESL-MORA-RNN improves the effectiveness of error prediction by utilizing cutting-edge computational techniques, giving teachers more tools to assist students as they progress through their language learning process. The increased precision of error identification leads to a better comprehension of students' language requirements, directing teaching methods toward areas that need development and optimizing student learning. The proposed AAIT-ASESL-MORA-RNN technique reaches in the range of 22.36%, 15.42%

and 18.27% higher accuracy for predict the Error of English Speaking Learning Compared with existing techniques such as ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN respectively.

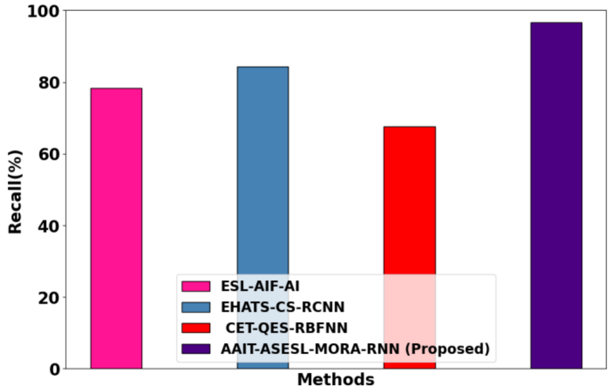

Figure 4: Recall analysis

Figure 4 displays Recall analysis. Higher recall suggests a more complete capacity to identify and rectify faults, which makes it possible to provide more efficient feedback systems and customized learning interventions for students who want to get better at speaking English. The AAIT-ASESL-MORA-RNN technique helps to better understand learners' language issues by recording a wider range of errors. This helps to develop more effective and targeted instructional strategies.The proposed AAIT-ASESL-MORA-RNN technique reaches in the range of 18.36%, 16.42% and 28.27% higher Recall for predict the Error of English Speaking Learning Compared with existing techniques such as ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN respectively.

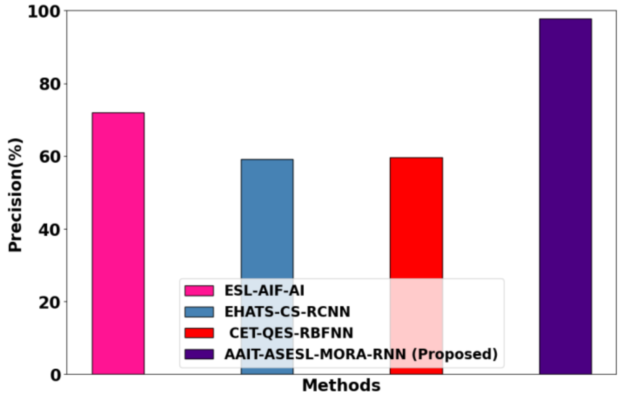

Figure 5: Precision analysis

Figure 5 shows Precision analysis. These developments represent significant progress toward identifying and correcting faults in English speaking acquisition. They also hold the promise of providing learners with more precise feedback and focused instructional strategies with the goal of improving speaking competency.The proposed AAIT-ASESL-MORA-RNN technique reaches in the range of 28.36%, 23.42% and 33.27% higher Precision for predict the Error of English Speaking Learning Compared with existing techniques such as ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN respectively.

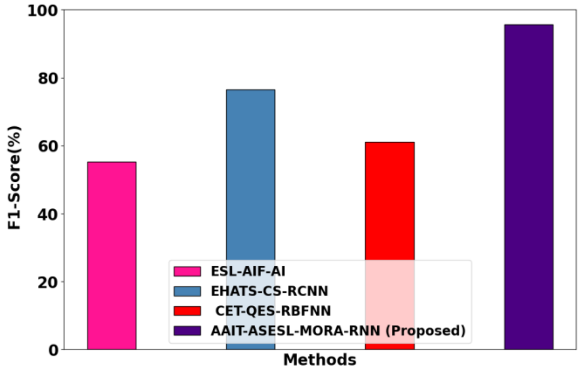

Figure 6: F1-Score analysis

Figure 6 displays F1-Score analysis.This development shows that error prediction for English language learners has advanced significantly, offering improved competency evaluation and focused learning interventions. The proposed AAIT-ASESL-MORA-RNN technique reaches in the range of 27.22%, 26.45% and 19.46% higher F1-Score for predict the Error of English Speaking Learning Compared with existing techniques such as ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN respectively.

C. Discussion

This study develops the AAIT-ASESL-MORA-RNN model's initial step toward a English Speaking Learning. MORARNN was contrasted with earlier findings from different investigations. Also found that the models were far better at English Speaking Learning. Ultimately, AAIT-ASESL-MORA-RNN classifies the English Speaking Learning. The benefits of MORARNN and HCO optimization methods were combined to create a proposed English Speaking Learning. It used the English Language Learning-Ensemble Learning dataset to examine the suggested Information from the English Speaking Learning methods. The dataset is first pre-processedthe identified the missing data's. Using various assessment metrics, the results confirmed the proposed method's outstanding performance and it has improved the traditional HCO exploitation and exploration phases, here infer that the proposed HCO performs much better than the traditional HCO. As a result, from an economic perspective, the proposed method is less costly than the comparison procedures. The cross-validation processes achieved overall accuracies.

V. CONCLUSION

In this paper, Application of Artificial Intelligence Technology in Adaptive System for English Speaking Learning (AAIT-ASESL-MORA-RNN)was successfully implemented. Here, English Language Learning-Ensemble Learning dataset were used in thorough evaluation tests to assess the presented technique. The proposed AAIT-ASESL-MORA-RNN technique is activated in Python. The presentation of AAIT-ASESL-MORA-RNN method covers 18.36%, 16.42% and 28.27% higher recall and of 27.22%, 26.45%, 19.46% greater F1-Score compared with existing ESL-AIF-AI, EHATS-CS-RCNN and CET-QES-RBFNN methods. Future work takes into account several HCO optimizers for English Language Learning-Ensemble Learning dataset.In works includes for creating models using various techniques and combining multiple machine learning or deep learning algorithms, the capacity to improve mobility as well as the goal and reach of cognitive learning. Incorporating data enhancement and analysis into English language training allows learners to assist learning more effectively.

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