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Application of Virtual Reality Technology for University English Culture Parenting

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Abstract: - Seeing something as reality (VR) is the term used to describe the visual perception of virtual reality, general assembly designs, patterns, and their conversion into part entities. In this manuscript, Application of Virtual Reality Technology for University English Culture Parenting (VRT-TTEDNN-BBWOA-UECP) is proposed. Initially, Virtual reality technology (VR) can offer English learners virtual experiences, such virtual chats or simulations of real-life situations, to practice communication skills and University English Culture Parenting. The data are taken from English language content database which contains eye movement of 19 students data are collected as input. Afterward, data are fed to pre-processing. In pre-processing, removes noise from data using Learnable Edge Collaborative Filtering (LECF). Then the preprocessed data are given to Temporal and Topological Embedding Deep Neural Network (TTEDNN) for classifying the eye track samples of the students as positive (+) and Negative (-). In general Temporal and Topological Embedding Deep Neural Network does not express some adaption of optimization strategies for determining optimal parameters to promise accurate classification. Hence, BBWOA is proposed to enhance weight parameter of Temporal and Topological Embedding Deep Neural Network. The proposed technique is executed by python, efficacy of VRT-TTEDNN-BBWOA-UECP technique is assessed by support of numerous performances such as accuracy, precision, F1-score and error rate is analysed. The performance of VRT-TTEDNN-BBWOA-UECP technique is analysed with existing techniques likes deep learning method by virtual reality technology for second language acquisition (VRT-CNN-SLA), 5G joint AI technology in innovation with reform of university English education (VRT-KNN-IUEE), big dyadic affect in parent-child multi-modal interaction: introducing dami-p2c dataset with preliminary analysis (VRT-GAN-PCMI) respectively.

Keywords: Binary Black Widow Optimization Algorithm, Learnable Edge Collaborative Filtering, Temporal and Topological Embedding Deep Neural Network, Virtual Reality Technology.

I. INTRODUCTION

AI-assisted language learning can intelligently assist humans in accomplishing communicative tasks, fulfilling social function of engaging by others, knowledge, surroundings. Several smart gadgets are directly related to language learning; these devices fall into three basic categories: integrated platforms, robotics, and specialised software [1]. The five primary categories of intelligent language devices are Dasai intelligent educational robots, Xunfei translators, lip recognition robots, chariots (Chatterbot), and Xiaobu English robot companions for education [2]. Professional software comprises Kingsoft, Lingoes Translator, Google Translator. E-learning systems comprise Sakai, SuperStar Pan-Asia, Moodle, Black-board, Library Genesis, and Goodreads [3, 4]. Artificial intelligent is the collective term for these three categories of intelligent technologies [5]. The distinction between them is in their varying degrees of intellect [6].Virtual reality is defined as seeing something realism, the process of visualising a virtual environment, creating overall assembly drawings and patterns, adapting them into part entities, automatically processing the parts by inputting CNC machine tools [6, 7]. The real world is machined into CNC machine [8]. Most immediate, a inspiring effects of VR technology are immersion, participation in immersion [9]. Computer devices are used to simulate visual, render, auditory scenes, such rendering methods stimulate people's visual, auditory senses, giving user better possible simulation of visual with auditory organs to made impressive [10, 11]. In briefly, these simulations are created using computer simulation and are made up of fictitious settings and consequences [12]. An interdisciplinary field centred on computer graphics, artificial intelligence, simulation, multimedia, sensing, and sensing-related technologies is called virtual reality technology [13,14]. Advanced sensor integration technologies, software, and high-performance computer hardware are all fully utilised by virtual reality technology [15, 16]. As learners enter the facility, it encompasses everything associated with it, including the usage of sensor-assisted facilities,

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which can create an immersive and authentic experience. [17, 18] Learners can simultaneously conduct real-time operation, reciprocal communication by environment in real world, and utilize human natural skills to modify objects in virtual environment depend on personal feelings with range of sensing devices [19].

The acquisition of English language skills and cultural knowledge is essential for pupils' overall growth. However, deep and captivating possibilities for students to dive into the subtleties of language and culture are often lacking in standard teaching approaches. Furthermore, parents may find it difficult to actively encourage and engage in their children's acquisition of the English language and culture despite being major stakeholders in their education. The suggested method doesn't gives sufficient accurateness, higher computational time, motivated us to do this investigation work.

Major contributions of proposed method are brief below,

- In this research, Application of Virtual Reality Technology for University English Culture Parenting (VRT-TTEDNN-BBWOA-UECP) is proposed.
- Initially, data are collected from English language content database. Develop a Learnable Edge Collaborative Filtering for removing the noise and prevent data leakage.
- Propose a BBWOA to optimize TTEDNN.
- VRT-TTEDNN-BBWOA-UECP method is executed at python, efficacy examined and several performance metrics.
- The efficacy of proposed method is analysed with existing techniques likes VRT-CNN-SLA, VRT-KNN-IUEE, VRT-GAN-SVM-SFT respectively.

Rest of this paper is arranged as below: part 2 describes literature review, part 3 defines proposed method, part 4 describes outcomes, part 5 conclusion.

II. LITERATURE REVIEW

Numerous research works presented in literatures were depend on Virtual Reality Technology for University English Culture Parenting; few of them were reviewed here,

Zhao and Liu [20] have presented DL method by VRT for SLA. Here, investigates the attention patterns of English language learners as a second language while they perform online tasks using DL-VR technology. Young second language learners' linear attentional control model was closely correlated with how well they accomplish online tasks, according to tests, and this relationship helps to graphically explain how their linear attentional control affects the completion of online tasks. It attains higher precision, lower accuracy.

Sun [21] have presented5G joint AI technology in IUEE. Here, gives case study project to investigate novel online oral teaching method, summarising its benefits, offering fixes for its drawbacks. It also demonstrates the precise procedures, execution scales of "5G" technology. To help pupils learn, system shows all stage of gesture recognition. Under guidance of interactive interface, students experience process of gesture recognition. Afterwards, a figurative example is used to explain the intricate and abstract gesture recognition process, which helps primary, secondary school students gain deeper understanding, develop logical thinking. It provides high recall and low F1-Score.

Chen et al. [22] have suggested the dyadic affect in PCMI: presenting dami-p2c dataset with preliminary analysis. Here, it offers a dataset known as "dyadic affect in multimodal interaction - parent to child", was gathered from 34 parent-child pairs participating in storybook reading activities together. The children ranged in age from 3 to 7 years old. Unlike other publicly available datasets on social-emotional behaviours in dyadic encounters, every event for both participants in our sample had three labellers annotate it for affect. The dataset also includes audiovisual recordings, affect labels, body joints, co-reading behaviours, and socio demographic profiles of each pair. This method provides high F1-Score and low ROC.

Lu et al. [23] have presented supervision system of English online teaching depend on ML. Here, improve online English teaching audit procedure, this article proposes to merge machine learning algorithms (IRS-MLA) with remote supervision. Here, IRS-MLA mimics application of supervision approaches in teaching process in accordance with the actual requirements of online English instruction. Additionally, evaluating student achievement and outlining learning process from both teachers', students' viewpoints gauges effectiveness of the teacher. This research examines the functional impact of classic English language online supervision approach, includes the evaluation studies. This method provides low computation time and low precision.

Abu-Arqoub et al. [24] have presented interactive multimedia-depend educational scheme for children utilizing interactive book by augmented reality. Here, offers augmented reality learning system concept that uses multimedia and Glyphs (TAGs) to transform a regular book into an interactive book. A teacher, parent, or child can utilise the interactive book to add fun to the learning process. The book's graphics and imagery come to life as the kid reads through its contents, promoting concept acquisition and understanding in an engaging and dynamic manner. A printed book can be made interactive by inserting special TAGs (Glyphs) in the appropriate locations, which are then ready to view by a webcam, transformed into audio, video, 2- or 3-D graphics, explanation text. This method provides low recall and high accuracy.

Wang et al. [25] have presented using VR to aid social competence education with social help for children from under-represent backgrounds. Thus, there was need to pay close consideration to bridging gap among urban, rural education schemes to maximise benefits of immersive technology in raising social competence, apparent social help for children living in remote regions of world, decrease disparity enhance education quality. It developed three social competence educational methods-VR aided social competence education, Lego social competence education and traditional classroom learning-based on three representative paedagogies and implemented them as interventions in two rural South-west Chinese schools. This method provides high recall and low F1-score.

Xu et al. [26] have suggested design with application of VR-depend college English game teaching. Here, the goal of the research is to develop and build a virtual reality-depend English game education with teaching system. The HMM-DNN process was added to virtual system to enhance it after the first English game teaching system was constructed using current VR technology. To attain good voice acoustic method, attain accurate speech recognition in virtual world, robot control command speech recognition scheme was built using CMUShinx speech recognition platform. Lastly, confirm the viability of the system concept, a performance analysis of constructed scheme was conducted. This provides low precision and high computational time.

III. PROPOSED METHODOLOGY

VRT-TTEDNN-BBWOA-UECP is discussed in this section. This section presents the clear description about the research methodology used in Virtual Reality Technology for University English Culture Parenting from eye movement data. The block diagram of VRT-TTEDNN-BBWOA-UECP is represented by Figure 1. Thus, the detailed description about VRT-TTEDNN-BBWOA-UECP is given below

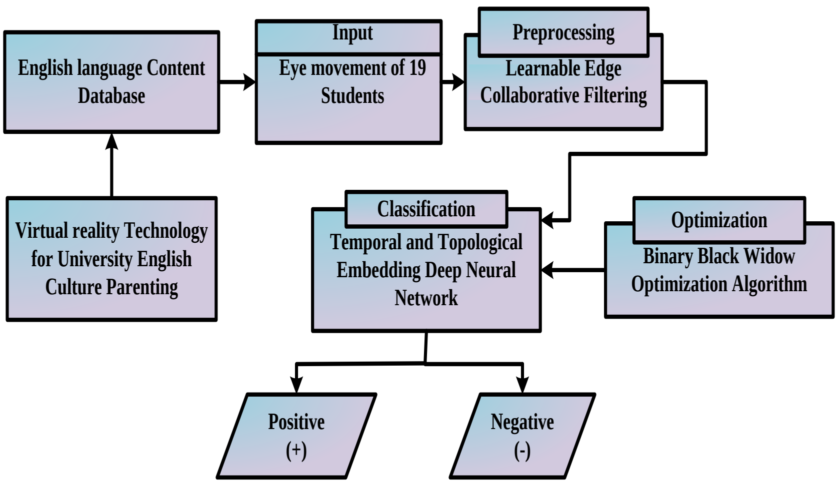

Figure1: Block diagram of VRT-TTEDNN-BBWOA-UECP Virtual Reality Technology for University English Culture Parenting

A. Virtual Reality Technology

The term "virtual reality" describes the application of artificial intelligence, multimedia, multi sensor interaction, three-dimensional graphics production, and human. To create three-dimensional, realistic virtual environment, high-tech technologies such as interfaces and high-resolution displays are used. Give users the ability to simulate their vision, hearing, touch, and other senses so they may quickly and endlessly observe objects in three-dimensional space as if they were actually there. Four essential features of virtual reality are multi-sensory, immersive, interactive, and conceptual. There are differences between using virtual reality (VR) technology to teach university English culture and integrating deep learning into parenting. The goal of incorporating VR technology into university English culture is to improve language learning through immersive and interesting experiences. With the use of virtual reality (VR), students can practice language in context while immersed in surroundings that mimic real-world English-speaking situations. Students can interact with English in a variety of contexts through virtual classrooms, language labs, and interactive simulations, which promote a more engaging and useful learning environment. Furthermore, virtual reality (VR) can help with cultural immersion by taking students to English-speaking countries virtually. This allows them to be exposed to a variety of cultural elements and develop a stronger knowledge of the language within its cultural context. However, incorporating deep learning into parenting entails.

B. Data acquisition

Initially, data are collected from the English language content database. Ten boys and nine girls in the first grade of a university, by mean age of 6.42, SD = 0.507.Participants watched a video of an English reader reading aloud for about four minutes. The vocabulary in video, such young second language learners had never seen before, utilized eliminate attentional distractions from familiar words to reflect learners' ability control effort to second language stimuli. Eye-movement data was collected using a TutiiT120.

C. Pre-processing using Learnable Edge Collaborative Filtering

In this step, Learnable Edge Collaborative Filtering (LECF) [27] performs the data pre-processing utilized for the removal of noise and prevent data leakage from raw data. Based on the bipartite graph, LECF builds a line graph, and a binary edge function provides latent representation of node in. Next, using the biased random walk, LECF extracts a sub graph from l-hop neighborhood of node, determines significance weights of nodes in the sub graph regard to query edge. In order to represent an edge $g_{f(a,u)}$, it introduces binary function associated by user embedding mu, item embedding g_a, which is motivated by link prediction task and given in equation (1),

$$g_{f(a,u)} = k(g_a, g_u)\,. \tag{1}$$

Where, the binary function's objective is to use g_a and g_u to create an edge embedding $g_{f(a,u)}$. In specifics, it model a biased random walk of length l that begins at the line graph's query edge, e. Given that the d^{th} node in the walk is indicated by the notation the transition probability for the subsequent node, e_{d+1}, is expressed as in equation (2)

$$H(e_{d+1} \mid e_d) = \begin{Bmatrix} \dfrac{1-\lambda}{\left|F(h_f)\right|} & if\ e_{d+1} \in F(h_f) \\ \dfrac{\lambda}{\left|F(h_{f+1})\right|} & if\ e_{d+1} \in F(h_{f+1}) \end{Bmatrix} \tag{2}$$

Where $\left|F(h_f)\right|$ is the number of edges in $F(h_f)$, and $F(h_{f+1})$ is the set of edges in the bipartite graph that are associated to node v. It devalues the edges of high degree nodes by introducing the $F(h_{f+1})$ as they are typically the source of noise. Next, it use the observed edges' importance as the reaching probability and the formula is given in equation (3)

$$m_e^j(e') = \sum_{t \in T^l : e \to e'} H[t] \tag{3}$$

Where $H[t]$ is the probability of walk t and $T^l : e \to e'$ indicates set containing each walks of length j beginning e, ending e'. By this, the noise will be removed from the raw data and prevent data leakage and it undergoes classification process.

D. Classification using Temporal and Topological Embedding Deep Neural Network

The input data is fed to TTEDNN [28] to for classifying the eye track samples of the students as positive (+) and Negative (-). is discussed. A GCN layer, a batch normalisation (BN) layer, and a final layer make up each GC module in that order and an activation function using a rectified linear unit (ReLU). An undirected directed graph can be used to depict the GCN layer's structure. In the GCN layer, the renormalized adjacency matrix $\hat{Y}'$ is frequently employed in equation (4)

$$\hat{Y}' = \hat{G}^{-\frac{1}{2}}\hat{Y}\hat{G}^{-\frac{1}{2}} \tag{4}$$

Where $\hat{G}$ is the diagonal node degree matrix of thedata, $\hat{Y}'$ indicates the adjacency matrix with self-loop, and $\hat{G}_{u,v}$ is the identity matrix and it is denoted as in equation (5)

$$\hat{G}_{u,v} = \sum_{v} \hat{Y}_{u,v} \tag{5}$$

The operation of the u^{th} GC module is defined as in equation (6),

$$S^{u+1} = \mathrm{Re}\,LU\left(Ba\left(\hat{Y}'S^{u} M^{u} + y^{u}\right)\right) \tag{6}$$

where Ba is the batch normalisation function of the data; M^{u} is the network weight of the GCN layer; y^{u} indicates the bias; $\mathrm{Re}\,LU$ indicates the activation of the ReLU function; and S^{u} indicates the output of the datastates of the u^{th} GC module as well as the input of the datastates of the $(u+1)^{th}$ GC module. As a result, the TC module can consider all past data at a lower network depth. More specifically, for r th residual blocks, the dilated convolution operation $z(v)$ can be described as a 1D time sequence data a dilated transformation and it is given in equation (7)

$$z(v) = \sum_{u=0}^{s-1} z(u) a_{v-g_h \cdot u} \tag{7}$$

Where g_h indicates the dilation factor of the h^{th} residual block, k indicates the filter size, and $z(u)$ is the convolution filter of the data. As a result, the operation of h^{th} residual block is defined as in equation (8) as follows,

$$j^{h} = \mathrm{Re}\,LU\left(a^{h} + linor\left(z\left(a^{h}\right)\right)\right) \tag{8}$$

Where the layer normalisation approaches is indicated by $linor$, and the input and output of the h^{th} residual block are denoted by a^{h} and j^{h}, respectively. Finally, TTEDNN for classifying the eye track samples of the students as positive (+) and Negative (-). Due to its convenience, pertinence, AI-depend optimization approach is taken to account in TTEDNN classifier. The BBWOA is employed to enhance TTEDNN optimum parameter y^{u}, j^{h}. Here, BBWOA employed for tuning weight with bias parameter of TTEDNN.

E. Optimization using Binary Black Widow Optimization Algorithm

The weights parameter μ, γ proposed TTEDNN is enhanced using the proposed Binary Black Widow Optimization Algorithm (BBWOA) [29]. The search members typically travel locally during the exploitation phase, which is different from 169 exploration phase. The members have a tendency to abruptly migrate to some position in the search space during the exploration phase. The higher 171 number of offspring high possibility of exploring larger 172 search space. The process of cannibalism enables algorithm 173 to pass on improved parents to following generation, ensures 174 quick convergences to the closest ideal solution.

1) Stepwise procedure of BBWOA

The stepwise process defines to obtain ideal value of TTEDNN depend on BBWOA. BBWOA make equally distributing populace to enhance optimum parameter μ, γ of TTEDNN.

Step 1:Initialization

The BBWOA population is stochastically initialised as a matrix of potential binary black widow (A). The population vector lies between the optimisation problem's upper bound (U) and lower bound (L). It is initialized in equation (9) as follows,

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,d-1} & a_{1,d} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,d-11} & a_{1,d} \\ \vdots & \vdots & a_{u,v} & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,d-1} & a_{m,d} \end{bmatrix}, \tag{9}$$

Where, $a_{u,v}$ and m represent the number of black widow in a mound indicates where the v^{th} dimension of the u^{th} population. Figure 2 shows Flowchart of BBWOA for enhancingTTEDNN parameter

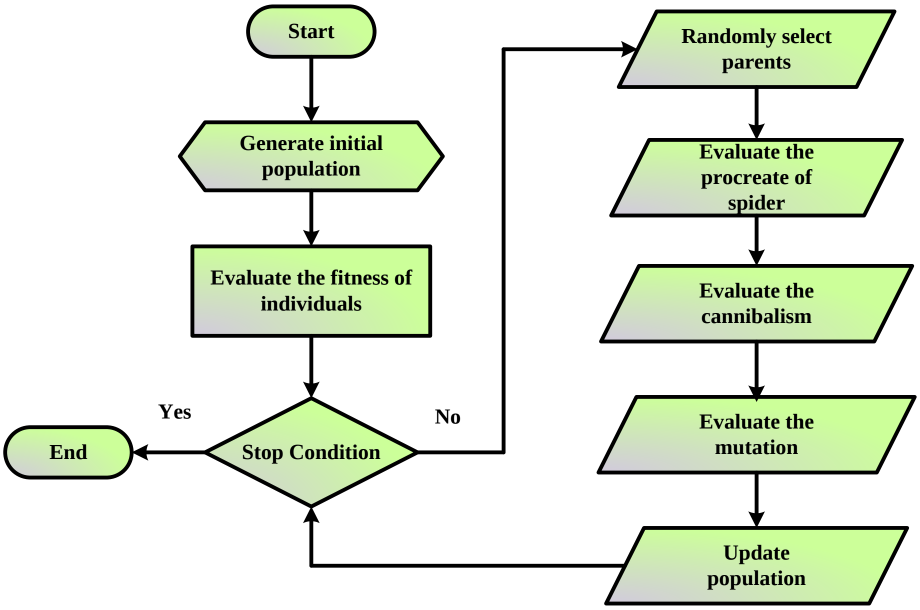

Figure 2: Flowchart of BBWOA for enhancingTTEDNN parameter

Step 2:Random Generation

Input parameter created at randomly. Best fitness value is depend upon their explicit hyper parameter situation.

Step 3:Fitness Function Estimation

Initialized assessments are utilized to create random solution. It is assessed by parameter optimization value for optimizing weight parameter μ,γ of classifier. It is shown in equation (10),

$$fitness \quad function = optimizing \quad (\mu,\gamma) \tag{10}$$

Step 4:Exploration Phase

Following that, two parents were chosen for the procreating stage based on the pre-established selection mechanism in accordance with the employed approach, i.e., rank selection for BBWO and randomization 267 for BBWO. For this phase in the regular BWO, randomization was used. The offspring 269 were generated by applying Equations (11)

$$\begin{Bmatrix} B_1^u = \nu \times a_1^u + (1-\nu) \times a_2^u \\ B_2^u = \nu \times a_2^u + (1-\nu) \times a_1^u \end{Bmatrix} \tag{11}$$

Where the value of the u^{th} bit of first, second offspring, respectively, are represented by B_1^u and B_2^u.

Step 5: Exploitation phase for optimizing μ,γ

The 182 reproductive process that male spiders are devoured by females, 183 is initiated and specified pairs of parents. Fitness values of the spiders used to determine genders. It is presumed that spider 186 is the female with the higher fitness value. It is given in equation (12),

$$\begin{Bmatrix} B_{1,2}^u = 1, & B_{1,2}^u > 0.5, \\ B_{1,2}^u = 0, & else \end{Bmatrix} \tag{12}$$

Where, $B_{1,2}^{u}$ are the offspring pair. Upon mutation, final candidates were preserved as novel population, upon unification, all populations numbered 310. 311 was the best member returned by population.

Step 6:Termination

The weight parameter values of generator μ, γ are segmentation Virtual Reality Technology for University English Culture Parenting enhanced by support of BBWO Algorithm, iteratively repeat until the halting conditions $A = A + 1$ .Then finally VRT-TTEDNN-BBWOA-UECP detects Virtual Reality Technology for University English Culture Parenting higher accuracy by lessening the recall.

IV. RESULT AND DISCUSSION

Experimental results of suggested technique are deliberated. The suggested method is implemented in python using stated performance indicators. TheVRT-TTEDNN-BBWOA-UECP method is executed in python. Obtained outcome ofVRT-TTEDNN-BBWOA-UECP approach is analyzed with existing systems likesVRT-CNN-SLA, VRT-KNN-IUEE, and VRT-GAN-PCMI.

A. Performance Measures

It is crucial step for selecting optimal classifier. It evaluated to assess performance, comprising accuracy, recall, computation time, error rate, precision, F1-Score and ROC. To scale the performance metrics, performance metric is deemed. To scale performance metric, True Negative, True Positive, False Negative, False Positive samples are needed.

- TN: Presents number of samples which correctly predicted as negative.
- TP: Presents number of samples values which correctly predicted as positive.
- FP: Presents number of positive samples which incorrectly predicted as positive.
- FN: Presents number of samples which incorrectly predicted as negative

1) Accuracy

It scales proportion of samples (positives, negatives) besides total samples. It calculated using equation (13).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

2) Precision

It is one indicator of ML method's performance quality of positive forecasts made by method. It signifies to number of true positives divided by total positive forecasts as given in equation (14).

$$\Pr ecision = \frac{TP}{TP + FP} \tag{14}$$

3) Recall

It also known as true positive rate, is percentage of data samples that ML method correctly detects as belonging to class of interest. It calculated using equation (15).

$$\operatorname{Re} call = \frac{TP}{TP + FN} \tag{15}$$

4) F1-Score

It is a metric used to evaluate performance of ML technique. It combines precision, recall into single score as given in equation (16).

$$F1 - Score = 2 * \frac{precision * recall}{precision + recall} \tag{16}$$

5) Computational time

The time complexity only scales process's execution time dependent on algorithm, its inputs. It refers time required to execute algorithm. It is given in equation (17)

$$CPU\ Time = {IC * CPI} \big/ {Clockrate} \tag{17}$$

6) Error rate

It is simply one minus accuracy. The accuracy of a method is 90%, it would be 10%. It is given in equation (18)

$$Error\ Rate = 1 - \frac{FP + FN}{TP + TN + FP + FN} \tag{18}$$

7) ROC

It is ratio of false negative to true positive area. It is given in equation (19)

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \tag{19}$$

B. Performance Analysis

Figure 3 to 10 portrays simulation outcomes of VRT-TTEDNN-BBWOA-UECP method. Then, VRT-TTEDNN-BBWOA-UECP method is evaluated to existing techniques likes VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-PCMI.

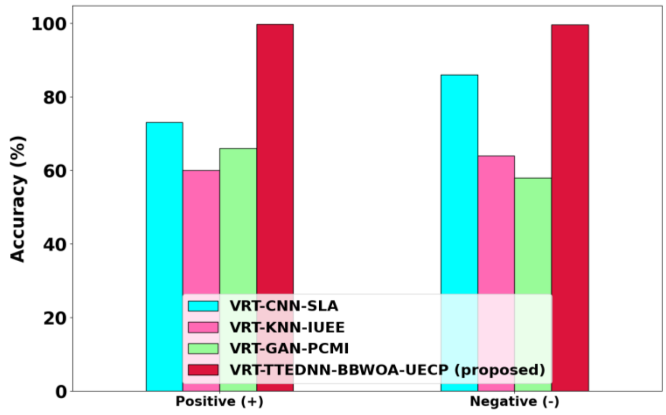

Figure 3: Accuracy analysis

Figure 3 determines accuracy analysis. TheVRT-TTEDNN-BBWOA-UECP attains 25.9%, 14.64%, and 23.6%higher accuracy for Positive (+); 31.4%, 23.79% and 24.75% higher accuracy for Negative (-) analyzed with existing VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFTmethods.

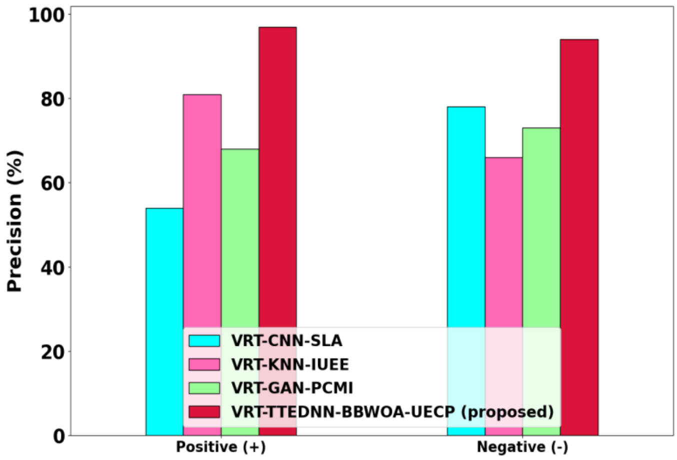

Figure 4: Precision analysis

Figure 4 demonstrates precision analysis. The VRT-TTEDNN-BBWOA-UECP attains 25.64%, 26% and 27.5 greater precision for positive (+); 28.4%, 29.79%, 20.75% greater Precision of Negative (-) analyzed with existing VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFTmethods.

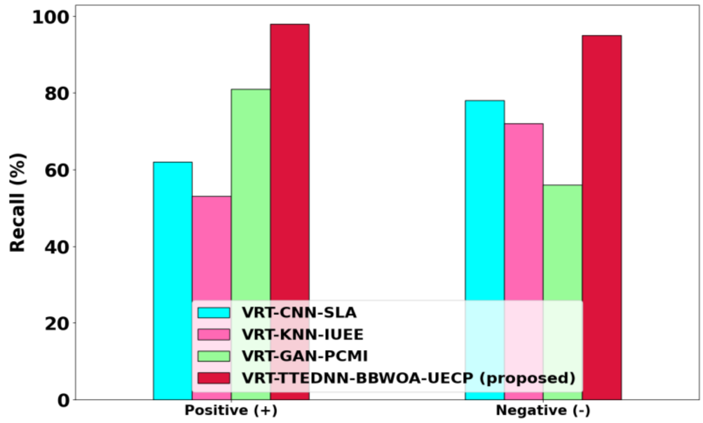

Figure 5: Recall analysis

Figure 5 demonstrates recall analysis. The VRT-TTEDNN-BBWOA-UECP attains 25.20%, 26.21% and 27.22% higher Recall for Positive (+);9.98%, 10.98%, 5.65% higher recall for Negative (-) evaluated with existing VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFTmethods.

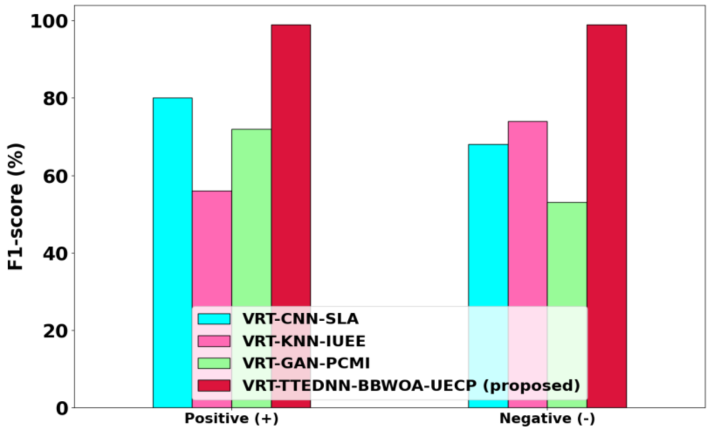

Figure 6: F1-score analysis

Figure 6 demonstrates FI-score analysis. The VRT-TTEDNN-BBWOA-UECP attains 29.20%, 16.21% and 17.22% higher F-1 score for Positive (+); 18.23%, 19.24%, 10.25% greater F1-score for Negative (-) analysed with existing VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFT methods.

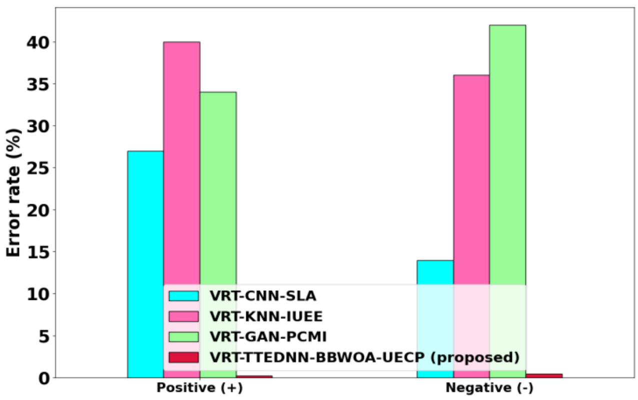

Figure 7: Error rate analysis

Figure 7 portrays error rate analysis. The VRT-TTEDNN-BBWOA-UECP attains 21%, 14.8% and 17.33% lower error rate for Positive (+); 17.75%, 24.55% and 12.66% lower error rate for Negative (-); analyzed with existing technique likes VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFT.

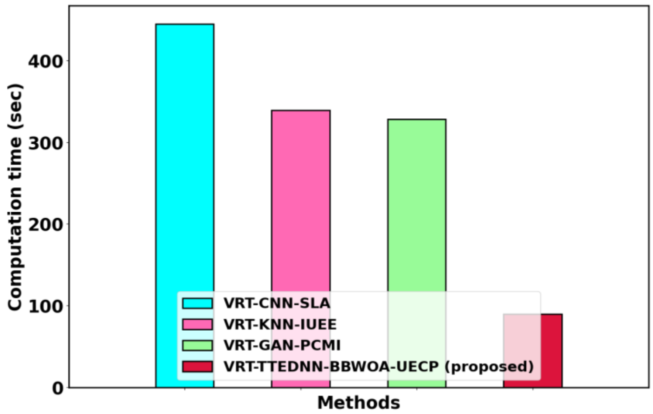

Figure 8: Computation time analysis

Figure 8 portrays computation time analysis. The VRT-TTEDNN-BBWOA-UECP method attains 21.3%, 25.1% and 22.3% lesser computation time analyzed with existing method such as VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFT.

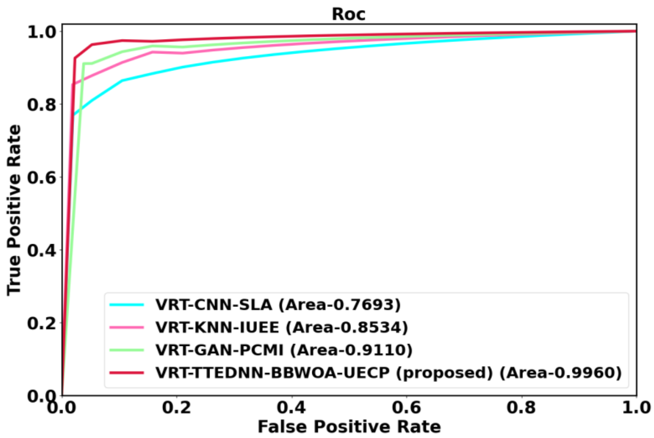

Figure 9: ROC analysis

Figure 9 depicts RoC analysis. The VRT-TTEDNN-BBWOA-UECP method attains 15.20%, 20.21% and 10.22% higher ROC than existing VRT-CNN-SLA, VRT-KNN-IUEE and VRT-GAN-SVM-SFT methods.

C. Discussion

A novel VRT-TTEDNN-BBWOA-UECP model for classifying the eye track samples of the students as positive (+) and Negative (-) from English language content databaseis developed in this paper**.** The communication within a virtual environment Distance and time do not impede learning, as all students engage in conversation through virtual personas. Learners are free and equal during the virtual interaction process, and the relationship that is created is also virtual. They can talk openly and more easily in this setting when it comes to experience learning and expressing their actual ideas. Learners obtain realistic experience, achieve superior learning outcomes through several means, such as interactive learning in a virtual laboratory, historical, cultural experience in a virtual setting, or experience perception in virtual environment.

V. CONCLUSION

In this section, Virtual Reality Technology for University English Culture Parenting (VRT-TTEDNN-BBWOA-UECP) is successfully implemented. The proposed VRT-TTEDNN-BBWOA-UECPmethod is executed in python. The performance of VRT-TTEDNN-BBWOA-UECP approach contains 25.9%, 14.64%, and 23.6%

high accuracy; 9.98%, 10.98%, 5.65% higher recall analyzed with existing techniques likesVRT-CNN-SLA, VRT-KNN-IUEE,VRT-GAN-SVM-SFT methods respectively.

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