Investigation on the use of Virtual Reality in the Teaching of Engineering Education Based on Functional Linked Neural Network

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Abstract: Contemporary teaching mode principally uses the tools of information technology to achieve the natural integration of information technology, education and teaching. Digital instructional resources are impacting the traditional classroom. Although research on applying Virtual Reality (VR) technology to engineering education remains in its theoretical stages, lacking practical application strategies and plans, the integration of VR with physical education has been a popular trend recently. This paper examines the purpose of VR technology in teaching engineering. The examination architecture on use of VR in the Teaching of Engineering Education based on Functional Linked Neural Network (VR-TEE-FLNN) is proposed. Initially, the data is gathered from student dataset. The control group is instructed using traditional teaching. Deep learning basis Virtual Reality assisted teaching is provided to study the group under Functional Linked Neural Network. In general, FLNN classifier does not adopt any optimization method to define the optimal parameters, in order to achieve the accurate student groups. Therefore, Quantum Henry Gas Solubility Optimization is employed to optimize Functional Linked Neural Network, which accurately classifies the student groups. The statistical analysis is performed by students t-test, logistic regression analysis, and analysis of variance (ANOVA). The metrics, like precision, recall, accuracy, F1-score, specificity, ROC, computational time are analyzed. The proposed VR-TEE-FLNN achieves a greater accuracy of 16.65%, 18.85%, 16.45% and a greater F1-score of 16.34%, 12.23%, 19.12%, when compared to the existing methods, like Deep learning in English Education Blended Teaching under Virtual Reality (DL-EEBT-VR), Combining Real-world in Deep Neural Network of Virtual Reality Biometrics (CRW-DNN-VRB), Virtual Reality based on Chemical and Biochemical Engineering Education Training (VR-CBE-ET), respectively.

Keywords: Functional Linked Neural Network, Virtual Reality, Quantum Henry Gas Solubility Optimization.

1. Introduction

Nowadays, Virtual Reality (VR) technology undergone significant transformations and has simplified its form, while gaining new features and capabilities (Juan, 2021; Porcino et al., 2022). It is now also used for teaching purposes across a variety of academic disciplines (Cho et al., 2020; Delgado et al., 2020). The delivery and experiences of instructional information across several educational sectors have been revolutionized by VR applications (Almarzouqi, Aburayya & Salloum, 2022). By exploring geographical areas portrayed in VR, the students experience and learn about near and far locations without leaving classroom and, in some cases, without ever leaving their homes (Gandedkar, Wong & Darendeliler, 2021). Students cooperate with environment and experience content present on the scene in contrast with video depictions of the same learning material (Villena Taranilla et al., 2022; Pandit et al., 2023). Instructional VR is used in medical science education to enable safe, close-to-real-life medical trials, so that students are not taught unsafe or expensive to maintain technical skills (Sood & Rawat, 2022, Liu, Sathishkumar & Manickam, 2022). Many students find abstract technical topics difficult to understand and too theoretical to relate to (Zhang, Ren & Lu, 2022; Munawar et al., 2022). Such students can find it difficult to create cohesive mental representations of abstract engineering concepts, which prevent them from conceptually understanding those concepts. VR learning environments can be extremely helpful in assisting students when understanding this type of materials (Rzanova et al., 2023; Riva, 2002). Multisensory signals in VR have been suggested as a way to enhance learners' engagement in electrical engineering tasks in a Virtual Reality-Based Learning Environment (VRLE) (Cinar et al., 2023; Lavanya et al., 2023). These applications include those for conceptual understanding, problem-solving, skill training.

To ensure the continual progress of the pedagogical process, it is important to be actively involved in the development, evaluation and correction of techniques. Education that prioritizes the growth of the masses of students and their interest is more effective than the typical lecture model. The goal of ability building is to assist students in developing their capacity for learning, thinking, and acting. Teachers who flip their classrooms have a deeper understanding of their students' learning circumstances.

This research fills critical gaps in engineering education by innovatively integrating Virtual Reality technology with Functional Linked Neural Network (FLNN) architecture, optimizing

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the model using Quantum Henry Gas Solubility Optimization (QHGSO), and leveraging a student dataset for real-world applicability. The comprehensive analysis of performance metrics and comparison with existing models offer valuable insights into the effectiveness and efficiency of the proposed VR-TEE-FLNN approach, contributing significantly to the advancement of VR-based education in engineering.

- The primary contributions of this paper are summarized below:
- Investigation on the use of VR-TEE-FLNN is proposed;
- The student dataset is used as the source of the input data, which is divided into 2 groups: 1) study group, 2) control group;
- The control group receives typical teaching, the experimental group receives FLNN (Xie et al., 2022) based VR education optimized by QHGSO (Mohammadi et al., 2021);
- For statistical analysis, students' t-tests, regression analyses, ANOVA are utilized;
- The performance metrics, including accuracy, recall, specificity, F1-score, ROC, and computational time is analyzed. This analysis confirms the effectiveness of the model;
- The efficiency of the VR-TEE-FLNN is compared with that of the existing models, such as DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET.

Remaining paper is organized as: Section 2 portrays the literature review, section 3 designates about the proposed method, section 4 demonstrates the results, finally, section 5 presents the conclusion.

2. Literature Review

Many researches have been suggested in the literature to categorize Virtual Reality in engineering education utilizing deep learning; some recent works are revised here.

HanLiang & LiNa (2022) presented deep learning based on big data analytics with the purpose of examining the use of VR on flipped learning of Taijiquan martial arts. The authors presented the manner in which VR technology based on deep learning algorithms was used in martial arts instruction. After gathering the student dataset, the pupils were divided in 2 groups: study and control. The study group receives deep learning-based VR-assisted training, whereas the control group receives typical teaching. These lessons were delivered utilizing Deep Binary Hashed CNN. The students' t-tests, logistic regression analysis, ANOVA were used for statistical analysis. It obtained high accuracy with low F1-score.

Wu & Qiu (2022) presented deep learning exploration for English blended teaching in VR. Their paper provided an extensive study on deep learning and VR technology and developed a learning method for engineering learning environments based on VR. For the most part, the lack of motivation comes as a result of the lack of interactive course material necessary for a good visualization of the concept through student interaction in the classroom. It was investigated, through experimental research, if a Virtual Reality-based learning environment could support deep learning. It provided high accuracy with low F1-score.

Miller, Banerjee & Banerjee (2022) suggested the Conjoining real-world constraints on user behavior through deep neural networks in VR biometrics. Combination displacement vectors, which are the input data for neural networks, define the spatial interactions between device pairings as well as the device-centric, translation- and scale-invariant position and orientation features. The method undertook worldwide data normalization and utilized the raw data directly. It provided high F1-score with low precision.

Halabi (2020) presented Immersive Virtual Reality to enforce teaching in engineering education. VR and PBL (project-based learning) were combined to create a self-directed product design. An implementation process that employed 3D software and an immersive Virtual Reality CAVE display were also combined to assess the design. It was hypothesized that using Virtual Reality in conjunction with a project-based learning strategy would improve students' achievement of course learning objectives, foster better communication, and make it easier to achieve desired goals in the engineering design project. The research findings indicated that the distribution of cumulative project grades was greatly impacted by the VR technique. The grade of students' project improved, especially for the implementation area. Additionally, the VR technique yielded improved course outcomes linked to project design. The presented study provided better accuracy with low precision.

Soliman et al. (2021) presented the application of Virtual Reality in engineering education. VR was a better tool for engineering learning. The review concluded that VR contains good cognitive and pedagogical effects in engineering teaching, which eventually enhance pupils' performance and grades, their overall educational experience, and their comprehension of the material. The university or other organization can also benefit from reduced responsibilities, infrastructure costs, and expenses by substituting Virtual Reality (VR) for real laboratories. Students with specific needs and distance learners, who might not have access to physical laboratories, can also benefit from equal educational opportunities. Moreover, current evaluations have shown that learning theories and objectives are not integrated into the design of VR apps for education. It provided high F1-score with low precision.

Kaur, Mantri & Horan (2020) presented Enhancing student motivation under augmented reality. To maximize the learning effect, it was crucial to augment theoretical notions with technological introductions. In several fields, despite having a theoretical understanding of the basics, students were unable to apply their knowledge in practical ways. It was mostly linked to a lack of enthusiasm caused by the lack of interactive course materials, which was necessary for helping students visualize the topics through active participation in the classroom. Consequently, individuals who struggled to understand the material presented by conventional learning methods were unable to gain a comprehension of the concepts. If teachers provide their students with the resources they need to envision and interact with the subject being taught in the classroom, it will boost their drive to learn. As a visualization tool, augmented reality can be used in educational contexts to achieve this objective. It concentrated on how augmented reality may be utilised to enhance interactive learning in various engineering education domains and how stimulate students' enthusiasm in classroom settings. It reached a greater learning rate, but lower accuracy.

Kumar et al. (2021) introduced Virtual Reality in chemical as well as in biochemical engineering teaching and addressed the benefits and drawbacks of integrating Virtual Reality into the training process, with a focus on the core areas of socioeconomics, pedagogy, and technology. To create sophisticated immersive learning applications, the study highlighted the requirement of enhancing Virtual Reality interfaces with mathematical models. The reports emphasize the requirement for innovative educational impact assessment models to assess Virtual Reality-based learning. Lastly, a current case study application was given to outline the social with economic ramifications and pinpoint the obstacles preventing Virtual Reality tools from being widely used in chemical and biochemical engineering education. It provided greater achievement rate with lower learning efficiency.

Enzai et al. (2021) suggested augmented reality (AR) development for new teaching in the education of engineering. Using the Assemblr application, AR was developed in accordance with the system development methodology. Selected instructors were provided the produced AR system so that their knowledge and ability to use the system could be assessed. A questionnaire survey was used to collect the replies from the instructors, and the results were examined. The feedback was considered to improve the AR system, and more testing was conducted concurrently with the development process. Later, the completed prototype was used in actual classroom settings. It reached greater accuracy, but a reduced achievement rate.

3. Proposed Methodology

This section discusses about the proposed VR-TEE-FLNN. The control and the study group consist of two sets of students. The control group is given conventional instruction. The study group is given FLNN. Students' t-tests, regression analysis, variance analysis are used in statistical analysis. The block diagram of the proposed VR-TEE-FLNN is depicted in Figure 1. The explanation of each stage is described below.

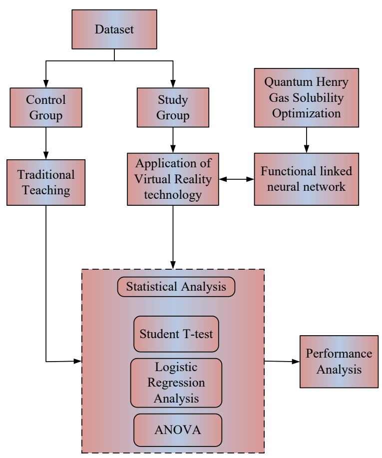

Figure 1. Block diagram for proposed VR-TEE-FLNN methodology

3.1 Student Dataset

The Nankai University in Tianjin, China, provides the student data. Online study platforms are used to register students, and groups have been created for the remote learning component of the upcoming semester.

3.1.1 Splitting of Groups

The collected data is divided into 2 groups: (i) control, (ii) study. The control group includes 3522 contestants, it offers students traditional instruction, while the study group has 3700 participants, it uses FLNN to deliver FLNN-based VR instruction.

3.2 Traditional Teaching

Normally, pupils try to take notes as the teacher speaks. Thus, instead of paying attention to the information of the courses, they focus their efforts on writing. The teacher's instructions to pause and reflect on lecture cause students to overlook some important details. Students have more control over their learning when using prepared resources like movies, since they may pause, rewind, skip a part of the course that doesn't interest them. The courses are utilised regularly by anyone studying English as a second language. The capacity of pupils to assist one another learn and collaborate is improved. In a classroom, activities including different levels of skill are facilitated by socialization, practical exercises, teamwork, and cultural variety that collaborative learning projects may also foster.

3.3 Application of Virtual Reality Technology

New VR technology combines graphics, sensor technology, technologies using artificial intelligence. The user interacts with a dynamic, three-dimensional scene that is created by the computer simulation system; this scene has inherent cooperative and theoretic aspects because of the user's dependency. Multimodal input can be obtained through the senses of sight, sound and touch. The demands of differentiated education can be satisfied by using the deep learning algorithm to create interactive teaching activities, but instructors' capacity to perform their duties is also improved. Depending on the features of the classroom, learning activities in an interactive Virtual Reality classroom can be divided into two groups: activities that take place inside and outside the classroom. Real-world environments are converted to three-dimensional immersive learning environments that blend the physical and digital worlds through VR technology. Flipped classrooms give teachers the freedom for collaborative learning events inside as well as outside of the typical classroom when providing course material. By examining data gatherings of certain learners and identifying useful learning patterns, intelligent learning environments create innovative methods of learning. These techniques provide advices and ideas to students throughout time, perhaps during their future employment.

3.4 Classification using Functional Linked Neural Network

This subsection discusses the student groups utilizing FLNN. FLNN has a single layer of architecture, is an illustration of an ANN. This architecture aims to overcome FLNN's several layer weaknesses and complexity. A neural-based paradigm with many practical applications is also known as FLNN. Functional expansion, estimation, and adaptation are the three processes that comprise an FLNN. Consequently, in the first phase, functional expansions, the input values are transferred to higher dimensions via expansion units. They are then utilized as extra inputs for the network. The next phase uses their sum as the output layer to estimate additional inputs through functional expansions. The functional expansion is described in equation (1):

$$M_r(y) = \left(\frac{1}{6}(-y^3 + 9y^2 - 18y + 6)\right) \tag{1}$$

where M_r denotes multilayer network, y represents the Legendre polynomials. The input data depend on least mean square process and network's weights are modified using error.

The functional estimation is described in equation (2):

$$B_r(y) = \frac{1}{2}\left(5y^3 - 3y\right) \tag{2}$$

Where B_r signifies hyper plane generated by the network; when the networks were trained using met heuristic algorithms rather than gradient techniques, initial weights had no influence on the neural networks.

The functional adaptive network is described in equation (3):

$$D_r(y) = 4y^3 - 3y \tag{3}$$

where D_r represents the network output layer.

The determination coefficient is described in equation (4):

$$\beta = \frac{1}{m}\sum_{j=1}^{m}\left| X_{i\_K} - \hat{X}_{i\_K} \right| \tag{4}$$

where m signifies complete network layer, $\hat{X}_{i-K}$ indicates i^{th} actual deflection value, represents the average of deflection values in real life.

Finally, FLNN model analyses the student groups. The optimization approach is considered in FLNN classifier owing to its convenience, pertinence and comprehensive structure. QHGSO is employed to optimize the FLNN parameter β. QHGSO is used for tuning weight with bias parameter of FLNN.

3.4.1 Stepwise process for Quantum Henry Gas Solubility Optimization

Here the procedure of using QHGSO in order to achieve the best FLNN values is described step-by-step. First, QHGSO creates a population with a uniform distribution in order to optimize the FLNN parameters. QHGSO is employed to enhance the better option.

Step 1: Initialization

The weight parameter of β generator from the spatial temporal synchronous graph transformer network is used to initialize the population of quantum Henry Gas Solubility Optimization. The primary population of gases and locations are expressed in equation (5):

$$D_i(h+1) = D_{\min} + t \times (D_{\max} - D_{\min}) \tag{5}$$

where D_{max}, D_{min} denote the problem bounds, D_i denotes the positioning of i^{th} gas in populace, t as random number within the range [0,1] and h displays iteration.

Step 2: Random Generation

The intensity of the light source is thought to have an impact on the Quantum Henrys Gas Solubility Optimization during random creation. The updating procedure of Henry's coefficient is exhibited in equation (6):

$$X_j(h+1) = X_j(h) \times s^{\left(-e_j\left(\frac{1}{H(h)} - \frac{1}{H^{\phi}}\right)\right)} \tag{6}$$

where X_j signifies Henrys Constant Value, s signifies sectorial pressure of every gas and h signifies iteration. Figure 2 shows the Flowchart for QHGSO for enhancing the FLNN Parameter.

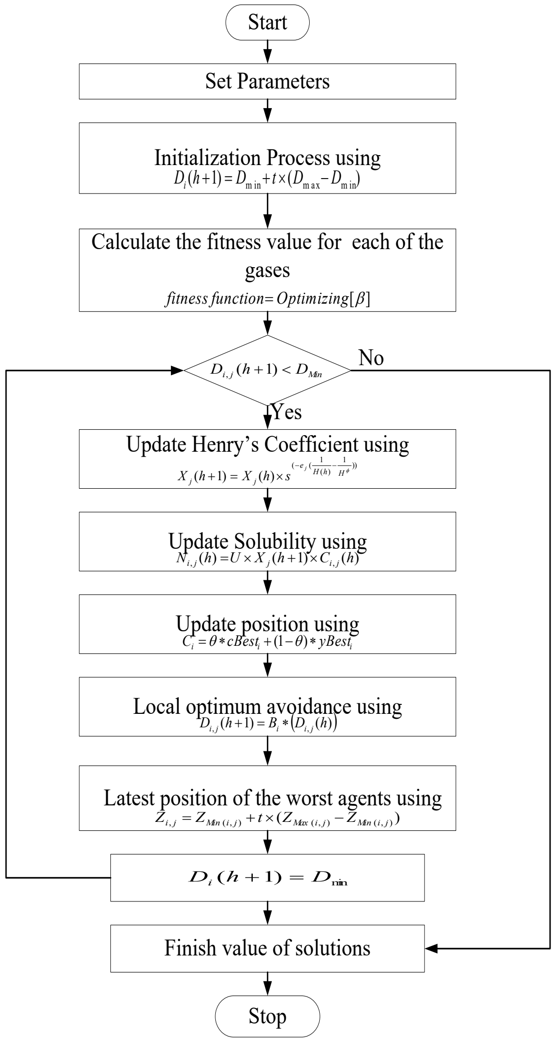

Figure 2. Flowchart for QHGSO for optimizing FLNN Parameter

Step 3: Fitness Function

The initialized assessments generate the random solution. The fitness evaluation functions considering the results of parameter optimization for the generator's weight parameter β. Thus, it is expressed in equation (7):

$$fitness\ function = Optimizing\ [\beta] \tag{7}$$

Step 4: Exploration phase

After successfully determining a new orientation, the quantum formula performs better when using the QHGSO's ability to generate a variety of numbers to explore search space rather than random numbers. Thus, the formula is expressed in equation (8):

$$N_{i,j}(h) = U \times X_j(h+1) \times C_{i,j}(h) \tag{8}$$

where $N_{i,j}$ represents gas population, U represents fixed value X_j indicates the Henry's constant value, $C_{i,j}$ denotes contraction expansion coefficient.

Step 5: Exploitation phase to optimize β

This is the last phase, in which a safety tester exploits safety holes in the system being tested.

QHGSO's exploitation phase is expressed in equation (9):

$$C_i = \theta * cBest_i + (1-\theta) * yBest_i \tag{9}$$

where C_i presents local attractor, $Best_i$ depicts the greatest position of i^{th} that gas has attained and the ideal position for every gas at iteration represented by $yBest_i$.

The local optimum avoidance in expressed in equation (10):

$$D_{i,j}(h+1) = B_i * \left(D_{i,j}(h)\right) \tag{10}$$

where $D_{i,j}$ displays the location of i^{th} gas in the population, B_i indicates the random number in the optimum position.

Then the latest position of the worst agents is expressed in equation (11):

$$Z_{i,j} = Z_{Min(i,j)} + t \times (Z_{Max(i,j)} - Z_{Min(i,j)}) \tag{11}$$

where $Z_{i,j}$ represents every gas status i on group j uniformly distributing within the range [0,1], $Z_{Min(i,j)}$ and $Z_{Max(i,j)}$ epitomizes algorithm bounds.

Step 6: Termination

Weight parameter β from Functional Linked Neural Network is optimized under QHGSO, the procedures will be repeated until the position information $D_{i,j} = D_{min}$ is satisfied.

3.5 Statistical Analysis

The following three procedures are employed here.

3.5.1 Student's t-Test

The idea that there is no difference between the three groups is supported by the results of the student's t-test. It can be applied in various situations.

The certain group mean is described in equation (12):

$$L = \frac{N-p}{H1} \tag{12}$$

where N denotes sample mean, p represents population mean, $H1$ signifies standard mean error.

The determination of data is described in equation (13):

$$Q = \frac{N_1 - N_2}{H1_{X_1 - N_2}} \tag{13}$$

where $N_1 - N_2$ indicates the distinction. Using t-test, component variation is assessed. The t-test makes use of variance percentage.

3.5.2 Logistic Regression Analysis

The framework known as "proportional" odds is a typical logistic design. The polychromous logistic regression technique is used, but is does not influence data categorization. Utilizing cumulative possibilities, cumulative odds, and cumulative logics is one manner to account for the sorting.

The sorted group is described in equation (14):

$$W(A \le i) = w_1 + ... + w_i \tag{14}$$

where W signifies cumulative possibility, i represents the term of intercepts. An essential type of ordinal variable is discovered by examined.

3.5.3 ANOVA Test

A statistical method called ANOVA is used to divide total variability reports into more adaptable categories for use in subsequent investigations. When three or more databases are available, a single route ANOVA is used to scale the correlation among the variables.

The parameters are described in equation (15):

$$K = \frac{MR}{MR_{error}} \tag{15}$$

where K represents the least square and indicates the identical variance.

Then finally VR-TEE-FLNN identifies the student group's modules with better accuracy by reducing computational time without error.

4. Result and Discussion

This segment discusses the experimental outcomes of the VR-TEE-FLNN approach. The VR-TEE-FLNN approach is tested in Python simulation with the mentioned metrics. The method proposed for investigating the use of VR-TEE-FLNN is compared to existing approaches like DL-EEBT-VR (Wu & Qiu, 2022), CRW-DNN-VRB (Miller, Banerjee & Banerjee, 2022) and VR-CBE-ET (Kumar, Mantri & Dutta, 2021), respectively.

4.1 Performance Measures

The following metrics are used to validate the efficiency of the VR-TEE-FLNN method. The acquired outcomes are compared with those of the existing methods.

4.1.1 Accuracy

Accuracy shows how accurately the classification is performed and it is given by the equation (16):

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

where TP signifies True Positive, TN denotes True Negative, FP signifies False Positive, FN denotes False Negative.

4.1.2 Precision

Precision calculates a count of true negatives divided by a count of true negatives plus false positives using equation (17):

$$precision = \frac{TN}{FP + TN} \tag{17}$$

4.1.3 Specificity

Specificity estimates the proportion of negative samples through equation (18):

$$specificity = \frac{TP}{FN + TP} \tag{18}$$

4.1.4 Sensitivity

Sensitivity finds the proportion of positive samples and it is given by equation (19):

$$sensitivity = \frac{TN}{TN + FN} \tag{19}$$

4.1.5 F1 Score

It is computed by equation (20):

$$F1\ score = \frac{TN}{TP + \frac{1}{2}\left[FP + FN\right]} \tag{20}$$

4.1.6 ROC

It is the rate of false negative to the true positive area and is given in equation (21):

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \tag{21}$$

4.2 Performance Analysis

Figures 3-13 depicts the simulation results of VR-TEE-FLNN method. Then, the proposed VR-TEE-FLNN is analyzed with existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET models.

Figure 3 illustrates the precision analysis. The proposed approach reaches a more extensive analysis of the student groups and has a higher precision than the of the existing methods, due to its wider consideration of factors. The proposed VR-TEE-FLNN method attains a higher precision of 0.56%, 21.76%, and 20.67% when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET models, respectively.

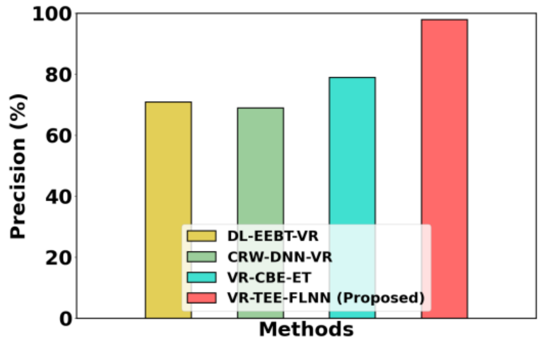

Figure 3. Performance analysis of precision

Figure 4 depicts the comparison of F1-score between the method proposed in this paper and the existing methods. In order to demonstrate how F1 measure of the suggested method is higher, direct comparison is provided here. By taking into consideration a larger range of parameters, the suggested method has a greater F1-score than those of the earlier methods and allows for a more thorough study of the student group. The proposed VR-TEE-FLNN method attains a higher F1-score of 22.56%, 21.76% and 19.67% when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET methods, respectively.

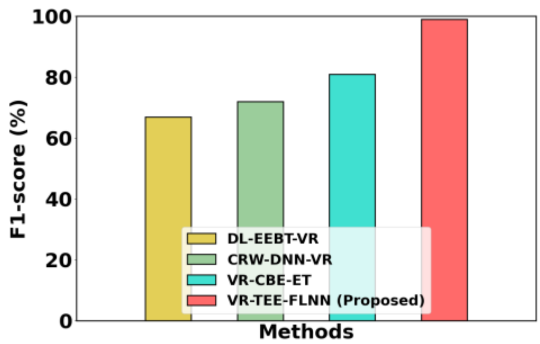

Figure 4. Performance analysis of F1-score

Figure 5 depicts sensitivity analysis. The suggested performance shows that the system can accurately identify cancerous breast masses with a sensitivity of up to 98%. The proposed VR-TEE-FLNN method attains a higher sensitivity of 30.56%, 21.76%, and 20.67%, when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET models, respectively.

Figure 6 portrays the specificity analysis. The VR-TEE-FLNN attains a higher specificity of 20.53%, 23.34%, and 18.64% when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET models, respectively.

Figure 7 represents computation time analysis. The proposed VR-TEE-FLNN method attains a lower computational time of 10.11%, 10.26% and 11.20%, when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET methods, respectively.

Figure 8 depicts ROC analysis. The proposed VR-TEE-FLNN attains a higher ROC value of 3.49%, 6.45% and 6.78%, when compared to the existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET methods, respectively.

The "learning efficiency" is the correlation among learner's perceived mental effort (PME) and the value of the performance outcome. Figure 9 displays the comparison between learning efficiencies. In this figure, the existing DL-EEBT-VR has 75%, CRW-DNN-VRB has 65%, VR-CBE-ET has 84% learning efficiency, while the proposed VR-TEE-FLNN has 96% learning efficiency.

Figure 10 shows the accuracy analysis. Here, the exiting DL-EEBT-VR has 55%, CRW-DNN-VRB has 88%, VR-CBE-ET has 66% accuracy, while the proposed VR-TEE-FLNN has 98% accuracy.

Figure 11 depicts achievement improvement rate analysis. Here, the existing DL-EEBT-VR attains 85%, CRW-DNN-VRB attains 66%, and VR-CBE-ET attains 75% achievement improvement rate, while the proposed VR-TEE-FLNN attains a better achievement improvement of 94%.

Students studying with sentimental frankness are proven to be educators by their involvement with the topic and readiness to learn, but only if they have been appropriately motivated to do so. Self-confidence is the confidence in one's own capacity to complete a task, whereas

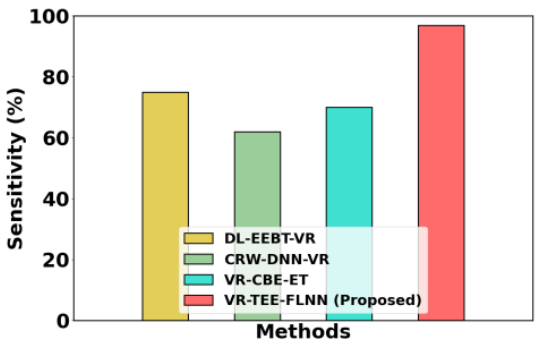

Figure 5. Performance analysis of sensitivity

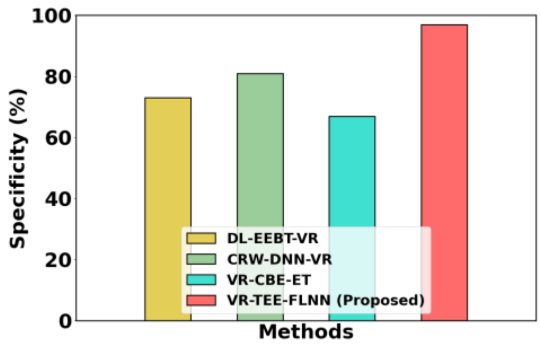

Figure 6. Performance analysis of specificity

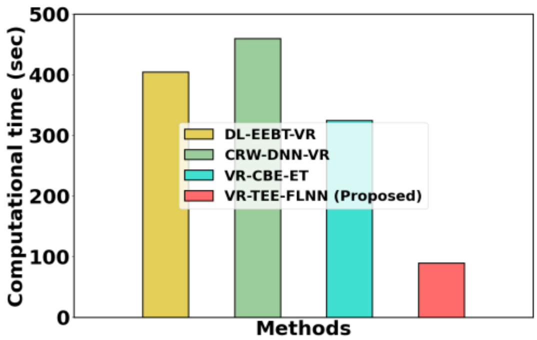

Figure 7. Computational time analysis

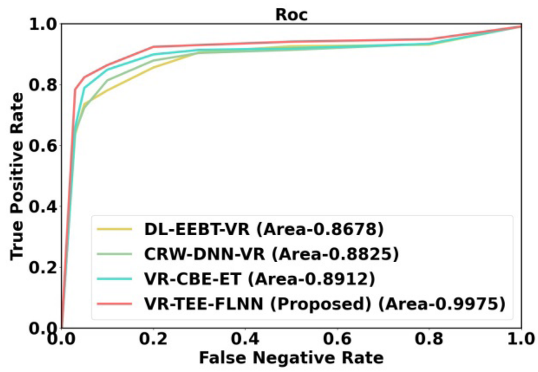

Figure 8. ROC analysis

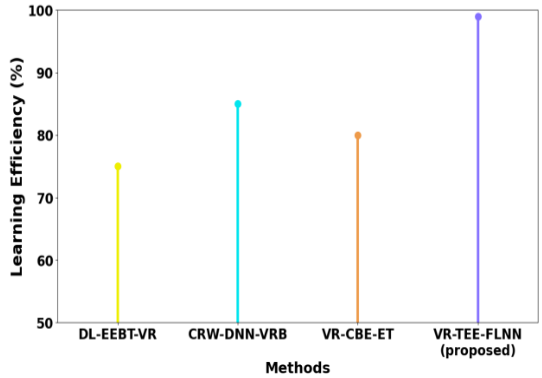

Figure 9. Learning efficiency

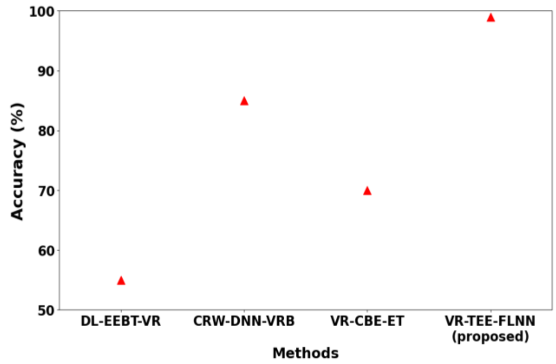

Figure 10. Accuracy analysis

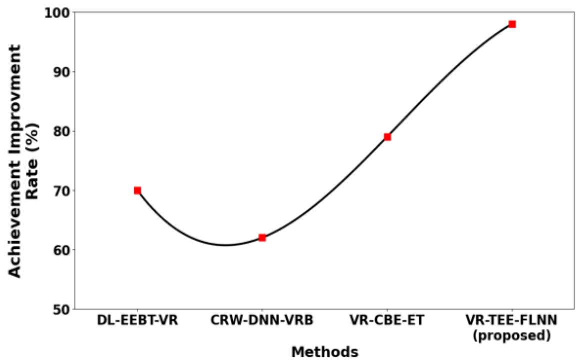

Figure 11. Achievement improvement rate analysis

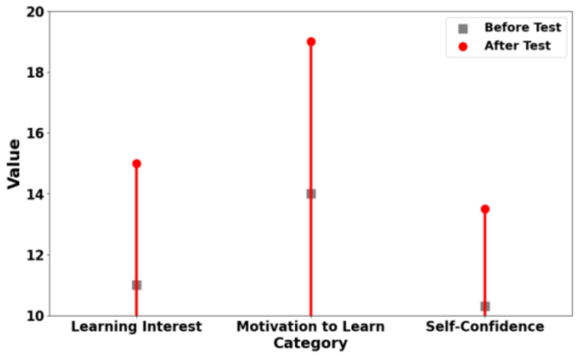

Figure 12. Comparative evaluation of the affection and attitude markers of two student groups both before and after the experiment

learning motivation is the internal desire to support and motivate oneself towards academic success. Figure 12 displays the output of primary statistical analysis for emotional disposition test markers of pupils group when learning.

Compared to pupils in the control group, individuals in the experimental group exhibited greater zeal, ambition, and self-assurance in their capacity to study engineering. Since the investigational group pupils were VR headset prior to class, they gained access to a novel educational opportunity.

In Figure 13, five feasible levels of agreement (robust agree, agree, somewhat agree, uncertain, disagree) are epitomized through A, B, C, D, E. As per the survey, students are open to the idea of using Virtual Reality in engineering instruction, because the stereoscopic rotation makes it possible to watch the movie from any direction and from any angle.

VR may enhance students' ability to observe and analyze actions as well as help them correct faulty movements more completely, based on proper comprehension and identification, all while offering them a more interesting learning environment. It is a helpful addition to the curriculum for students learning. It alters the way that children learn, while encouraging greater autonomy as well as curiosity inside the classroom. But all students not feel comfort using this approach.

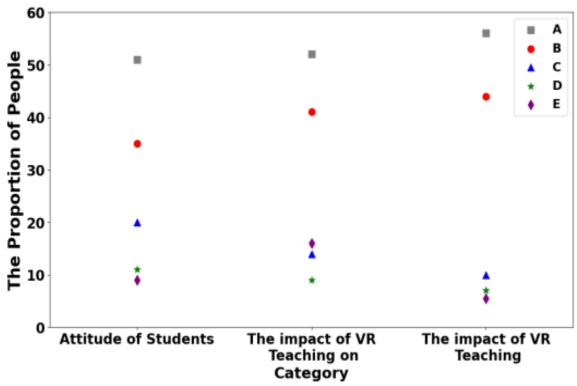

Figure 13. VR technology cognition with application

4.3 Discussion

A novel VR-TEE-FLNN model to detect the student groups classification is used in this paper, based on a student dataset. The VR-TEE-FLNN model involves FLNN based classification. Finally, the FLNN performs the classification that detects the student groups. In the student dataset, the average highest outcomes are compared with existing DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET models respectively. The accuracy values of DL-EEBT-VR, CRW-DNN-VR, and VR-CBE-ET are 87.5%, 82.6% and 85.4% respectively, represent lower values than those of the proposed method. The suggested framework achieves an average accuracy of 99.94%, compared to the accuracy of 86.95% of the other approaches. Similar to this, the specificity of VR-TEE-FLNN attains 97.92%. The proposed method VR-TEE-FLNN has high accuracy and specificity evaluation metrics than those of DL-EEBT-VR existing methods. Therefore, the existing methods contain higher implementation costs compared to the proposed technique. Finally, the VR-TEE-FLNN technique detects student groups more effectively.

5. Conclusion

Although there are always problems with the way activities are carried out in the classroom, traditional methods still have their uses. Scientific and technological developments have a slight but noticeable effect on pedagogic investigation and educational reform. The proposed VR-TEE-FLNN method is implemented in Python utilizing the student dataset. Learning how to employ state-of-the-art scientific and technological tools in the classroom more effectively is essential for promoting the reform of pedagogical methods. The activity is presented in a more multi-angle, intuitive, and three-dimensional manner in a video presentation. To increase their understanding as well as retention of the material, students use Virtual Reality technology to mimic realistic scenarios and an improved version of the video with action explanations and music. It conducts multidirectional observation and benefits from an immersive learning experience, both of which increasing the students' abilities. When compared to other existing approaches, like DL-EEBT-VR, CRW-DNN-VRB, VR-CBE-ET the VR-TEE-FLNN has 99% accuracy. While the VR-TEE-FLNN research shows promise in enhancing engineering education, it faces limitations in practical application, generalizability across diverse contexts, and reliance on adequate technology infrastructure, comprehensive evaluation metrics, and ethical considerations. Future efforts should prioritize empirical validation in real classroom settings, address variations in educational environments, ensure accessibility to technology, incorporate qualitative measures for evaluation, and address ethical concerns the effectiveness and ethical use of the method. In the future, the results will be thoroughly validated quantitatively, and their effectiveness will be compared to that of traditional techniques like GIS.

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