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Development and Application of Big Data-Driven Intelligent Evaluation System for Physical and Aesthetic Education

Abstract: - Big data driven intelligence evaluation system for physical and aesthetic education are used to leverage vast amounts of data to provide more objective, nuanced, and personalized assessments of student performance and progress. This paper proposes a hybrid approach for development of big data driven intelligence evaluation system for physical and aesthetic education. The proposed hybrid approach is the combined performance of both the Dual attention graph convolution network (DAGCN) and Weibull time to event Recurrent Neural Network (WRNN).Commonly it is named as WRNN-DAGCN technique. The major objective of the proposed approach is to provide for development of big data driven intelligence evaluation system for physical and aesthetic education. WRNN is design to enhancing the efficiency of physical training. Enhance the physical training from the WRNN by using the DAGCN. By then, the MATLAB/Simulink working platform has the suggested model implemented, and the present processes are used to calculate the execution. The proposed method shows better results in all existing methods. The accuracy level of proposed BDEPA-WRNN-DAGCN approach is 98% that is higher than the other existing methods. From the result, it is conclude that the proposed approach based error rate is less compared to existing techniques.

Keywords: Big data driven, Physical education, Aesthetic education, Evaluation system, Dual Attention Graph Convolutional Network, Weibull time to event Recurrent Neural Network, Deep learning.

I. INTRODUCTION

The creation and Implementation of an Intelligent Assessment System for Physical and Aesthetic Education are essential to enhance personalized learning, optimize curriculum design, identify learning patterns, allocate resources efficiently, monitor health and fitness, promote inclusivity, ensure accountability, engage stakeholders, facilitate continuous improvement, and prepare students for future opportunities [1]. By harnessing data-driven insights, this system enables educators to tailor their approaches, address disparities, and create a more effective and inclusive learning environment, contributing to the holistic development of students in the realms of physical and aesthetic education [2]. A physical training facility is intended to provide an appropriate and productive teaching and learning environment along with a logical and coherent learning approach for the undergraduate curriculum [3]. There is an increase in blood flow to the brain during physical exercise [4]. The key to a child's development is increased intellectual capacity, attentiveness, memory, thinking, and brain activity [5]. Through natural, all-encompassing conditioning, play-based physical activity aims to develop people on a physiological, social, intellectual, and creative level [6].

One primary concern drawback is the quality of the data underpinning these systems. Incomplete or inaccurate data used for training can lead to biased or flawed evaluations [7]. The handling of vast amounts of data raises significant security and privacy issues, requiring meticulous attention to data protection measures and compliance with regulations [8]. Bias and fairness represent another critical challenge. If the training data incorporates biases, the system may perpetuate or even exacerbate these biases, resulting in unfair evaluations [9]. A lack of diversity in training data may lead to systems that are inherently biased against specific demographic groups. The complexity and interpretability of these systems present substantial hurdles. Many employ sophisticated machine learning models often regarded as black boxes making it difficult to understand the rationale behind specific decisions [10]. This lack of transparency may erode trust among stakeholders and impede widespread acceptance of the system's recommendations. Scalability challenges are also prevalent. The resource-intensive nature of implementing and maintaining large-scale systems can strain infrastructure, necessitating substantial investments in processing power and skilled personnel [11]. The volume of data grows scalability issues may emerge, impacting system performance and responsiveness. These systems are heavily dependent on historical data, which may limit their predictive power, especially in rapidly evolving environments. Concerns arise when historical data becomes out dated quickly, affecting the system's relevance and accuracy [12]. User resistance and trust issues are notable drawbacks. Automated evaluations may face resistance from users, particularly if the decision-making process is not transparent or easily understood [13]. There is also concern about the loss of the human touch in evaluations, potentially leading to a decrease in empathy and understanding. Ethical and legal considerations pose additional challenges [14].

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Meeting legal and regulatory requirements related to data privacy and protection is complex, and the decisions made by these systems may raise ethical dilemmas, such as concerns about sensitive information use, privacy, and consent. There is a risk of overemphasizing quantitative metrics at the expense of qualitative aspects [15]. Focusing solely on data-driven metrics may neglect essential qualitative dimensions of evaluation, potentially resulting in a skewed understanding of complex phenomena.

Implementing machine learning algorithms for automated data cleaning and predictive analytics to guarantee data quality is a comprehensive strategy for leveraging artificial intelligence (AI) to overcome the shortcomings of Big Data-Driven Intelligent Evaluation Systems. While interpretable AI models improve system understanding, transparency and bias detection algorithms in AI-driven models address biases. Distributed AI frameworks and cloud services with auto-scaling features enable scalability [16]. Reinforcement learning and online learning strategies enable dynamic learning, which allows the system to adjust to shifting data patterns. Personalized experiences and NLP-driven interfaces improve user education and involvement [17]. Block chain integration and algorithm monitoring help AI support ethical compliance. Analytics tools powered by AI are able to achieve a balance between quantitative and qualitative metrics, offering a comprehensive perspective. For continued success, domain experts and AI experts must collaborate and monitor each other constantly [18].

Major contribution of this paper as follows;

- WRNN combined with dagcn is used for Development and Application of Big Data-Driven Intelligent Evaluation System for Physical and Aesthetic Education is proposed.
- In enhancing the efficiency, the Weibull time to event Recurrent Neural Network (WRNN) emerges as a prominent technique. WRNN’s primary function to enhance the efficiency.
- In enhancing the physical training, the Dual attention graph convolution network (DAGCN) emerges as a prominent technique. DAGCN’s primary function to enhance the physical training.

The document's remaining sections are arranged as follows: The background and current research projects are covered in Segment 2. Segment 3 describes the proposed methodology of big data driven intelligence evaluation system for physical and aesthetic and provides an illustration for the proposed technique WRNN-DAGCN to big data driven intelligence evaluation system for physical and aesthetic using hybrid WRNN-DAGCN method. In segment 4, the discussion and results are explained. Finally, Segment 5 presents the finish [19].

II. METHODOLOGY

Several works have presented previously in literatures were depending on the development of big data driven intelligence evaluation system for physical and aesthetic education. Few of them were mentioned here,

Gil-Martín et al. [20] have investigated three modules make up the Human Activity Recognition system. First, frequency domain data is extracted by splitting the acceleration signals into overlapping windows. The 2nd module ascertains the activity carried out at each window by means of a CNN-based deep learning structure. The second part of this structure combines all of the sensor outputs to classify the physical activity. Each sensor is individually connected to several layers in the first section of the structure. By integrating window-level decisions over longer time horizons, the third module achieves a notable boost in performance.

Wang and Du [21] have investigated this research will analyze physical education and training data, pinpoint sports training characteristics and action prediction, and develop a system of physical training and instruction based on these technologies to boost the efficacy of training and physical education. It will accomplish this by utilizing Internet of Things and machine learning technologies. In order to progressively overcome some of the original extreme learning machine's shortcomings and increase prediction accuracy, in this paper, parameter optimization and hidden layer mapping are optimized. This study also employs Internet of Things technology to continuously collect data over a long duration. After processing the data, the state of sports training was predicted using an powerful machine for learning.

Wang et al. [22] have suggested to address the issues of high complexity and poor accuracy in assessing the outcomes of physical education instruction, an assessment technique based on deep learning for training quality and instruction in physical education was employed. The instructional strategies, content, attitude, and effects that influence instruction quality were considered when developing the assessment index system. Evaluation was based on score progression and score distribution. The resolution coefficient was dynamically determined and the weighted index correlation relationship was established following the quantification of each index's influence factors.

Wang et al. [23] have investigated of The IoT made it possible to connect inexpensive heterogeneous devices to mobile applications, allowing physical education to be conducted in connected, uncontrolled environments. According to game-based learning, the Internet of Things offers a wealth of chances for improved education and learning. A crucial component of higher education systems and national health plans was college physical education. As a result, the IoT-DPARS for higher education has been suggested in this paper. This system collects relevant IoT data and uses the real-time data it obtains to communicate with the mobile terminal through the cloud. An IoT system requires a mobile user to follow a set of steps and even monitors their heart rate.

Huang and Tao [24] have suggested a way to incorporate clever algorithms and increase productivity. Nevertheless, there are still no well-developed methods for digitally evaluating design works. To address this problem, the purpose of this paper is to apply big data analysis to build a prototype for an application. In this paper, an organized investigation of an intelligent system driven by big data for digital assessment of design works was carried out. The relevance of multi-source influential factors was investigated using the grey correlation analysis. Based on this, a digital evaluation algorithm was created using the original feature data to produce a digital assessment of design works. The data analysis process was optimized using the grey correlation algorithm, and the results' degree of confidence in efficacy was raised by precise data detection and pre-processing.

Liang and Yin [25] have investigated The Internet of Things (IoT) made it possible to connect inexpensive heterogeneous devices to mobile applications, allowing physical education to be conducted in connected, uncontrolled environments. According to game-based learning, the Internet of Things offers a wealth of chances for improved education and learning. A crucial component of higher education systems and national health plans was college physical education. As a result, the IoT-DPARS for higher education has been suggested in this paper. This system collects relevant IoT data and uses the real-time data it obtains to communicate with the mobile terminal through the cloud. An IoT system requires a mobile user to follow a set of steps and even monitors their heart rate.

Gao et al. [26] have suggested the rapid advancement of computer and communication technology ushers in a new era of education marked by big data and artificial intelligence. Two new trends in education are mobile learning and educational fragmentation. Furthermore, artificial intelligence in education and mobile network technology were becoming popular research topics. Long-distance learning is changing traditional education and has many benefits. However, there remained a great deal of unresolved scientific and engineering problems. The mobile network issue was one of the primary problems in education-based IT that needed to be fixed. In addition, the latest wave of mobile networks and the use of IT in education have emerged as significant research areas. At the same time, there are a lot of problems with big data-driven remote learning and education and the engineering application of AI.

A. Background of Recent Research Work

The recent studies reveal the development of big data driven intelligence evaluation system for physical and aesthetic education by using various methods and aspects. Privacy concerns may arise due to the sensitive nature of health-related data collected from IoT devices, potentially leading to user reluctance. Issues such as data accuracy, algorithm complexity, and limited generalization may impact the reliability and universality of the proposed systems. Additionally, ethical considerations, integration challenges, and the requirement for substantial resources pose potential barriers. Striking a balance between technological advancement and preserving human-centric educational values is crucial to ensure the effective and ethical implementation of these systems. The above mentioned advantages and disadvantages are motivated me to do this work.

III. PROPOSED INTELLIGENT PHYSICAL EDUCATION TRACKING SYSTEM (IPETS)

The proposed IPETS system's workflow is shown in Fig 1. It tracks the athlete's performance using a controller and human-machine interface module. It shows the machine- and Internet of Things-based physical school curriculum data collection architecture. The sensor sends velocity data moving from the module for speed collection through the transmitter to the real training systems whenever the client is working out for a sport. After receiving the velocity data, the appropriate training system instructs the media player on the image's movement. The technology provides the trainer with the necessary tracking data in real time. The platform replicates the sporting tea process, changes the module's size, and collects statistics on sports education. It offers a real way to control athletic training programs. The primary innovations made by the algorithms are the crucial stages of the original athletic training program's computation by athletics and the early data processor. The method can enhance the teaching the environment, raise the correctness of training examples, and ultimately raise the system's overall efficiency and scientific performance. Table 1 illustrates Analysis of the proposed IPETS's average participation ratio. Table 2 shows that an analysis of the proposed IPETS's evaluation scores.

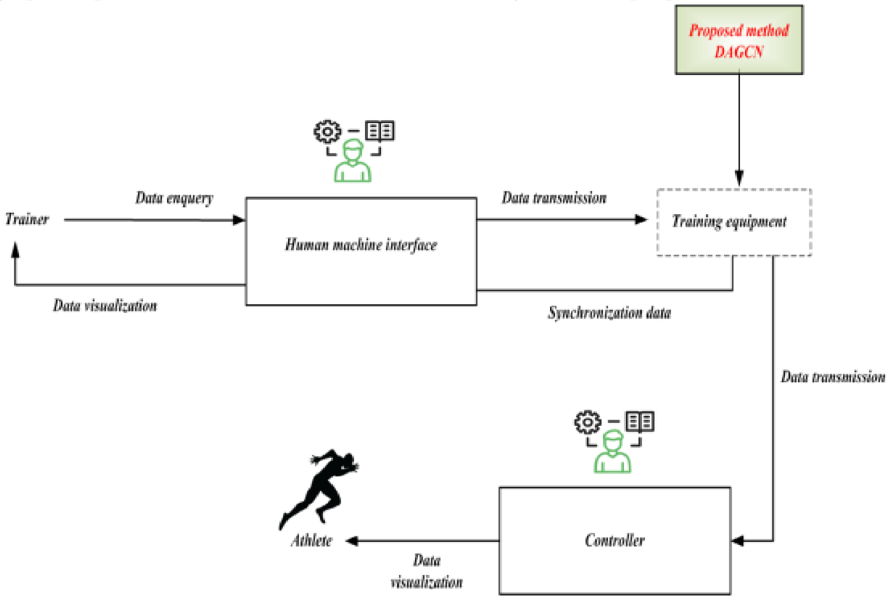

Fig 1: The proposed IPETS system's workflow

A. Data collection

Table 1: Analysis of the proposed IPETS's average participation ratio.

Number of dataset	Male (%)	Female (%)
50	79	69
100	81	72
150	83	75
200	79	71
250	75	68
300	72	65
350	71	62
400	68	59
450	64	57
500	62	55
550	59	52
600	57	49

Table 2: An analysis of the proposed IPETS's evaluation scores.

Number of dataset	Male (%)	Female (%)
50	42	76
100	46	78
150	49	75
200	51	72
250	48	68
300	46	71
350	45	75
400	48	78
450	50	81
500	53	78
550	51	75
600	49	72

B. Enhancing the Efficiency Using Weibull time to event Recurrent Neural Network (WRNN)

In this section WRNN is discussed. WRNN is used to enhancing the efficiency of physical training. Conventional neural networks have inputs and outputs that are independent of each other. On the other hand, the preceding words must be retained in cases where guessing the next word in a sentence requires knowledge of the preceding words. In order to solve this issue, WRNN was developed, and it made use of a Hidden Layer. The Hidden state of a WRNN, which contains certain sequence-related information, is its primary and most significant feature. The state is also referred to as memory state since it keeps track of previous inputs to the network. It applies the same function, with the same parameters for each input, to all inputs or hidden layers in order to generate the output. The parameter complexity is lower when compared to other neural networks [26].

$$h_t = \sigma(W_i.h_t - 1 + V_i.x_t + b_i) \tag{1}$$

$$z_t = \tanh(W_o.h_t + b_o) \tag{2}$$

Where, d is the cell dimension and ∈ indicates the WRNN cell's hidden state. In the WRNN cell, this is the only type of memory. The weight matrices are denoted by ∈ and Vi∈, the bias vector for the hidden state is indicated by bi ∈ Rd, and the input and output are indicated by ∈ and zt∈, correspondingly, at time stept. Similarly, ∈ and ∈denote the cell output's weight matrix and bias vector, respectively. In the trials, we activated the hidden state using the sigmoid function (shown by σ) and the output using the hyperbolic tangent function (shown by tanh).

$$f_t = \sigma(W_f.h_t - 1 + V_f.x_t + b_f) \tag{3}$$

Where W_f denotes forget gate, $h_t \in R^d$ is a vector that represents the cell's hidden state, d is denoted as the cell dimension. $x_t \in R^m$, the same as for the basic WRNN cell, V_f and b_f denotes the weight matrices for the bias vectors and the current input.

$$r_t = \sigma(W_t.h_{t-1} + V_r.x_t + b_r) \tag{4}$$

Where, r_t denotes reset gates, h_t denotes candidate hidden state.

$$E = \sum_{t=1}^{T} e_t \tag{5}$$

Where, E denotes accumulated error, et denotes error for each time step t.

C. Enhance the Physical Training using Dual Attention Graph Convolutional Network

This section discusses the application of DAGCN to improve physical training. GCNs are becoming one of the most useful tools for graph analytics tasks due to their ability to capture the intricate relationships between concepts. Social networks, chemo informatics, bioinformatics, and natural language processing are a few of these applications. These days, most GCNs train a continuous and compact vector through a neighborhood aggregation framework, and then use a pooling procedure to generalize graph embedding for the classification task. When it comes to the task of graph classification, these approaches have shortcomings. In the graph convolution stage, neighbourhood aggregation based solely on the largest sub-graph structure results in a significant loss of early-stage information. Simple average/sum pooling or max pooling must be used, which loses the topology between nodes as well as the characteristics of each node. To tackle these issues, we present a novel architecture in this study called dual attention DAGCN. Equation [27, 28] can be used to calculate the dynamics of the system.

$$H^{k+1} = \phi(\tilde{A}\tilde{D}^{-1}H^k W) \tag{6}$$

Where W is denoted as the model parameter to be trained, $\tilde{A}$ is represent as each node's adjacency matrix with self-connection, $\tilde{D}$ is indicated as the node degree matrix diagonal of $\tilde{A}, \tilde{A}\tilde{D}^{-1}$ denotes the graph structure that has been normalized. k times through this operation, H^k becomes a vector of node properties with k-hop local structure information in it. Be aware that the results of each step in the equation can only be utilized to produce the following convolution result, apart from H^k, during its repetition. The largest sub-graph is represented by the final convolution result, H^k, may be used for tasks in the future because a lot of information will be lost during this process. Significant information loss may result from this kind of operation. The convolutional layer's capture would be limited to the k-hop local structure. The attentional aggregation of the output from every convolution step is the goal of our attention convolution layer.

$$\gamma_{v_n} = \sum_{i=1}^{k} \alpha_i H_{v_k}^k \tag{7}$$

Where, γ_{v_n} represents Convolution module for attention graph to produce a superior final node γ_{v_n}. $H_{v_n}^k$ denotes the local structure of node v_n in k − hops, and α is the attention weight. Vanilla attention is used to determine the significance of the aggregation result for each hop. The hierarchical structure information is contained in the final node representation.

$$\gamma_{v_n}^{m+1} = \sum_{i=1}^{k} \alpha_i H_{v_n}^{k} \tag{8}$$

Where, m denotes the attention convolution layer, γ_{v_n} represents Convolution module for attention graph to produce a superior final node. $H_{v_n}^{k}$ represents node v_n local structure in k − hops. X indicates that each AGC layer's input is equal to the sum of its original and previous layer's output. i denotes 1 to n.

$$H_{v_n}^{0} = \gamma_{v_n}^{m} + X \tag{9}$$

Where, m denotes the attention convolution layer, γ_{v_n} represents Convolution module for attention graph to produce a superior final node. In k hops, the node v_n local structure is represented by $H_{v_n}^{k}$. X indicates that each AGC layer's input is the total of the output from the layer before it and the original

$$B = soft\max(u_2 \tanh(u_1 G^T)) \tag{10}$$

Where, the function is represented by $soft\max$ along the 2nd dimension of its input, and the weight matrices u_1 and u_2 have the respective shapes of c-by-c and c-by-r. The hyper parameter r determines the quantity of subspaces from which the node representation of the graph can be learned. G stands for graph matrix. T stands for updating iterations.

IV. RESULT AND DISCUSSION

In this section a hybrid BDEPA-WRNN-DAGCN technique for Big Data-Driven Intelligent Evaluation System for Physical and Aesthetic Education in this research. The hybrid technique that has been suggested combines the capabilities of the Weibull time to event Recurrent Neural Network (WRNN)and Dual Attention Graph Convolutional Network (DAGCN). It is called the BDEPA-WRNN-DAGCN method most of the time. The main goal of the proposed method is to develop the big data driven intelligent evaluation system for physical and aesthetic education.

Fig 2 displays the analysis the average participation ratio of male candidates. It displays the relation between number of dataset and average participation. At 150 dataset the average participation ratio is 84% that is the highest participation ratio. Then the value of average participation ratio gradually decreases from 84% to 56% at 150 to 600 number of dataset. Fig 3 displays the analysis the average participation ratio of female candidates. It displays the relation between number of dataset and average participation. At 150 dataset the average participation ratio is 75% that is the highest participation ratio. Then the value of average participation ratio gradually decreases from 75% to 52% at 150 to 550 number of dataset.

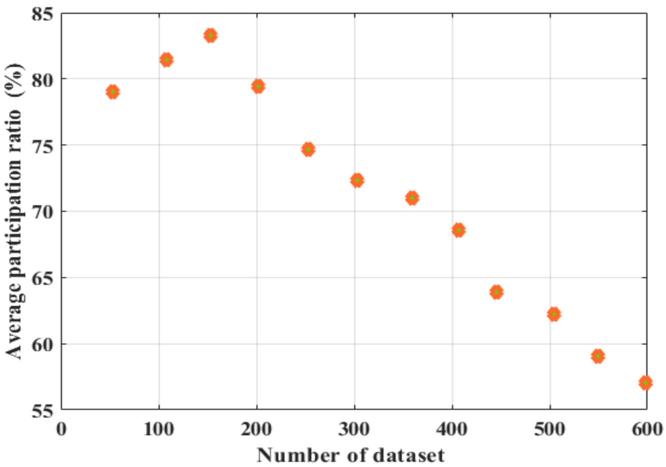

Fig 2: Analysis the average participation ratio of Male candidates.

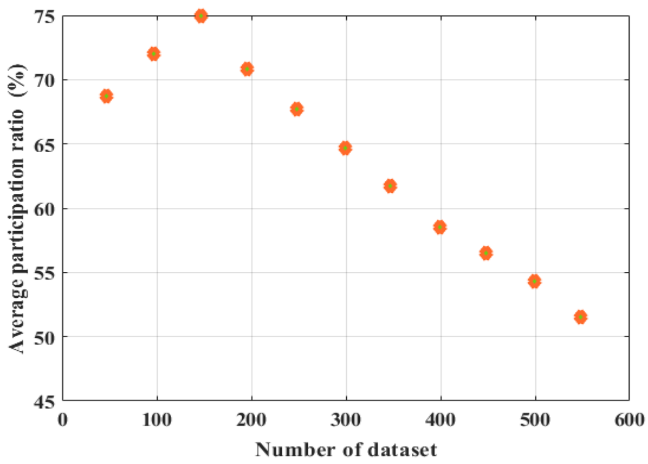

Fig 3: Analysis the average participation ratio of Female candidates.

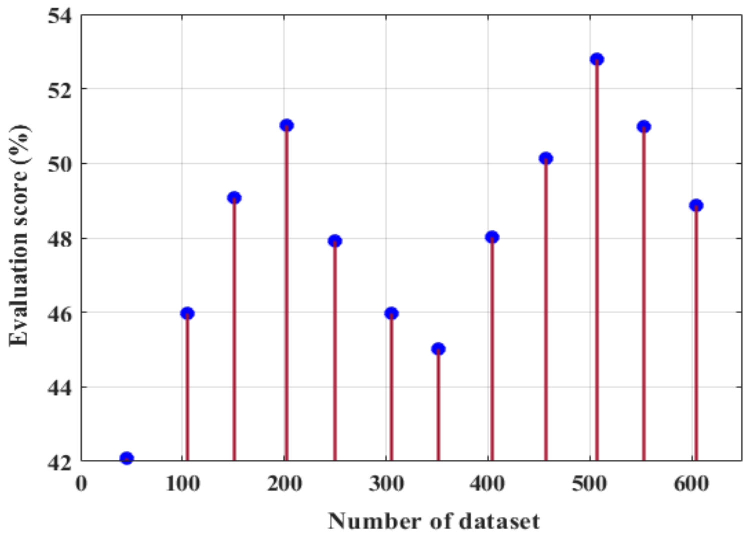

Fig 4: Analysis the Evaluation score of Male participants.

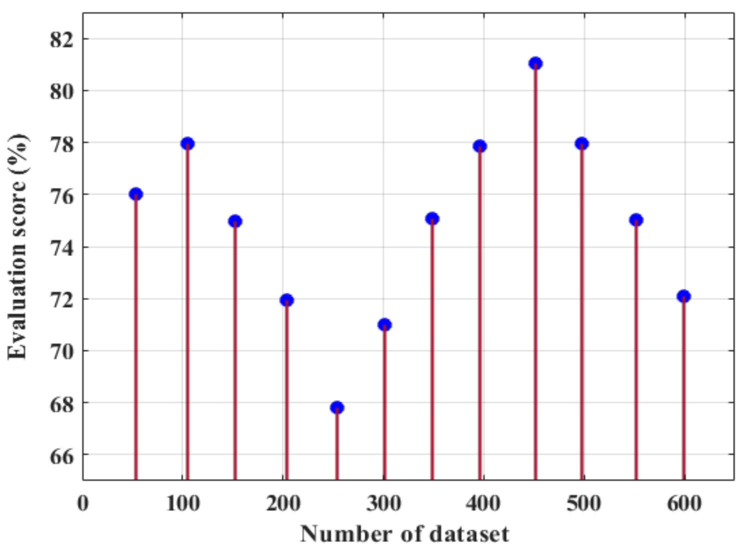

Fig 5: Analysis the Evaluation score of Female participants.

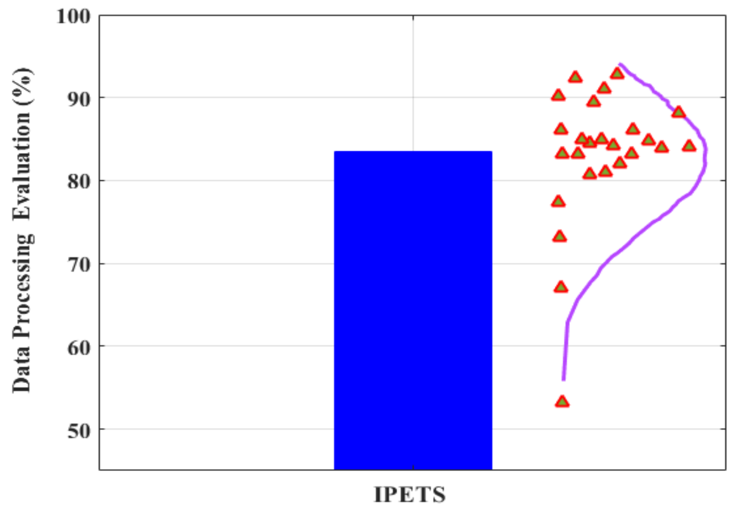

Fig 6: Analysis Data processing evaluation of IPETS.

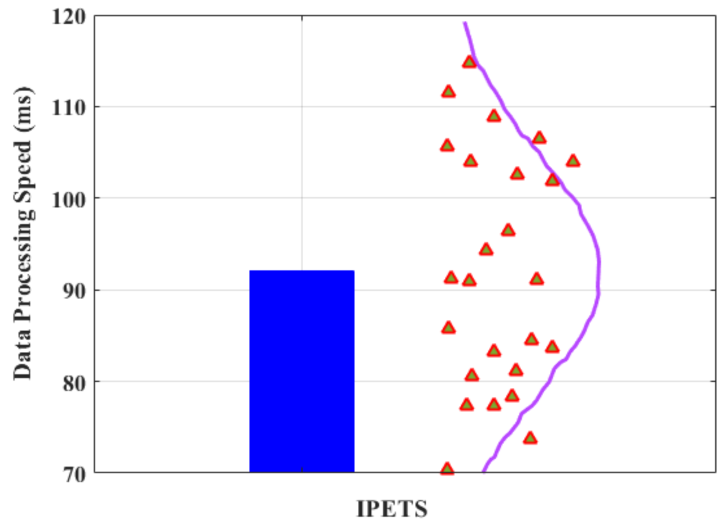

Fig 7: Analysis Data processing speed of IPETS

Analysis the evaluation score of male shown in fig 4. Fig 4 displays the relationship between evaluation score and number of dataset for male participants. The evaluation score start with 42% at the dataset number 50.Then the evaluation score gradually increased to 53% at dataset number 500. Then the evaluation score is decreased to 49% at dataset number 600. Analysis the evaluation score of female participates shown in fig 5.Fig 5displays the relationship between evaluation score and number of dataset for female participants. The evaluation score start with 76% at the dataset number 50.Then the evaluation score gradually increased to 81% at dataset number 450. Then the evaluation score is decreased to 72% at dataset number 600.Analysis the data process evaluation of IPETS shown in fig 6. Fig 6 shows the relation between IPETS and data processing evaluation. From the provided dataset, 25 candidates both male and female were selected for analysis. Their individual simulation results, including speed and score for data processing, are plotted. Analysis the data process speed of IPETS shown in fig 7. Fig 7 shows the relation between IPETS and data processing speed.Analysis is done on the simulation results, comprising evaluation score, processing speed, and the recommended IPETS based on the given dataset.

A. Performance measures

This section describes the proposed approach's performance in light of the simulation's results. To develop the big data driven intelligent evaluation system, in this paper utilize the hybrid BDEPA-WRNN-DAGCN approach. The objective of the proposed method helps in developing the big data driven intelligent evaluation system for physical and aesthetic education. Performance metrics like accuracy, error rate, sensitivity, and specificity are looked at in order to assess the performance.

1) Accuracy

It is the ratio of count of exact prediction with total amount of predictions made for a dataset. It is measured by given eqn (11),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{11}$$

2) Error Rate

One less accuracy equals the error rate. A model with 90% accuracy would have a 10% error rate. It can be computed using equation (12).

$$Error\ Rate = 1 - \frac{FP+FN}{TP+TN+FP+FN} \tag{12}$$

3) Sensitivity

A metric called sensitivity is employed to assess a model's capacity to forecast true positives for every category for which data is available. Any categorical model can use these metrics. Equation (13) contains it.

$$Sensitivity = \frac{TP}{TP+FN} \tag{13}$$

4) Specificity

The metric used to assess a model's predictive power for true negatives in every data-rich category is called specificity. You can use these metrics with any categorical model. It is given in equation (14).

$$Specificity = \frac{TN}{TN+FP} \tag{14}$$

B. Performance Analysis

Figure 8 to 11 depicts simulation results of proposed BDEPA-WRNN-DAGCN method. Then the proposed BDEPA-WRNN-DAGCN method is likened to existing Wild Horse Optimization (BDEPA-WHO), Latent Semantic Analysis (BDEPA-LSA) and Recurrent Neural Network (BDEPA-RNN) methods.

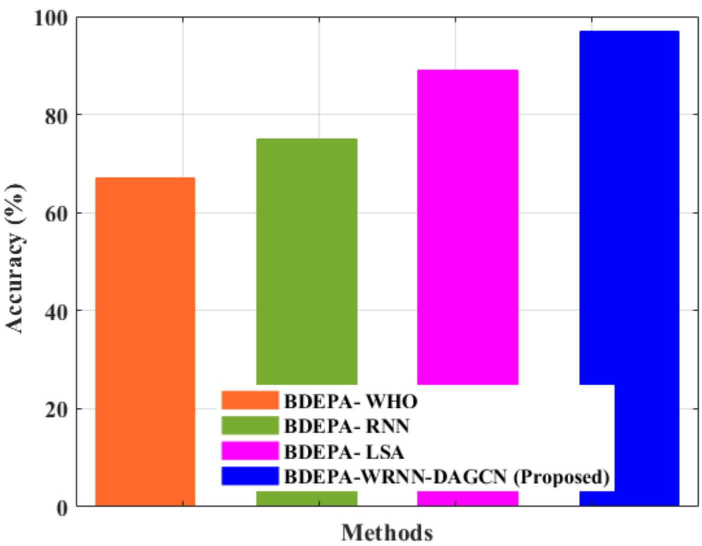

Fig 8: Comparison of proposed method accuracy with existing methods

Fig 8 depicts the Comparison of proposed method Accuracy with existing methods. The accuracy of BDEPA-WHO is 63% and the accuracy of BDEPA-RNN is 78% and the accuracy of BDEPA-LSA is 85%. Then the accuracy of proposed method BDEPA-WRNN-DAGCN is 98%. It shows that the proposed method have better accuracy than BDEPA-WHO, BDEPA-RNN and BDEPA-LSA.

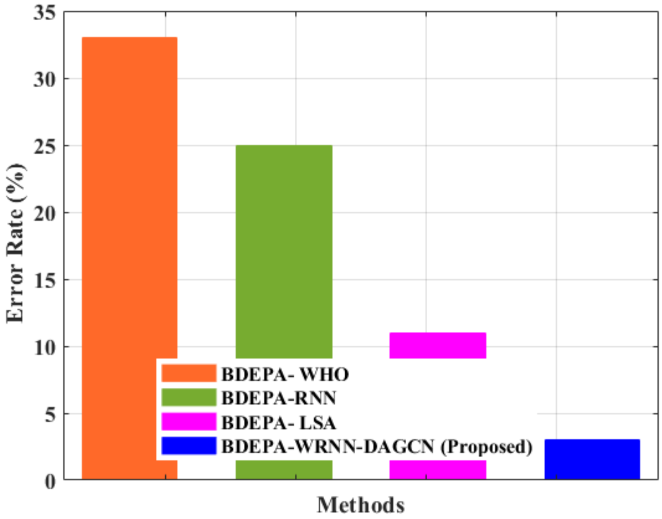

Fig 9: Comparison of proposed method error rate with existing methods

Fig 9 depicts the Comparison of proposed method error rate with existing methods. The error rate of BDEPA-WHO is34% and the error rate of BDEPA-RNN is 25% and the error rate of BDEPA-LSA is 12%. Then the error rate of proposed method BDEPA-WRNN-DAGCN is 3%. It shows that the proposed method have lower error rate than BDEPA-WHO, BDEPA-RNN and BDEPA-LSA.

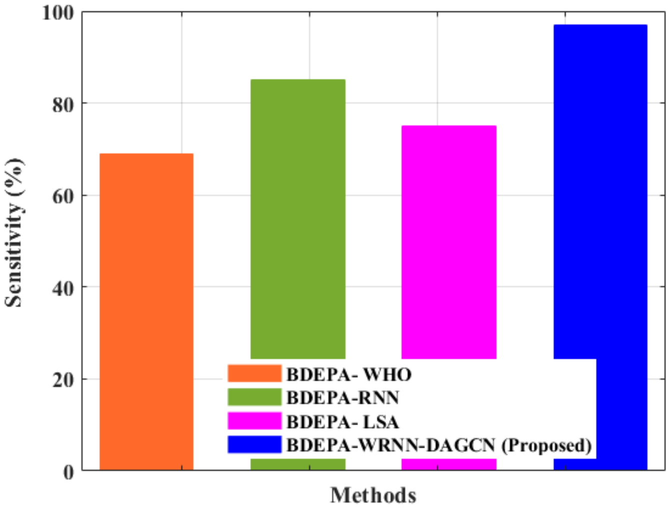

Fig 10: Comparison of proposed method sensitivity with existing methods

Fig 10 depicts the Comparison of proposed method sensitivity with existing methods. The sensitivity of BDEPA-WHO is 65% and the sensitivity of BDEPA-RNN is 82% and the sensitivity of BDEPA-LSA is 78%. Then the sensitivity of proposed method BDEPA-WRNN-DAGCN is 98%. It shows that the proposed method have better sensitivity than BDEPA-WHO, BDEPA-RNN and BDEPA-LSA.

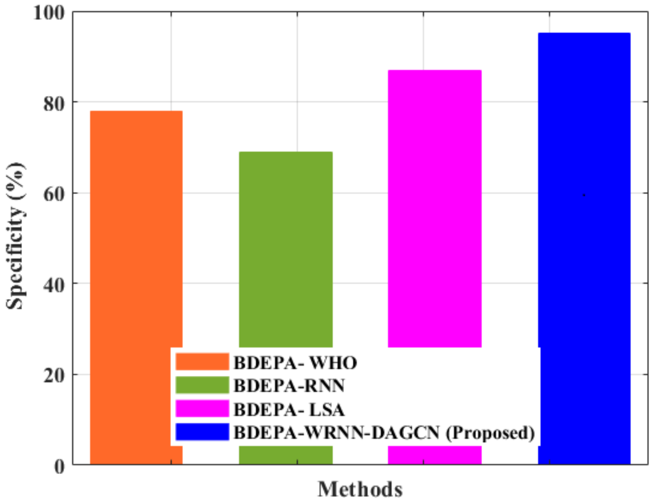

Fig 11: Comparison of proposed method specificity with existing methods

Fig 11 depicts the Comparison of proposed method specificity with existing methods. The specificity of BDEPA-WHO is 79% and the specificity of BDEPA-RNN is 68% and the specificity of BDEPA-LSA is 84%. Then the specificity of proposed method BDEPA-WRNN-DAGCN is 97%. It shows that the proposed method have better specificity than BDEPA-WHO, BDEPA-RNN and BDEPA-LSA.

V. CONCLUSION

This study is used for the development of big data driven intelligence evaluation system for physical and aesthetic education using theBDEPA-WRNN-DAGCN approach. Big data driven intelligence evaluation system for physical and aesthetic education are used to leverage vast amounts of data to provide more objective, nuanced, and personalized assessments of students' performance and progress. MATLAB platform is used to assess and compare the proposed strategy with other available techniques. The proposed method is evaluated in a wide range of scenarios, including random and optimal scheduling and a complex WRNN. The outcome indicates that the proposed approach's based error is lower than that of exiting methods. The result shows that the accuracy level of proposed BDEPA-WRNN-DAGCNapproach is 98% that is higher than the other existing approaches. The rate of error of the proposed BDEPA-WRNN-DAGCNapproach is 3%,which is very less compared to other existing techniques. The outcome indicates that the proposed approach is based big data driven intelligence evaluation system is accurate compared to existing techniques. The goal of the proposed model is to develop the big data driven intelligence evaluation system for physical and aesthetic education. The results also display that the proposed approach outperforms the alternative approaches by a significant margin.

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