Research Article

Study on the Evaluation of Exercise Effect in Physical Education Teaching under the Application of Random Forest Model

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Physical education is a school-based topic that emphasizes the development of physical fitness and the capacity to do and enjoy everyday physical activities. Children also get the skills they need to participate in a wide range of activities. Engaging classes, skilled P.E. teachers, proper instructional hours, and student evaluation should all be part of an effective physical education program. The basics of physical education start with exercises. A remarkable change can be observed when individuals practice exercises in their physical education. In this research work, exercise requirement in physical education teaching is analyzed under students of certain groups under different dimensions. The work analysis is performed by implementing a random forest algorithm and comparison with the support vector machine and fuzzy set based on hesitation algorithms. The performance is evaluated based on teaching and learning, evaluation, and exercises with the support of all the equipment. In all these categories, the proposed random forest algorithm has achieved 98%, 98%, and 43%, respectively.

1. Introduction

In an ever-expanding and fascinating field, education has a profound effect on everyone's lives. Several times, techniques and tactics for establishing high-quality educational experiences, beginning with learning, and advancing to e-learning have been discussed [1]. In many cases, additional hands are needed to bring new ideas and views to the table, which can be accomplished with the help of the public. One of the most significant processes in education is the assessment of students/learners. To evaluate and enhance the learning process, educational evaluation is a strategy used in the classroom. The purpose of the evaluation is to see how effective teaching tactics, methods, and approaches are. It provides teachers with feedback on their instruction as well as students with feedback on their learning. Student motivation and development are influenced greatly by this process and have been dubbed “one of the most potent forces shaping education” [2]. Assessment feedback “has a direct impact on students’ performance and persistent effort in subsequent projects”, according to Harlen and coauthors [3]. Many schools and institutions around the world still use this method as their primary method of student evaluation. With the present focus on enabling children to establish their own distinct and diverse growth, it is vital to properly understand students’ abilities and traits as well as complete signals in all areas [4]. Students in higher education need an assessment system that is reasonable and scientific and that considers the various aspects of the evaluation process, such as concepts, evaluation content, evaluation format, and evaluation methodology. Evaluations should consider how students learn math as well as how they progress through the process. The emotional shifts in pupils’ actions should be taken into account while assessing their learning [5]. A major goal of curriculum reform in China is to develop a variety of evaluation methods and objectives. To enhance their teaching methods, teachers can learn more about their students’ learning processes and outcomes by evaluating their students’ learning [6]. For the benefit of education, greater research is needed into how to conduct effective teaching...
assessment research. Grade evaluation of student performance has historically been the most important material for teacher evaluation.

Many different industries can benefit from machine learning (ML), such as healthcare, agriculture, and media. Machine learning (ML) is a fundamental component of artificial intelligence (AI). Agriculture, anatomy, adaptive websites, affective computing, astronomy, automated decision-making, banking, bioinformatics, brain-machine interfaces, climate science, and other tasks involving machine learning can benefit from real-time solutions that save time and effectively reduce the need for human intervention [7]. A few examples of the approaches that are utilized in this industry include supervised learning algorithms and natural language processing (NLP) algorithms. Natural language processing (NLP) is pattern recognition and understanding method. It then makes decisions or makes forecasts on its own, based on data and sometimes human input. Traditional multivariate statistical techniques such as factor analysis are integrated with an intelligent machine learning random forest algorithm (the random forest is a decision tree-based prediction and behavior analysis tool). It contains a large number of decision trees, each of which represents a distinct categorization of the data fed into the random forest. The random forest method considers each occurrence individually before selecting the forecast with the most votes to alleviate the shortcomings of past methods [8]. There are several ways to improve the quality of instruction in physical education, including the adoption of a comprehensive evaluation model that may be used in real time. We must use a “student performance evaluation model” to measure students’ performance accurately and comprehensively in physical education sessions. This model will help us better understand the factors that contribute to their success. To effectively fulfill the individual needs of each student in the classroom, teachers must be aware of the many learning settings in which their students find themselves [9]. In education, for example, data mining and machine learning are used to investigate learning environments, network-based teaching systems, and other educational challenges. Thanks to the discovery of information mining, students’ development could never be evaluated in this way before. Data mining and machine learning are being used to investigate students’ evaluations of their teachers’ performance in the classroom. Students’ online evaluation course information is modeled using decision trees and support vector machines, naïve Bayes, and random forests, respectively, to identify patterns (RF) [10]. The quality of a country’s educational system is directly related to the quality of its researchers and the other way around. Professional research can be eliminated by assembling a group of researchers who can pool their resources and collaborate on a collaborative project. Various platforms have been created to help students exchange ideas and become part of a large research group [11]. Bringing together a plethora of information from several fields could usher in a new era of teaching tools. It can be used to ensure that students are getting the most out of their education, and it can point out any flaws and give remedies. The mining of students’ contact information is a major concern in online education. One strategy is to use an online discussion board where students from various regions and nations may share their expertise. Crowdsourcing allows for timely responses to student input. Crowdsourcing is a method of obtaining work, information, or views from a large number of individuals using the Internet, social media, or smartphone apps [12]. Only one technique can benefit students who have few other options for finishing their education and must take online courses as their only option. To get the most out of your pupils, you need to focus on their involvement. Nonexpert staff members must therefore be routinely supervised to prevent wrong information or inaccurate remarks from being provided.

It is necessary to set a goal for one’s personal growth and development as a part of any educational effort. To make educational films available to a wider audience, the researcher built an Internet learning platform for crowdsourced videos [13]. The recommendation systems can help students select the best learning plan for their needs [14]. The usage of this platform allows for the input of as many teachers as feasible in large-scale professional assessments. Students are asked to submit assignments for examination and grading by the entire class [15]. In a group of peers, pupils may be sure they’re doing well and that the work they’re producing is of a high standard. Students use an algorithm to develop new questions, which they use as a guide for improving their performance by testing their knowledge on another system [16]. Students can generate assignments and peer-review one other’s work using an embedded tool for online courses. When students create their teaching resources to aid in their knowledge, the researcher says they can better understand concepts using the concept of crowd learning [17]. They provided a web-based platform for students to use for practice in class or online classes. Performance evaluation is the most complicated and time-consuming method for evaluating students. Audience opinions may lead to grades that are unjust or erroneous if they are used as the only basis for evaluation [18]. Any business can benefit from real-time responses that save time and do not require human intervention. Every industry might benefit from machine learning. Supervised learning in natural language processing in educational institutions, models of learning (ML) are used extensively (NLP).

In many cases, supervised machine learning models were utilized as the basis for many of the advised methods. When evaluating the responses, we used an algorithm to classify each one based on various factors [19]. An unbiased evaluation of community inquiry responses was feasible thanks to this method. Classification algorithms that learn from patterns in the data that have been accumulated can be used to predict future outcomes [20]. The first stage is to gather data from the community member, which is then used to build an initial categorization model. After all, is said and done, the quality of the new responses will be compared to the quality of the previously trained models. The author used a regression algorithm with a continuous and real output variable to oversee the model [21]. For the author’s benefit, he or she used modeling to better understand the underlying
causes of each student’s success. Teachers will be able to keep track of their students’ development and alter their teaching methods to match their individual needs by using this strategy [22]. All that is required to oversee a teacher in this paradigm is the teacher’s knowledge and experience in the classroom. The collection of information includes the user’s past knowledge of a computer language. Incorrect data collected could jeopardize the strategy’s planned implementation [23]. That’s why researchers must be able to select relevant data and models for every new educational research project to be successful. Several tools have been created, one of which uses natural language processing (NLP) to present the result of a model trained to estimate multiple-choice questions [24]. According to their likeness with an ideal answer, students’ exam responses are scored. NLP techniques are used to achieve this. The preferred method for calculating the student’s recommended score is to compare the two values [25]. This paper investigated the use of machine learning to assess students’ perceptions of teachers’ performance.

The remainder of the article is arranged as follows: Section 2 covers materials and methods, Section 3 covers results and discussion, and Section 4 covers the conclusion.

2. Materials and Methods

For many decades, teaching appears to have been an essential evolving field since it is a critical role in human civilization and evolution around the world, affecting both individuals and organizations. In general, maintaining high-quality educational activities has a substantial influence on worldwide literacy levels. In education, the assessment technique is critical since it is the primary instrument for assessing students’ research. It is clarified in the modern generation of education that the presidency of higher learning should establish an intelligent and differentiated teaching assessment methodology. This kind of evaluation can help to promote the efficacy of students’ physical education exercises and test scores while also emphasizing the growth of educators’ personality types and abilities. Keeping the significance of a sophisticated model for teacher fitness in mind, this article utilizes a structural equation model and an enhanced random forest algorithm. This model aids in decreasing the measurements of students’ multiple disciplines’ successes in physical education into a few pretty standard factors that aid in student achievement. The proposed approach allows for a more detailed evaluation of student’s achievements based on their scores at each factor level. For the first time, the company’s upgraded recursive random forest method is being applied in an observational teaching study on academic grade evaluation. The automated evaluation of students’ test scores is done utilizing the students’ academic results in many fields as well as a variety of criteria that identify them. In this section, we will discuss the Architecture of the Proposed System in detail.

2.1. Architecture of the Proposed System. Figure 1 represents the proposed model-making exercise that is needed in physical education teaching. From the figure, it is observed that physical education teaching and learning are made through different modes of education. Physical activities such as fitness monitoring, performing physical exercises, and sports participation are practiced in the ground environment under the traditional teaching process. This practice mode needs some upgradations concern to the technology. Hence, in the next block, the training is made through the random forest method. This training block involves cognitive and metacognitive learning methodology. Metacognitive procedures are methods for students to better comprehend how they learn; they are processes that allow students to “think” about their “thinking.” Learners’ ability to digest knowledge more fully, transfer, and apply information to new situations and retain information improves using cognitive learning methodologies. With these functions, everyone is given attention to their performance and obtaining knowledge related to the sports and the need for exercises in their training. This training mechanism can be elaborated with the involvement of interactive systems like mobile applications and the Internet. As an extension of the practice, classroom study is also encouraged, and the study is made through books and other activities. All the activities are monitored and updated in the database for analysis and increased performance strategies.

2.2. Propose Work. To automatically extract information on human physical education behavior and attitude from enormous volumes of visual data, as well as to observe and evaluate physical actions. Although science and technology advance at fast speeds and data transmission volumes skyrocket, the need to extract behavioral science data from enormous video data sets has become an essential issue in a range of industries. If intellectual security cameras are being used, the video can be instantaneously modeled and analyzed. Human behaviors could be identified in real time, ensuring the efficiency and timeliness of security alerts. Therefore, behavioral science recognition has theoretical and practical implications and has become a focal point of research in a variety of fields. Object recognition became a classification task when images can be identified as frames or time-based.

The use of Multicategory classification, on the other hand, is so much more common. There appear to be multiple alternatives for this a. Not only are classification model methods used but multiclassifier soft max-multiple linear regression analysis has also been distributed to regression analysis. Presently, a Multicategory classification is communicated as $k(i)1, 2, ..., a$, with such an $n$-category total. So for the testing data $u(i)$, (1) demonstrates the classification possibility assumed in Softmax similarity classification.
\[ M_\theta(u^{(i)}) = \begin{bmatrix} A(k^{(i)} = 1|u^{(i)}; \theta) \\ A(k^{(i)} = 2|u^{(i)}; \theta) \\ \vdots \\ A(k^{(i)} = a|u^{(i)}; \theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{a} \rho^{\theta_j u^{(i)}}} \begin{bmatrix} \rho^{\theta_1 u^{(i)}} \\ \rho^{\theta_2 u^{(i)}} \\ \vdots \\ \rho^{\theta_a u^{(i)}} \end{bmatrix}, \] (1)

\( \theta \) signifies the designer’s parameters, which also are supported by a line framework. As shown by (2), each dividing line can be regarded \( \rho \) as a classifier attribute for a single category.

\[ \rho = \sum_{j=1}^{a} \frac{1}{\rho^{\theta_j u^{(i)}}} \begin{bmatrix} \rho_1^H \\ \rho_2^H \\ \vdots \\ \rho_a^H \end{bmatrix}, \] (2)

The probability is \( H \) normalized in \( 1/\sum_{j=1}^{a} \rho^{\theta_j u^{(i)}} \) so that the total probability is the extract equation again for the scheme as shown in the following equation:

\[ G(\theta) = \frac{1}{R} \sum_{i=1}^{R} \sum_{j=1}^{a} 1\{k^{(i)} = j\} \ln \frac{\rho_j^{H u^{(i)}}}{\sum_{j=1}^{a} \rho_j^{H u^{(i)}}}. \] (3)

With such an evocative function, its \( R \) valuation rules apply. Softmax connection is then used to aggregate the scenarios of an \( a \) category. (4) computes the probability that \( u \) is categorized into \( j \) categories.

\[ \ln A(k^{(i)} = j|g^{(i)}; \theta) = \frac{\rho_j^{H u^{(i)}}}{\sum_{j=1}^{a} \rho_j^{H u^{(i)}}}. \] (4)

(4) depicts \( g^{(i)} \) the extract generalization of linear regression. The representation of the similarity in objective functions is shown in the following equation:

\[ G(\theta) = -\frac{1}{R} \sum_{i=1}^{R} \sum_{j=1}^{a} 1\{k^{(i)} = j\} \ln A(k^{(i)} = j|u^{(i)}; \theta). \] (5)
Similarly, the optimization techniques in this equation can be minimized using an iterative optimization technique, which includes the exact analysis. As a result, (6) demonstrates how to calculate the modified form of an energy functional.

\[ \Delta \delta_j G(\vartheta) = -\frac{1}{R} \sum_{i=1}^{R} u^{(i)}(1\{k^{(i)} = j\}) - \sum_{i=1}^{R} (A(k^{(i)}) = j|u^{(i)}; \vartheta). \]  

(6)

Load energy loss is added, and the solution is to enforce an increased set of parameters and ensure that the continuity equation is the restrictive set of parameters. Equation (8) represents the objective functions as it reaches the optimal better as a result.

\[ A(k^{(i)} = j|u^{(i)}; \vartheta) = \frac{\sum_{j=1}^{a} \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor) \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)}{\sum_{j=1}^{a} \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor) \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)} = \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor) \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor). \]  

(7)

In (6), \( \Delta \delta G(\vartheta) \) is indeed a variable, as well as its \( f^{th} \varphi j(\vartheta)/\varphi \vartheta_j \) seems to be the fifth in either \( f^{th} \) classification of the exchange rate function. To solve the optimization problem, the equation is given into the linear regression and iteratively adjusted. Since the same proportion is taken from each analytical solution parameter, the importance of a failure function remains constant, implying that the parameter will not be the only answer. Equation (7) depicts the scientific proof procedure.

\[ G(\vartheta) = -\frac{1}{R} \sum_{i=1}^{R} \sum_{j=1}^{a} 1\{k^{(i)} = j\} \ln \frac{\rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor) \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)}{\sum_{j=1}^{a} \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)} - \frac{\delta}{2} \sum_{i=1}^{a} \sum_{j=1}^{a} \theta_j^2. \]  

(8)

Step 9: in equation (8), \( \delta > 0 \). Equation (9) exemplifies the comparatively small, generated function.

\[ \Delta \delta G(\vartheta) = -\frac{1}{R} \sum_{i=1}^{R} u^{(i)}(1\{k^{(i)} = j\}) - \sum_{i=1}^{R} (A(k^{(i)} = j|u^{(i)}; \vartheta)) + \delta \vartheta_j. \]  

(9)

Finally, a usable soft max similarity classification model can be represented by solving the optimization problem as shown in the following equation:

\[ \Delta \delta G(\vartheta) = -\frac{1}{R} \sum_{i=1}^{R} u^{(i)}(1\{k^{(i)} = j\}) - A(k^{(i)} = j|u^{(i)}; \vartheta)) + \sum_{j=1}^{a} 1\{k^{(i)} = j\} \ln \frac{\rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor) \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)}{\sum_{j=1}^{a} \rho^{(j)} u^{(i)}(1\lfloor \vartheta_j \rfloor)} - \frac{\delta}{2} \sum_{i=1}^{a} \sum_{j=1}^{a} \theta_j^2. \]  

(10)

Finally, by reducing the cost function given in the equation, a useful activation functions correlation classification model may be represented (11). One of the system’s extract equations is a possibility.

\[ A(u, k|\vartheta) = \frac{1}{k(\omega)} \log(-G(u, k, \omega). \]  

(11)

In correlation classification, the probability of similarity classification as shown in the following equation:

\[ K(\vartheta) = \int_{\vartheta_k \in k} \log(-G(u, k, \vartheta)), \]  

(12)

\[ A(k|\vartheta) = \frac{\ln(-A(y, \vartheta))}{\int_{\vartheta_k \in k} \ln(-A(k, \vartheta))}. \]  

(13)

In (13), by utilizing concurrent positional information, goals scored goals probability prototype for \( A((k, \vartheta)) \) scenes are developed as shown in the following equation:
\[ A(k, \vartheta) = -\sum_{\varrho \in \varrho^{\alpha}} \ln (-A(k, u, \vartheta)). \] (14)

In most cases, maximum \( \varrho \) probability \( i, j \) pooling layer is being used in the deep network, which would be stimulated just after at least so many of the corresponding inaccessible deep networks are activated.

\[ (\varrho) = \frac{1}{R} \sum_{l=1}^{d} \sum_{j=1}^{t} \left\lfloor k^{(i)} = j \right\rfloor \ln \left( \frac{\rho \left( \varrho(u^{(i)}) \right)}{\sum_{l=1}^{R} \rho \left( \varrho(u^{(i)}) \right)} \right). \] (15)

As shown in (14) and (15), the probabilities of hidden nodes are procured by probability integrals that are distributed evenly in each layer.

As a result, this model is enhanced much farther by modeling separately in time and space, making it much more unique than spatial transformation. A hierarchy approach is being used here, with the dispersed probabilistic model, which learns to extract spatially and temporally features from video content using supervised learning. In particular, as the introduction module, its interpolation constrained machine efforts to learn the initial data structure’s hierarchy organization. Its framework becomes increasingly difficult as it progresses from the highest to the lowest. After a steady increase in interpretations, the spatially and temporally high redundancy network is given the name. The enhanced deep learning (deep belief network—DBN) model is trained using rapacious hierarchy before. In addition, the input layers of each framework are informed at random, starting with the lowest layer. The concealed nodes’ probability recognition is then reorganized, and knowledge to another layer is gained. This procedure is repeated indefinitely throughout training until all the layers are trained. After training, the entire infrastructure might retrieve the hidden node probability representations of any specific layer inside of the video.

3. Results and Discussion

The physical education teaching performance among the 4th- and 8th-grade students is represented in the above graph as shown in Figure 2. Performance analysis of effective teaching is made with a random forest algorithm, support vector machine, and the fuzzy set model based on hesitation. The computation is carried out by making the combined weight of the 4th- and the 8th-grade student’s performance. The random forest algorithm is the proposed algorithm showing a lower percentile at the initial stage of new technology. But at the later stage, the algorithm managed to obtain equivalent results compared to the support vector machine. In machine learning, a support vector machine is a data science algorithm that belongs to the supervised learning class and analyses the trends and characteristics of a data set to answer classification and regression issues.

The fuzzy model shows neutral results between the random forest and support vector machine algorithms. This comparison graph shows that repeated teaching and learning can make the students and teachers provide increased performance concerning the random forest algorithm. The numerical representation of the learning analysis is represented in Table 1. From Table 1, it can be observed that the random forest algorithm has provided lesser learning accuracy than the other algorithms for the average evaluation weight of 38 (combined for 4th- and 8th-grade). Also, there is a steady improvement in the accuracy rate with the random forest algorithm than with the other two algorithms of fluctuating results. At the later stage, the proposed algorithm has achieved an accuracy of 98%, and it is a minimum increased percentage of nine than the support vector machine and 17% than the fuzzy set model.

Next to the teaching and learning process is the evaluation process of the physical education courses, and the analysis is reported in Figure 3. The proposed automatic evaluation through the random forest algorithm has outperformed many assessments compared with the expert evaluation. The peaks in the graph represent the evaluation value for the specific assessment for the students of both grades. The numerical representation of the figure is given in Table 2. From this table, the proposed random forest algorithm showed fluctuating results in the learning process; however, it has shown steady and increased performance at the later stage. Towards the final considered evaluation weight range of 30–35, the proposed system has outperformed by 6%, 5%, and 16% the existing support vector machine, fuzzy set based on hesitation, and expert score, respectively.

Figure 4 depicts the results of the physical education teaching and learning process conducted on students of various grades. Students are encouraged to practice regularly to be eligible for contests in any sport. The analysis is carried out on people of four categories: normal people, major, junior, and senior ranges, using sports items, competition, and practice as criteria (see picture above). All the necessary equipment for practicing and participating in any specific activity is included in the sports item. In this research, it is
imagined that the player is equipped with all the required resources. Among the four categories of persons, the normal person without prior practice was able to achieve only 15% in the competition besides the availability of all the required resources. However, persons under the major, junior, and senior categories are given an increased performance of 23%, 35%, and 43%, respectively.

The graph above in Figure 5 shows that exercise is mandatory to perform any sport, and learning them through a coach also plays a very crucial role. In this graph, the number of indicators or the exercises increases with alterations, and the computation time or the player’s duration of achievement varies. Initially, every individual will take maximum duration for simple and fewer

| 4th- and 8th-grade evaluation weight | Random forest algorithm (%) | Support vector machine (%) | Fuzzy set based on hesitation (%) |
|-------------------------------------|-----------------------------|----------------------------|----------------------------------|
| 38                                 | 83                          | 85                         | 93                               |
| 40                                 | 84                          | 83                         | 96                               |
| 42                                 | 85                          | 79                         | 83                               |
| 44                                 | 88                          | 90                         | 85                               |
| 46                                 | 95                          | 93                         | 91                               |
| 48                                 | 97                          | 95                         | 84                               |
| 50                                 | 98                          | 89                         | 81                               |
exercises. As the players perform exercises and practice regularly, the duration of computation will get reduced.

4. Conclusion and Future Work

The field of education is important and has had a big impact on numerous civilizations. Determining the quality of physical education teaching is a critical strategy for improving the physical education teaching system. The random forest model was employed to assess the effects of physical activity in this study. This study helps to enhance the intelligent system which will empower the entire physical educational sector. The enhanced random forest algorithm is implemented for determining the efficiency of the system. The study results proved that the random forest algorithm performs better than existing algorithms. In future work, it is highly suggested to implement optimization machine learning methods to enhance the physical education system.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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