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RESEARCH ON PHYSICAL EDUCATION TEACHING IMPROVEMENT STRATEGIES AND ALGORITHMS BASED ON BIG DATA ANALYSIS

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Abstract. The study "Physical Education Teaching Improvement based on Deep Learning (PETDEL) which Combines Decision Tree with Fuzzy Level Algorithm" presents a novel method for improving teaching methods in physical education (PE) by involving advanced machine learning techniques. The novel framework PETDEL, which this study creates, combines fuzzy logic and decision trees to produce a strong model that can handle the difficult structures present in PE data. By defining exact pathways based on measurable data from physical education contexts, such as student attendance, performance indicators and exam outcomes, the decision tree algorithm helps structured decision-making. Similarly, the fuzzy logic feature provides variation and flexibility to the model by taking into consideration highly individualized and subjective variables, which may be difficult to accurately quantify, such effort and student involvement levels. With this combination, PETDEL is able to process and analyze large amounts of data collected in educational environments in an efficient manner, which results in more exact forecasts of student outcomes and more customized teaching approaches. Because of its ability to combine and analyze both clear and fuzzy data, the system is very good at giving useful information that can guide changes to programs and instructional strategies. The findings of the experiments show that PETDEL delivers notable increases in the variation of teaching approaches and greatly improves the prediction accuracy of student performance, both of which have a favorable impact on the overall quality of physical education. This research proves that physical education may be more responsive to the varied requirements of students by paving the path for more advanced instructional tools and improving teaching methods through data-driven insights.

Key words: Physical Education, Deep Learning, Decision Tree, Fuzzy Logic, Big Data, Student Performance, Teaching Strategies, Machine Learning

1. Introduction.

1.1. Physical Education Teaching Improvement Strategies. In recent years, there has been a substantial evolution in the teaching and improvement techniques of PE, with a growing focus on specific methods that address the various requirements of learners [6, 20, 15]. Using technology to monitor and evaluate student performance and health parameters in real-time such as through interactive software and wearable fitness devices is one of the key methods. Personalized workout plans that take into account each student's unique talents and goals may be created with the help of this data-driven approach, which improves engagement and results. In addition, modern PE programs are going beyond traditional sports to include things like yoga, dance and adventure sports, which support student's lifetime fitness habits and support a variety of interests[13, 17]. The professional development of PE teachers through workshops and ongoing education, providing them with the newest teaching methods and technology resources, is another essential improvement option. By addressing children with special needs and diverse learning preferences, this training assists educators in implementing education approaches in an efficient manner. Through team sports and cooperative games, focus is also placed on the development of social skills and emotional resilience, which are essential elements of a well-rounded education [10]. Additionally, it is becoming more increasingly observed that student and parent feedback channels are important for improving PE planning and instructional strategies, this fosters a more dynamic and responsive physical education environment by assisting in the ongoing adaptation and improvement of the educational experience to meet changing student expectations and educational standards.

1.2. Traditional Techniques Limitations. Traditional PE systems usually has a number of problems that can reduce student involvement and impair the efficacy of instruction. PE programs have traditionally placed a high value on standardized fitness exams and competitive sports, which may not be appropriate for all students' interests and can cause dissatisfaction among students who perform poorly in traditional athletics[8].

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This one-size-fits-all method ignores the unique requirements and possibilities of every student, including those who are more suited for varying physical capabilities. Furthermore, the quantitative metrics that are often the focus of traditional PE assessments such as the variety of seated poses recorded or the time recorded in races may not adequately represent a student's overall physical development[2, 16]. Furthermore, these systems commonly lack the adaptability needed to involve new technologies that may improve engagement and learning through adapted and interactive experiences. Furthermore, children' complete growth suffers by the traditional programs limiting focus on physical activities that address psychological, social and emotional development components[1]. Consequently, these conventional physical education programs may not be able to inspire students to follow a lifetime of physical activity and to lead healthy lifestyles, which will ultimately affect the overall educational goals.

1.3. Machine Learning Techniques and its Advantages Now a Days. In the field of PE, machine learning techniques provide benefits that allow for a more individualized, data-driven approach to teaching and learning[11]. Teachers can identify patterns and trends that are not immediately obvious by using these strategies to examine large volumes of data from student activities and performance. Machine learning, for example, might assist in predicting which students might find it difficult to engage in a given physical activity, allowing for protective intervention to provide extra support[18]. In order to increase engagement and efficacy, it can also modify exercise programs to meet the needs of specific students based on their performance metrics, health information, and personal preferences. Moreover, machine learning algorithms have the ability to automate the process of tracking and evaluating student progress, giving teachers accurate, useful feedback that is typically necessary[22]. This feature not only saves time but also improves evaluation accuracy, resulting in assessments that are more impartial and objective. Furthermore, based on continuous data from student activities, machine learning can allow dynamic real-time modifications to training programs and teaching methods[9]. By being responsive, physical education programs can effectively support students' total physical welfare and establish a lifelong habit of physical activity and health awareness.

1.4. Proposed PETDEL and its advantages. Considering advantages and impacts of the previous techniques and technologies, the proposed study introduced the novel approach called PETDEL. Decision trees and fuzzy logic are combined in PETDEL to produce a strong model that can handle the complexity of PE data [5, 4]. By setting out distinct pathways based on quantifiable data, such as student attendance and performance markers, decision trees facilitate systematic decision-making. Fuzzy logic, on the other hand, provides flexibility by through taking along random variables like student effort and involvement levels, which can be difficult to measure accurately. Because of this special fusion ability, PETDEL can handle big datasets quickly, leading to more precise predictions of student outcomes and individualized teaching strategies. Furthermore, PETDEL is an expert in analyzing data that is both clear and fuzzy, providing detailed evaluation that can inform program modifications and instructional methods. According to experimental findings, PETDEL considerably broadens the range of instructional strategies and improves student performance prediction accuracy, which eventually raises the standard of physical education as a whole. In order to address the varied requirements of students in physical education settings, this research emphasizes the possibility for advanced instructional tools and data-driven insights.

Numerous activities in physical education provide complicated data, including qualitative elements like student effort and involvement as well as quantitative ones like exam results and attendance. This complexity is frequently too much for traditional analytical tools to handle, especially when it comes to integrating and making sense of both organized and unstructured data sources. Better Decision-Making Is Necessary: In physical education, choices about curriculum modifications and instructional strategies are crucial, but they're frequently made without the backing of solid data analysis. Structured decision-making that can make use of tangible data to optimize and inform instructional techniques is desperately needed.

2. Related Work. This paper[21] presents the iSAES-DL system, which uses deep learning to monitor students in physical education. Convolutional neural networks (CNN) are used to categorize harmful behaviors, providing insights into student learning and recommendations for improvements. The study focus how learning analytics systems in physical education can be improved by using deep learning algorithms and Internet of Things devices (IoT). This article[7], which focuses on college physical education, suggests a deep learning-

Table 2.1: Techniques and Results of Previous Studies

Source	Techniques Used	Results	Need for Improvement
[21]	Deep Learning, CNNs, IoT	Improved student monitoring, Risky action classification	Further validation in real-world settings
[7]	Deep Learning, Neural Networks	Analysis of practical training, Innovation paths	Evaluation of scalability and applicability
[19]	Deep Learning, Yolo Algorithm, U-Net	Foul recognition, Real-time coaching assistance	Evaluation in diverse race-walking scenarios
[12]	Deep Learning, Human Center of Gravity Calculation, ALSTM-LSTM Model	Improved sports teaching analysis	Validation in larger-scale studies
[14]	Adaptive Genetic Algorithm, AGA-BP Model	Improved physical education evaluation	Exploration of long-term impact and scalability

based educational system reform and an analysis of practical training features. It finds and analyzes training characteristics and innovation paths in education systems using deep learning algorithms and neural networks. This work [19] presents a deep learning based foul recognition technique to address the technical issues in race walking. To help coaches make real-time training modifications, it employs a U-Net network with attention mechanisms to identify fouls and the Yolo algorithm for preprocessing. This research[12] explores the use of deep learning techniques to improve physical education instruction in colleges and universities. Using deep learning for position estimate and human center of gravity computation, it outperforms conventional methods in sports instructional movement analysis. This study [14] uses the AGA-BP model to assess physical education quality by using an adaptive evolutionary algorithm. Through the use of an adaptive evolutionary algorithm to improve a BP neural network and entropy measurement, it reveals notable gains in students' levels of physical activity following reform.

Table 2.1 Presents the techniques of the above studies and its improvement and drawbacks

Effective integration of different types of data is a common shortcoming of traditional educational approaches. For example, disparate processing of quantitative data, like exam results, and qualitative assessments, like student involvement levels, results in fragmented insights. This fragmented approach may make it difficult for teachers to have a comprehensive grasp of the requirements of their students.

The strict, rule-based decision-making procedures that are commonly used in educational institutions today typically fail to take into consideration the subtleties and variations that exist in student data. This inflexibility may result in less-than-ideal teaching methods that don't address the unique demands of each pupil.

3. Methodology.

3.1. Method Outline. To improve the efficacy of instruction in physical education, fuzzy logic and decision trees are combined into the proposed PETDEL architecture. The decision tree component of this creative framework is the first step in creating distinct pathways based on quantifiable data, such as exam results, performance indicators and student attendance. It does this by using structured decision-making. These data segmentation trees efficiently enable focused interventions and individual instructional approaches. In addition to the decision tree, the fuzzy logic component adds flexibility and adaptability of aspects like student effort and engagement levels that are harder to measure and less quantifiable. With the use of this dual approach, PETDEL can effectively handle both confusing and cut down data, producing more accurate predictions of student outcomes. Through the processing of vast amounts of data gathered from educational settings, PETDEL is able to modify teaching strategies in real time, increasing the variety of instructional approaches and raising the accuracy of student performance predictions. Overall, the design promotes an optimal learning environment in physical education by supporting an engaging environment in which decisions are based on data and sensitive to the specific needs of each student. The proposed methodology outline is visually presented in Figure 3.1.

Careful data collection and preprocessing are required in the first phases of the ANN-RSO process since they

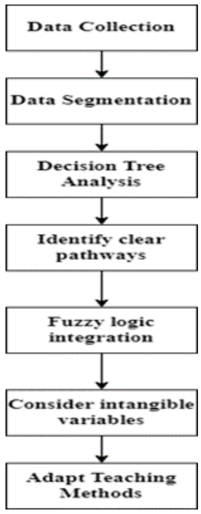

Fig. 3.1: Proposed PETDEL Outline

are essential for the analysis that follows. Through the collection of several types of data, such as structural measurements, material attributes, historical context, and visual documentation, the model guarantees an extensive dataset that accurately represents the complex nature of architectural history. Standardization and normalization are two preparatory techniques that convert this heterogeneous input into a format that is ideal for neural network computation. This guarantees consistency between various forms of information and improves the quality of the data, both of which are critical for precise analysis.

3.2. Decision Tree Analysis. The decision tree technique is widely used in data analysis and mining applications due to its ability to handle high-dimensional data and the fact that its creation does not need domain knowledge, making it ideal for exploratory knowledge mining. The biggest benefit of decision trees, among many other data mining and statistical analysis algorithms, is that they generate a set of rules from root to branch (or leaf), which analysts and business staff can readily comprehend. Furthermore, these general guidelines which include ready-to-use business optimization approaches and strategies even need to be somewhat sorted out. Moreover, decision tree technology is highly adaptive to data distribution and even a lack of data and is not easily hitted by extreme values.

The biggest information gain rate attribute is chosen as the splitting attribute to build branches using the fundamentals of the decision tree method. The algorithm is then called repeatedly for each branch until it is unable to divide any more branches. This can be expressed as

$$(GR\ (A) = \frac{G(A)}{Split\ I(A)} \tag{3.1}$$

The information gain of attribute A is represented by the formula above as $G(A)$, which may be computed using the decision tree algorithm's information gain. Split information is denoted by $Sp\ _tI(A)$. And the calculation of $Sp\ _tI(A)$ is expressed as follows

$$Sp\ _tI(A) = (D) = -\sum_{j=1}^{v} \frac{|E_r|}{D} \times log_2\left(\frac{|E_r|}{D}\right) \tag{3.2}$$

A training dataset Ci $(i = 1, 2, ...m)$ has m classes in D.If D is divided into v subsets, $\{E_1, E_2, ..E_v\}$, and A is a split attribute with v values $v_1, v_2, ..v_v$ if the number of tuples in subset E_r that belong to class Ci is $|E_r|$, then the probability pi that belongs to class Ci is $|E_r|/|D|$.

For training sample, the error between the actual and expected output is expressed as

$$err = \frac{1}{2}\sum_{k=1}^{c}\left(t_k - o_k\right)^2 \tag{3.3}$$

Here c is the number of output where t_k is the expected output and o_k is the actual output.

Let S be a set of s data samples, the class attribute contains m distinct classes Ci, and si is the number of samples in the Ci class. The following expression provides the information entropy needed to classify a given sample

$$I\left(s_1, s_2, \ldots s_m\right) = -\sum_{i=1}^{m} pi\ log_2(pi) \tag{3.4}$$

The dataset is divided into subsets according to attribute values during the process, and each attribute's information entropy is calculated using

$$I\left(s_1, s_2, \ldots s_m\right) = \sum_{i=1}^{m} -pi\ log_2(pi) \tag{3.5}$$

S is divided into v subsets $\{s_1, s_2, \ldots s_v\}$, where s_j comprises the data samples whose attribute A in set S takes a_j L value. This is the case if A is chosen as the test attribute and there are v values $\{a_1, a_2, ..a_v\}$. To partition the current sample set by attribute A, one uses the information entropy necessary, assuming that Sij is the number of samples in subset Sj that correspond to category Ci.

$$E\left(A\right) = \sum_{j=1}^{v} \frac{s_{1j} + s_{2j} + \cdots + s_{mj}}{s} \times I(s_{1j}, s_{2j}, ..s_{mj}) = -\sum_{j=i}^{v}\sum_{i=1}^{m} \frac{s_{1j} + s_{2j} + \cdots + s_{mj}}{s} \tag{3.6}$$

It calculates the information gain obtained by portioning the dataset based on the current attribute which is used to compute the gain.

$$G\left(A\right) = I\left(s_1, s_2, \ldots s_m\right) - E(A) \tag{3.7}$$

Limit theory understanding shows that when $0 \leq x \leq 1$, n goes to ∞. The previous formula's output after the third term will also get smaller as the power degree increases. The latter terms are roughly 0 when compared to the first two terms, and the final function $F(X)$ is reduced to

$$In\left(1 + X\right) = X - \frac{X^2}{2} \tag{3.8}$$

The calculation of information entropy is expressed as

$$I\left(s_1, s_2, \ldots s_m\right) = -\sum_{i=1}^{n} -pi\ log_2\ pi = -\sum_{i=1}^{n} \frac{s_i}{s}\ \log_2\ \frac{s_i}{s} \tag{3.9}$$

The above formulae is simplified into

$$I\left(s_1, s_2, \ldots s_m\right) = \sum_{i=1}^{n} \frac{s_i}{s}\ \log_2\ \left(1 + \left(\frac{s - s_i}{s}\right)\right) \tag{3.10}$$

While updating statistical data, the decision tree algorithm inserts training samples from the root node to the relevant leaf node. In the event that every sample that arrives is of the same class, the leaf node splits, and the number of decision attributes defines how many new leaf nodes are added. Through this method, decisions are made within the PETDEL framework in an efficient and effective manner, improving physical education teaching strategies through data analysis.

Structured decision-making based on measurable data, such as exam results, performance indicators, and student attendance, is made possible by the PETDEL framework's integration of decision trees. This methodical approach facilitates the development of focused interventions and defined routes, allowing teachers to modify their lesson plans to better suit the individual requirements of their pupils. Fuzzy logic adds the flexibility needed to manage more arbitrary components, such as student effort and engagement, which are important but more difficult to gauge. This two-pronged strategy guarantees that choices are informed by data and flexible enough to take into account the unique circumstances of each student.

3.3. Fuzzy Level Algorithm.

Step 1. Start by using the appropriate vector table activities py to calculate the cognitive function $s(py)$. Based on their participation in a variety of activities, this function represents the cognitive ability of learners.

$$s\left(py\right)=\frac{vpy\ \left(1\right)}{vpy\ \left(1\right)+vpy\ \left(-1\right)} \tag{3.11}$$

Step 2. The usage vector S, which has values between 0 and 1 and represents the extent to which learners use various activities, can be derived using the computed cognitive function.

$$S=\left(s_1,s_2,..,s_n\right)\in\left(0,1\right) \tag{3.12}$$

Step 3. Create a correct rate vector to represent the assessment accuracy. The values in this vector, which range from 0 to 1, show how accurate the evaluation results were, which is expressed as

$$S=\left\{\frac{2/3}{2,1/2},1,0,1\right\} \tag{3.13}$$

Step 4. To indicate the relevant range to apply, divide area M into fuzzy subsets that correspond to student performance ratings, such as "great," "good," and "bad." The "good" fuzzy subset's membership feature Mw(m) should be computed.

$$m_w\left(m\right)=\begin{cases}\frac{1}{1+m/0.14},\ m>0,\\ \quad 0,else\end{cases} \tag{3.14}$$

Step 5. Using the suitable utilization vector, verify the sub-cognitive abilities' participation rating. In this stage, the relative value of various activities for cognitive growth is weighted.

$$w=\left\{w_1,w_2,\ldots,w_n\right\}\in\left(0,1\right) \tag{3.15}$$

Step 6. Create an evaluation matrix (HM) that includes a number of assessment vectors for different types of activities. Every row in the matrix represents an evaluation vector for a set of questions, illustrating the many functions that various activities perform, the HM matrix are expressed as

$$HM=\begin{bmatrix} w11 & w12 & \cdots & w1n\\ w21 & w22 & \cdots & w2n\\ \vdots & \vdots & \vdots & \vdots\\ wp1 & wp2 & \cdots & wpn\end{bmatrix} \tag{3.16}$$

Step 7. Present a weight matrix B, in which each entry bi denotes the weight of a certain task. Make sure that the weight matrix's total element count is always one.

$$B=\left\{b_1,b_2,\ldots b_p\right\}and\ \sum_{y=0}^{p}b_y=1 \tag{3.17}$$

Step 8. Make use of the weighted mean approach to provide a thorough evaluation of a vector that represents learning ability. The weights given to various activities and their contributions to overall learning outcomes are taken into account in this stage.

$$k = B \times HM = \{k_1, k_2, \dots k_n\} \tag{3.18}$$

Step 9. Map test results, age, the effectiveness of learning, psychological conditions, and other input variables to output values that indicate learners' mastery of concepts, abilities, and application. A multimodal network that nonlinearly converts input data into output values achieved by this mapping.

$$o_t = \{grade\ k_1, k_2, \dots k_n, w_1, w_2, \dots w_n\} \tag{3.19}$$

$$c = \{c1, c2, c3\} \tag{3.20}$$

The process is started in Step 1 by computing a cognitive function that is dependent on engagement in different activities. This approach offers a mathematical foundation for dynamically measuring cognitive ability while taking learners' involvement variation into account. More individualized educational interventions are made possible by ensuring that cognitive evaluations are based on real, quantifiable participation metrics. The second step is to derive a usage vector that illustrates how much each activity is used by students. Teachers can better determine which activities are most engaging students and how those activities affect learning outcomes thanks to this level of detail. It makes it easier to identify highly productive activities, which allows for more focused enhancements to instructional strategies and material.

In order to provide a more accurate measure of student performance and guarantee that assessments accurately reflect the capacities of learners, this method recognizes and accounts for the variability in assessment accuracy. By segmenting the evaluation area into fuzzy subgroups that correlate to varying performance scores. The small differences in student performance are accommodated by this fuzzy classification, which permits nuanced interpretations of performance levels beyond conventional binary or rigid categorizations. Weighing the relative importance of different activities for cognitive growth is the main emphasis. This stage helps improve resource allocation and instructional emphasis by selecting activities based on their educational benefit, ensuring that the most beneficial activities are prioritized within the learning environment.

4. Results and Experiments.

4.1. Simulation Setup. The dataset used to evaluate the proposed PETDEL is adapted from the source[3], we extract only the valid data features for proceed the evaluation which is clearly presented in Table 4.1.

4.2. Evaluation Criteria. By comparing physical test results between the experimental group, which received advanced teaching techniques with a smart sports platform, and the control group, which received conventional teaching techniques, Figure 4.1 illustrates the effectiveness of the suggested PETDEL method. Figure shows that the experimental group beats the control group in every physical performance show that was tested, including strength, flexibility, and endurance. In particular, the experimental group outperforms the control group in endurance, scoring 75.74 as opposed to 65.63. Strength is another area where this pattern is evident, with the experimental group scoring 80.25 points, much higher than the control group's 70.89. This pattern is also shown in flexibility, with the experimental group scoring 78.94 points compared to the control group's 68.47. These findings highlight the benefits of the PETDEL strategy and imply that incorporating technology-enhanced and data-driven physical education techniques can greatly improve student performance. The increases in all of these variables point to a rise in physical prowess as well as possible gains in student motivation and engagement, two important aspects that make physical education programs successful in the long run.

The suggested PETDEL approach's efficacy is clearly shown by Figure 4.2 that compares the experimental and control groups' final test results. Across the three academic assessments, the experimental group consistently outperformed the control group due to the combination of innovative teaching methods and technology-based improvements into the physical education syllabus. With marks of 88.24, 91.86, and 89.21, the experimental group's scores show a consistent high performance, showing not just a gain in physical capabilities but

Table 4.1: Dataset Features

Feature	**Description**
Experimental Group	Group receiving experimental teaching, combining traditional methods with a smart sports platform
Control Group	Group receiving traditional teaching methods as per college syllabus
Experimental Teaching Hours	Total hours of experimental teaching provided to the experimental group (36 hours)
Number of Experimental Subjects	Total number of subjects in the experimental group (160 subjects)
Comparison of Physical Test Data	Evaluation of physical performance measures between experimental and control groups
Comparison of Final Test Results	Evaluation of academic outcomes between experimental and control groups
Comparison of Exercise Attitudes	Evaluation of attitudes towards physical exercise between experimental and control groups
Evaluation Criteria	Criteria divided into five dimensions: very reasonable, relatively reasonable, general, unreasonable, very unreasonable
Expert Evaluation of Questionnaire	Evaluation of teacher questionnaire by 10 experts: 6 experts found it generally reasonable, 4 experts found it more reasonable
Reliability Testing	Test-retest method used for reliability testing of the questionnaire, involving 15 physical education teachers
Correlation Coefficient	Correlation coefficient of the questionnaire, showing high reliability 0.88 and statistical significance ($P < 0.05$)

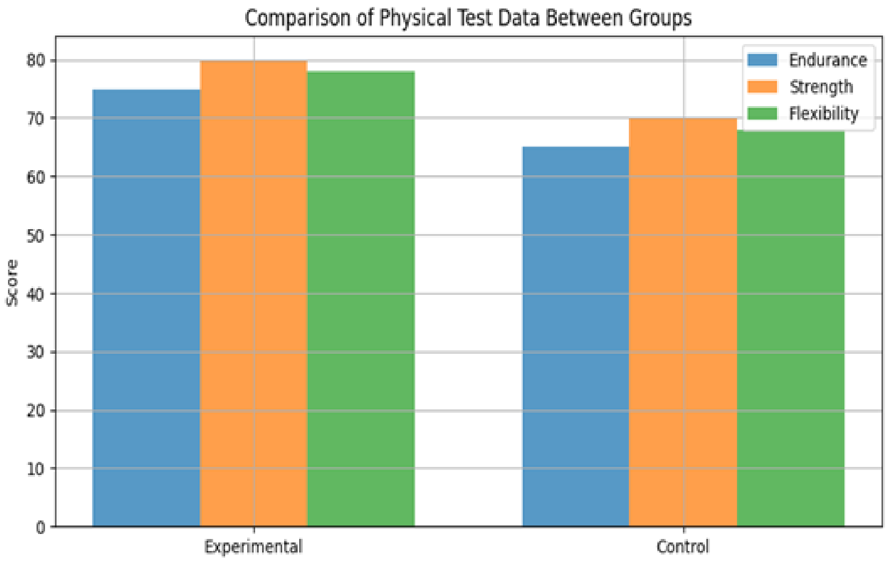

Fig. 4.1: Physical Test data Results

also increased understanding and memory of physical education ideas. The control group's ratings, which were 71.99, 75.76, and 70.48, demonstrated a more conventional and ineffective teaching approach, even though they did gradually improve. This pattern highlights the effectiveness of the PETDEL approach is in producing improved academic results, which are probably the result of more individualized and engaging teaching strategies that inspire students to perform better. The figure visual trend shows the technology and data-driven training

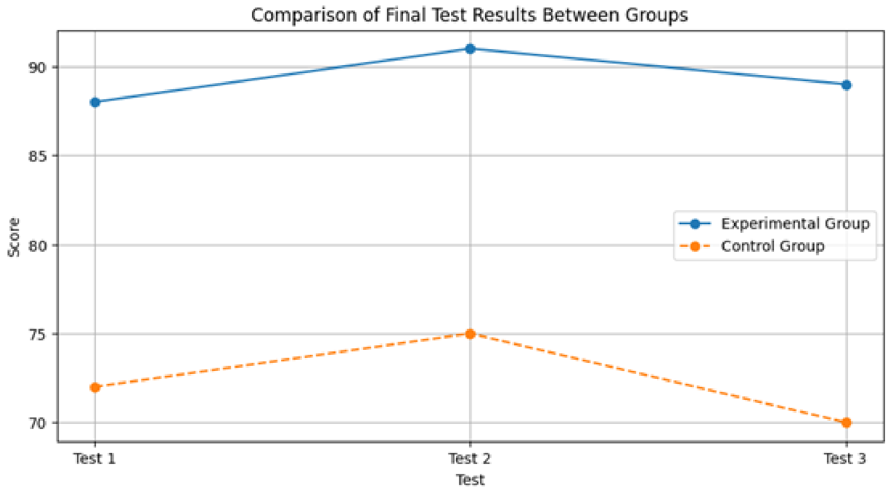

Fig. 4.2: Final test results comparison

can result in better learning experiences and outcomes, confirming the PETDEL's ability to significantly and sustainably alter physical education teaching methods.

Figure 4.3 shows the result on exercise attitudes clearly displays the efficacy of the proposed PETDEL strategy in influencing students' attitudes towards physical exercise. Regarding the figure, the experimental group (85.21%) has a significantly higher percentage of positive attitudes than the control group (65.23%), which was not showing to the innovative teaching methods that included technology and personalized strategies. This suggests that the PETDEL technique has a major impact on establishing a more favorable view towards physical education among students. Next, the experimental group had a lower percentage of neutral (10%) and negative attitudes (5%) than the control group, highlighting the novel teaching approaches' beneficial psychological and motivational impacts. The control group, on the other hand, used conventional teaching methods and had a higher incidence of neutral (25%) and negative attitudes (10%), which suggests poorer motivating impact and less engagement. This shows the PETDEL framework's integration of data-driven insights advanced teaching tools not only improves students' physical performance but also dramatically improves their attitudes toward exercise, which are critical for fostering long-term healthy behaviors and a supportive learning environment.

5. Conclusion. The proposed study is a novel approach which investigates about the physical education teaching improvement strategies based on big data. By combining the advanced machine learning algorithms, we introduce the novel approach called PETDEL a unique technique which combines decision tree and fuzzy logic to obtain the better result in PE improvement. Here the decision tree algorithm helps for structured decision making, at the same time fuzzy logic is used to provides variations and flexibility to the model. By combining these two strengths the proposed model achieves the ability of expected improvement in PE teaching and training. Regarding simulations the datasets are split in two groups experimental group and control group, by using the proposed model the experimental group achieves the expected improvements than the control group which uses the traditional methods. Overall, the proposed model sets a new way in the domain of physical education domain by using the advanced technologies to achieves the expected development not only the present but in future. Subsequent studies can concentrate on enhancing PETDEL's algorithms to increase processing speed and computational efficiency. In order to handle larger datasets more efficiently, fuzzy logic techniques and decision tree structures must be improved. Improving the decision tree forecasts' and fuzzy logic interpretations' accuracy will help to increase the system's dependability.

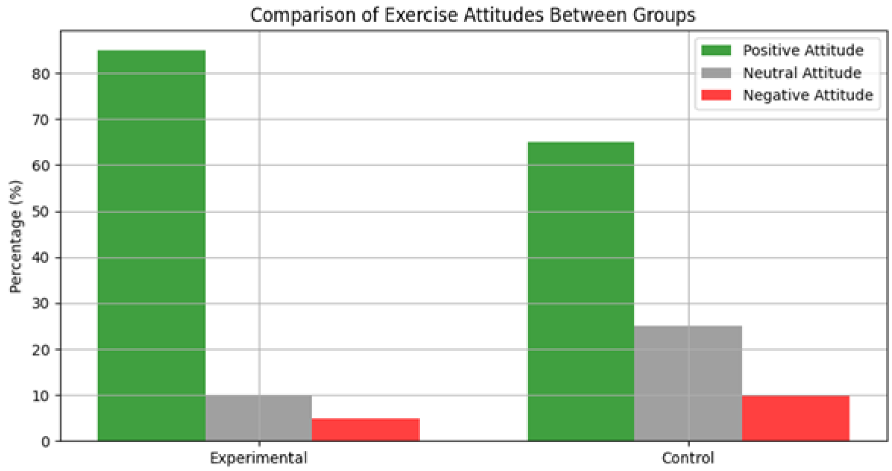

Fig. 4.3: Exercise Attitudes

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